An Operations-Structured Model for Strategic Prediction of Airport Arrival Rate and Departure Rate Futures

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Motivated by needs in strategic Air Traffic Flow Management, we propose a model for forecasting airport arrival and departure capacity over a full-day look-ahead horizon. The focus of the modeling effort is on a small set of high-congestion airports, for which we propose a multi-stage prediction model. In this article, a core piece of the model – an operations-driven prediction for airport runway configurations and baseline capacities in terms of weather and operational regressor – is developed. We demonstrate the model’s performance through case studies for two high-congestion airports, Chicago O’Hare International Airport (KORD) and Boston Logan International Airport (KBOS).

I. Introduction

The Next Generation Air Transportation System (NextGen) requires strategic decision-making capabilities that facilitate allocation of traffic management initiatives (TMIs) across the United States National Airspace System (NAS) over a full-day look-ahead horizon. In recent years, several promising concepts and methodologies for such strategic traffic management have been advanced, including our team’s flow contingency management (FCM) solution\(^1,2\). The tools being developed for strategic full-day traffic management, including the FCM solution, crucially require forecasts of aviation weather (winds, convective weather, snow, etc) and their impact on NAS capacities (including en-route and terminal area capacities). At the strategic look-ahead horizon, these weather phenomena and their impacts are often subject to significant uncertainty, which may influence the design of traffic management plans. As such, forecasts are needed that acknowledge possible uncertainty in weather and impact futures. One means for developing forecasts under uncertainty, which we have adopted within the FCM solution, is to generate representative probabilistic futures or scenarios of weather impact on sector capacities and airport arrival and departure rates (AARs and ADRs), over a full day forecast horizon.

Several recent studies have introduced promising techniques for forecasting weather impacts and generating impact scenarios\(^3-5\), however many challenges remain in developing and validating useful and accurate models. The research presented here is focused particularly on the problem of forecasting airport-capacity futures at a strategic horizon under weather uncertainty. Prediction of airport capacity (including airport arrival rates or AARs, and airport departure rates or ADRs) at look-ahead times (LATs) of up to six hours has been thoroughly studied\(^6\). Other studies in the literature are focused on specific terminals\(^7\), and are not flexible enough for a NAS-wide scaling. Fewer results are available for AAR and ADR prediction at a full-day look-ahead, as is needed for strategic traffic management. Very recently, several groups (including our team) have pursued strategic AAR forecasting, in particular seeking methods for generating probabilistic futures of AAR\(^8-10\). These efforts have represented the dependence of AAR on terminal-area weather conditions (e.g., wind, ceilings, presence of convective weather) using highly-abstracted (black-box-type) models, and have sought to parameterize these models from historical data. While these black-box approaches are appealing because of their simplicity, there is a concern that the models do

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not capture airport operations in sufficient detail for effective prediction, especially during crucial off-nominal conditions occurring at larger airports.

In this paper, we discuss an alternate operationally-driven approach for modeling the dependence of airport capacities on weather conditions (and other regressors), as well as its application in generating probabilistic capacity futures. In contrast with the black-box models, here we pursue a multi-stage modeling framework that distinguishes high- and low- congestion airports, and then applies an operationally-based procedure to predict capacities at the high-congestion airports. For the high-congestion airports, we first pursue forecasting of runway configurations based on operational rules (which depend on winds and meteorological conditions) to obtain nominal AAR and ADR values. These nominal values are then scaled further in extreme low-visibility circumstances, and to reflect convective-weather impact. In this article, following a conceptual discussion of the multi-stage modeling framework, we focus primarily on presenting the runway-configuration prediction model, and demonstrate the model’s performance for two high-congestion airports, KORD and KBOS. We note that this structured modeling approach also has the benefit of modularity: as improved predictors are obtained for model stages or regressors, the model can be readily updated.

The rest of the article is organized as follows. In Section II, we present our modeling framework. Section III discusses the operation-structured prediction model for deriving runway configurations and nominal capacities from Meteorological Conditions (MC) and wind forecasts. Our discussion of the model also includes a brief review of current literature on runway configuration prediction (Section III-A). We present the case studies for KBOS and KORD in Section IV. In Section V we discuss possible methods to integrate the model into the FCM framework. We conclude and discuss further work in Section VI.

II. Multi-Stage Modeling Framework

Our multi-stage modeling framework for airport capacity prediction depends on an understanding of the multi-time-scale operational procedures used at airports to manage traffic. The operational procedures that are common to most airports are diagrammed in Figure 1. The shaded boxes describe the various actions taken by airport managers at different time-scales, while the un-shaded boxes represent the environmental and operational factors that may affect the airport managers’ actions. The solid arrows represent factors that have a direct bearing on the operational procedure at a given time-scale, while dashed arrows are factors that may have been taken into account by managers during decision-making. As shown in Figure 1, the operations can be classified in three main categories:

1. Selection of runway configuration based on forecasts for the terminal wind and weather conditions, as well as other factors such as demand, time-of-day, etc. This is usually done at a strategic LAT (multiple hour to a day ahead), and may have a significant impact on AAR/ADR.
2. Tactical Terminal Radar Approach Control (TRACON) operations, which are concerned with spacing and scheduling of traffic, are primarily determined by prevailing runway configurations, visibility, ceiling, and MCs. Wind conditions have some degree of influence on these tactical operations. Typically, changes in tactical operations will have a more moderate impact on AAR and ADR.
3. Tactical airport operations, which are concerned with immediate (within minutes) modification of traffic patterns due to convective weather (and other severe weather). These weather events may require drastic modification of operational procedures at short time scales (e.g., airport closure or exclusion of departure/arrival streams), which may result in a significant reduction in airport capacities.

The model that we propose here distinguishes these stages in runway operations with the aim of developing a predictive yet still easy-to-use model.

A. Proposed Model

Our proposed method for AAR and ADR forecasting accounts for the environmental and operational regressors shown in Figure 1, while leveraging knowledge about the relationship between these regressors and AAR/ADR. It is worth stressing that we seek a parsimonious model, in the sense that the mapping between regressors and hourly capacity is represented with only as much detail as is needed for strategic forecasting and operational planning.

The proposed model distinguishes airports by congestion level. Only a relatively small number of major airports are congested enough that routine environmental variations (elevated directional winds, stratus) can frequently

†† Capacity at each hour is the sum of AAR and ADR for the hour.
constrain flow. These highly-congested airports are a subset of the Operational Evolution Partnership (OEP) 35 airports, perhaps 10-15 in total. Our approach for AAR and ADR forecasting distinguishes these high-congestion airports from other airports, which primarily constrain traffic flows only during severe weather events (primarily convective weather, possibly also winter weather). Specifically, for each low-congestion airport, we model the AAR and ADR as being maintained at nominal level, and only being subject to reduction due to convective weather impact. Meanwhile, for the high-congestion airports, forecasts for local environmental conditions (wind, ceilings) need to be used to identify the AAR and ADR, which reflect both runway configuration selection and subsequent capacity reduction due to poor meteorological conditions. For both the congested and non-congested airports, capacity reduction due to convective weather is modeled as an overlaid capacity reduction. We are developing the model according to the following procedure:

Step 1) Distinguishing High-Congestion and Low-Congestion Airports. An initial list of high-congestion airports, i.e. airports for which routine environmental variations constrain flow, has been determined from experience (the airports in the New York and Washington DC TRACONs, the Chicago-area airports, SFO, ATL, KDTW, KDFW, and KBOS). A more systematic approach is also being pursued: the fraction of time that each airport is near capacity is being determined from historical data; airports that are most frequently near capacity can be chosen as high-congestion ones.

Step 2) Modeling Nominal Capacity for the Low-Congestion Airports. For each low-congestion airport, the VMC AAR and ADR for the most-frequently-used runway configuration are being used as nominal capacities. We are also pursuing development of a slightly more sophisticated model, wherein the most-frequently-used configuration for each hour of the day is used to determine the AARs and ADRs for that hour. By doing so, we expect to roughly account for the tradeoff between arrival and departure traffic for typical flow patterns, and for the variability in runway operation due to demand, staffing, etc.

Step 3) Modeling Baseline Capacity for the High-Congestion Airports. For the high-congestion airports, the impact of routine terminal-area weather (winds, ceilings) as well as operational factors (demand, staffing) needs to be captured in the model. These factors are viewed as governing choice of runway configuration and hence setting a baseline or nominal capacity, which can be further reduced due to meteorological conditions (visibility) and convective weather. We have developed a two-stage model for the mapping between these factors or regressors and the “Baseline Capacity” (Capacity prior to severe-weather reduction), for these airports. The first stage determines
the runway configuration in terms of (forecast) winds, MC, and operational factors. The runway configuration is then mapped to a baseline capacity based on the historically reported capacity under similar MC. In particular, we use average historical capacity as the baseline capacity for a runway configuration under a particular MC. This operation-structured prediction scheme for baseline capacity is the focus of this article.

**Step 4** Reduction from Baseline Capacity for High-Congestion Airports. Once the baseline capacity is determined, tables indicating the capacity reduction due to instrument meteorological conditions, such as low ceiling and visibility, can be used to estimate the reduction from baseline capacity.

**Step 5** Forecasting Capacity Reduction Due to Convective Weather. In our framework, severe weather impact (specifically, convective weather impact) is modeled as a probabilistic capacity-reduction overlay. Specifically, if an airport is affected by convective weather, its capacity (as determined in Step 2 or 3) is multiplied by a probabilistic reduction fraction to capture the impact. The reduction-fraction model is being developed from historical data: we refer the reader to our previous work for some preliminary results in this direction.

III. Prediction of Runway Configurations and Baseline Capacities

In this section, we describe a model for predicting baseline/nominal capacities from forecasts of terminal-area conditions. In particular, we present an approach for predicting the runway configuration that is most likely to be chosen given a combination of MC, wind speed and wind direction. The nominal capacity is then derived from this prediction of the configuration, as the average historical capacity for the configuration. The philosophy of the runway-configuration prediction model can be stated as follows: given a combination of MC, wind speed and wind direction, choose a configuration that is operationally viable, favorable to wind conditions, and has the best possible (highest) nominal capacity. We believe that, despite the wide range of operational protocols that are employed by airports to determine a configuration at the strategic time-frame, these three criteria are common to all airports and have the most impact on configuration selection.

We begin with a brief literature review on runway configuration prediction, and then introduce our model.

A. Literature on Runway Configuration Selection/Optimization

Existing literature for predicting runway configurations can be broadly classified into two groups. One group is focused on predicting configurations that are most likely to be chosen given a forecast for the operating conditions. The second group consists of decision-support tools to help airports choose an optimal runway configuration.

Most of existing literature on runway configuration prediction and design are airport-specific. Such airport-specific approaches are not ideal for FCM purposes that aim at designing Traffic Management Initiatives at a NAS-wide scale. Literature on generic approaches is limited. Several of these studies employ machine-learning and estimation theory-type methods to develop runway configuration predictions from predicted operating conditions. For example, Ramanujan et al. explore discrete-choice models to estimate the relationship between influencing factors (like terminal area weather and arrival/departure demand) and favorability of a particular runway configuration. The authors also compare the discrete-choice models with a Markovian transition process constructed from observed data. The discrete-choice model is a very good model for smaller time horizons (on the order of 3 hours). Similarly, Houston and Murphy have explored runway configuration prediction at JFK and LGA using a logistic regression. The Houston-Murphy approach permits longer-time horizon predictions, but does not account for operational specifics of airports in any direct way.

A different approach to the problem of predicting runway configuration from forecasted operating conditions (demand, time of day, ceiling, wind speed etc.) is studied by Ramamoorthy and Hunter. Specifically, the authors develop a deterministic as well as a probabilistic prediction model for runway configuration. In their approach, the forecasted winds, ceiling, etc are classified into discrete levels before being used as an input to the prediction models. The deterministic prediction model, which is a classification decision tree created from historical ASPM data, predicts the most likely configuration to be chosen while assuming that the snapshot forecasts of the operating conditions are accurate. The model does not account for uncertainties in the forecasts. The probabilistic prediction model, overcomes this limitation by predicting a Probability Mass Function (PMF) for all possible runway configurations for the given forecast. The PMF for the runway configuration is created from an empirical
conditional PMF created from historical Aviation System Performance Metrics (ASPM) data and the National Oceanic and Atmospheric Administration’s Localized Aviation MOS Program (LAMP) forecasts. The two models are tested for the 35 OEP airports over a 2-hour look-ahead horizon. The approaches discussed in this article, especially the probabilistic prediction model, may prove to be a good starting point for more sophisticated models for longer look-ahead times.

Among the tools that aim at finding the optimal runway configuration is NASA’s System Oriented Runway Management (SORM) initiative. SORM is a high-level management tool that takes a holistic approach towards developing runway management procedures at strategic and tactical time-frames. Reference [18] discusses some other aspects of planning various runway operations, including runway configuration selection, at a high level. Alternative approaches seek to maximize a throughput function for feasible runway configurations, while taking into account the uncertainty of forecasts. We stress the decision-support tools based on these approaches may not work well at strategic time horizon because of the large uncertainty in forecasts.

B. Methodology - Overview

Broadly our approach for predicting runway configuration is a mapping from a given combination of the MC, wind speed and wind direction to a particular runway configuration. In particular, each combination of the MC, wind speed and wind direction, which we refer to as inputs to the model, generates a particular runway configuration. The mapping is deterministic in nature. For a given input, the model selects a configuration that is:

1. Operational under the airport’s wind protocols (headwind and crosswind limits under the given MC);
2. Aligns traffic in a head wind direction;
3. Has been used frequently in the past;
4. Allows for high capacity.
5. Prefers persistence of runway configurations (limits configuration changes)

The first of these criteria directly encodes the operational protocol that any runway that is used for departures and arrivals must have both crosswind and tailwind components within certain limits. The second criterion is motivated by the well-known preference of pilots to operate in headwinds conditions, as opposed to cross- and tailwind conditions. We capture this preference using a pilot-reward function, which generates a ranked-list from the list of all historically employed configurations. Criteria 3 and 4 are then used to select candidates for the best runway configuration choice. Once a set of candidates is determined, the final modeling stage is to choose the best among the candidate as the prediction for the hour. It might seem tempting to select (among the candidates) the configuration that has the highest average historical capacity. However, we note that changing runway configurations at an airport is a fairly involved process and is usually done at intervals of at least 3 hours. Because of the complexity, operators prefer to maintain runway configurations for an extended period if possible. Any viable model for runway configuration prediction needs to account for this preference, which we refer to as memory in system (Criteria 5 above). In our model, we address this by comparing the prediction for the previous hour with the candidates for the current hour. If the previous hour’s prediction is among the candidates for the current hour, then the previous hour prediction is maintained for the current hour as well. Otherwise, the model predicts a change in configuration. This memory-inclusion step can be viewed as an acceptance of a slight deterioration in capacity for the tradeoff benefit of changing the configuration less frequently. Once a configuration is predicted for a given hour, we use the average historical capacity (respectively, AAR, ADR) under the input MC as the nominal capacity (respectively, AAR, ADR) for the hour. Let us now describe the configuration prediction model in detail.

C. Operations Structured Runway Configuration model

Our runway configuration model involves five stages, which are summarized in Figure 2. In this section, we describe the details for each stage.

Sorting of Historical Runway-Configuration Data: Airports largely follow different operational procedures for different weather conditions. Most significantly, prevailing MC conditions determine the allowable crosswind and tailwind conditions for traffic operations. With this motivation, we categorize the historical data into separate databases for each MC. Additionally, the databases include the number of times the configuration has been used in the historical data (or frequency) and the average capacity, for each MC. Figure 3 shows the most-frequently used configurations (as given by the percentage of total number of hours in our historical record) categorized by MC for ORD. We note that the historical data must have an equal or higher temporal resolution compared to the needed resolution for capacity prediction. In the discussion so far, we have assumed that capacity predictions are to be made

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at an hourly resolution, and therefore we need to use historical data with an hourly (or higher) resolution. We discuss various possible historical data sources in Section V.

**Checking Eligibility for each Hour:** Each runway has specific limits on the maximum allowed crosswinds and tailwinds for traffic operations. If a runway’s wind components violate any of these limits, the runway becomes inoperable under the given wind conditions. Further, the limits depend on the prevailing flight rules. Limits for visual flight rules typically are greater than those for instrument flight rules by a factor of three. Using the runway heading information and specific wind limits at the airport, the model determines the set of runways that are eligible for traffic operations. Based on runway eligibility, the model creates a sub-list of the eligible configurations. A configuration is said to be eligible if it does not contain any ineligible runways.

**Wind-based Reward Computation:** The previous stage provides us with a list of configurations that can be used under the given input MC and wind condition. Pilots prefer to operate in a relative head wind direction (i.e., to take off and land into the wind), since this reduces the runway length needed for takeoff/landing and increases stability. This step encodes this preference by using a trigonometric pilot-reward function. In particular, the pilot-reward for a configuration is given by

$$C = \sum_{\text{Rnwy } x \text{ in Conf.}} C_x$$

where,

$$C_x = \text{sgn}(HW_x) \left( \frac{HW_x^2}{CW_x^2 + HW_x^2} \right)$$

$HW_x$ and $CW_x$ are the headwind and crosswind (measured in knots) for runway $x$. A tailwind is the represented as negative headwind. The
notation $\text{sgn}(HW)$ indicates a standard signum operation on the headwind. Notice that the reward scheme gives preference to headwinds over crosswinds and tailwinds.

We remark here that other reward functions may also be used. In general, any reward function that promotes runways with headwinds over those with crosswinds and tailwinds is suitable for capturing the pilot preferences. In addition to the above reward function, we tested a reward scheme where, $C_x$ scales with wind speed. Our simulations did not show any significant difference in performance.

**Candidate Selection:** Once each configuration’s reward has been computed, a pre-specified number of configurations with the highest pilot-reward are extracted as a separate list. For each of these high-reward configurations $C$, the product $C_p = \text{freq} \times \text{avg. cap}$, where $\text{freq}$ is the number of times the configuration has been used in the historical data, and $\text{avg. cap}$ is the average capacity of the configuration in the historical data. The top five configurations based on the descending order of the products are selected as candidate configurations for the current hour. Our simulation indicated five candidates to be a reasonable choice. This number can be viewed, as the extent of memory in the process. Selecting a larger number effectively increases the chances of previous hour configuration to be used during the memory-inclusion step.

**Memory Inclusion:** Once a set of candidate configurations are selected, the model then compares whether the MC for the current hour is different from the previous hour. If the MC remains the same as the hour before, the model checks whether the predicted configuration for the previous hour is among the candidates for the current hour, in which case the previous hour’s prediction is continued as the prediction for the current hour. If the predicted configuration for the previous hour is not a candidate for the current hour, the model selects the configuration with highest $C_p$ as the prediction for the current hour. The nominal capacity for the hour is the corresponding average capacity for the selected configuration under the given MC. The corresponding average AAR and ADR are then used as predictions for the nominal AAR and ADR. Notice that our model changes a configuration when using the previous hour configuration under the current hour’s MC and wind conditions results in a significant reduction in total benefit. In our simulations, removing this final memory-inclusion step caused our runway-configuration predictions to fluctuate every hour in certain periods, and was not representative of actual airport operations. We view this final step as a stabilizing mechanism for runway configuration prediction over consecutive hours.

The model that we described here provides a prediction of the nominal capacities (and AARs and ADRs), for a given set of weather inputs. The selection of the runway configurations is based on highest total capacity. We note that if additional information is known as to how AAR compares to ADR, then the approach can be modified to select high AAR/ADR configurations. For example, if it is known that a particular hour generally has a AAR significantly greater than ADR, then one can modify the candidate selection step in our model to select configuration that allow the best possible AAR as opposed to best total capacity.

**IV. Case Studies: Model Performance for KORD and KBOS**

The runway configuration and nominal capacity model were developed for two high-congestion airports, KORD and KBOS. The historical data for both airports were collected from the Federal Aviation Administration’s Aviation System Performance Metrics (ASPM) database. In particular, hourly weather, runway configuration, and AAR/ADR reports were gathered for both airports for the period of April 1st, 2013 to September 30th, 2013. The data archives for building the model, as well as data for model characterization/validation, were derived from these ASPM reports. Since this study is focused on construction of the model rather than real-time operations, historical weather data rather than forecasts were used for model characterization and validation.

**Selection of Validation Days:** In order to validate the models’ performance we selected some representative days from the historical data as follows. First, the days with the most number of hours with severe weather impact were selected. Among the remaining days, a subset was chosen so that the relative distribution of the severe-, moderate- and no-impact- hours in the validation set as a whole was close to that in the full historical data set. We adopt this

\[ \text{sgn}(HW) \] 

\[ C_x \] 

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approach (as opposed to selecting validation days randomly from historical data) primarily because hours with severe weather events are comparatively rarer than hours with no weather events. On the other hand, achieving sufficient accuracy in our model’s performance for severe weather events is important to overall efficiency of FCM. Therefore, it is important to include some of severe weather days in the validation subset. Using this approach, we selected 15 validation days for KORD and 16 days for KBOS. The remainder of the data set, excluding the test days, was used to build the models as detailed above.

Runway Configuration Prediction Performance: In order to characterize the model’s performance in predicting runway configuration, we computed three statistics for every hour of prediction in the test data. The first statistic indicates the fraction of runways in the actual overall configuration that were predicted by our model. We also compare the fraction of arrival and departure runways, respectively, that were predicted by our model. For example, if our model predicts a configuration of “4L,4R|9” for KBOS for a particular hour, while “4L,4R|4L,4R,9” was actually used, then the fraction of the actual overall configuration that was predicted by our model is 0.6. The arrival and departure matching fractions are 1 and 0.33 respectively.

Figure 4 shows the model’s performance in predicting runway configurations at KBOS, while Figure 5 shows the model performance for KORD. Each figure presents histograms for the three performance statistics across the test data set. For KORD, the model has approximately a 70% success rate in predicting at least 80% of the total configurations, and 45% success rate for exact prediction. In other words, for about 250 hours of total 360 hours, 80% (or more) of the runways in the predicted configurations were actually used, while for 162 of the 360 hours, our prediction was exactly equal to the used configuration. In addition, our model achieves success rates of 70% and 45% in predicting individual arrival and departure configurations exactly. The performance is much more consistent.
for KBOS, with success rates of about 75% for all three comparison-statistics. Table 1 tabulates our model’s performance for the three cases.

The lower accuracy of prediction for KORD as compared to KBOS is to be expected. KORD handles significantly more traffic than KBOS, and naturally adopts a wider variety of runway configurations to accommodate its traffic demands. This fact is highlighted in our historical data. The data record shows that KBOS used 42 different configurations over the summer months of 2013. In comparison, KORD employed 133 different configurations during the same period. Further, each KBOS configuration was a combination of one of 12 arrival and 14 departure configurations. KORD used 14 different arrival configuration and 26 different departure configurations. For KORD, the departure-configuration-selection performance is significantly lower than the arrival-configuration-selection performance. In fact, the departure selection is a bottleneck for overall performance: our success rate for exact total configuration prediction is as good as our rate for exact departure configuration selection. The limitation in departure-configuration-selection performance may be reflective of unmodeled aspects in departure operations (e.g., surface operations), and the higher flexibility allowed in departure operations compared to arrivals.

**Capacity Prediction Performance:** Although we have focused on predicting runway configurations, our primary motivation is to develop a model for predicting trajectories of nominal capacities at a strategic look-ahead. Based on predicted ceiling, visibility and convection, a secondary model will give the final capacity trajectories required by FCM. Except under extreme weather conditions, these capacities should be close to the nominal capacities associated with the predicted runway configuration. With this in mind, we compare the predicted nominal capacities to the actual capacity reported in the historical data.

Figure 6 and Figure 7 compare predicted nominal capacities with the actual historical capacity for KBOS and KORD respectively. Specifically, the figures compare the distribution of actual-minus-predicted capacity, which we term under-prediction. (Over-prediction is therefore represented as negative under-prediction.) For ease of presentation, the under-prediction values are binned into multiples of five, with the fraction in each bin indicated on the pie chart. The figures show that the nominal prediction is very close to the actual capacity (within 5) for a significant portion of the time (~40% in both cases). Also, in both cases, the prediction is relatively close to the actual capacity (within 30) for a majority of the time (about 85% and 60% of the time for KBOS and KORD, respectively). The model does make significant errors for a small fraction of hours; particularly, the model has a tendency to significantly over-predict the capacity with some small frequency. We believe that many of the significant over-prediction events at KORD are for hours with convective-weather impact.

As a whole, the two case studies indicate that the model is promising for predicting runway configurations and AARs/ADRs. Relative to the regression-based approaches that have been proposed before, this operationally-structured model is appealing in the sense that it 1) enforces operational limits in predicting configurations and
capacity, 2) explicitly captures persistence in operations, and 3) can naturally be extended to reflect improved knowledge or modification of operational procedures. Since the model uses a generic depiction of airport operations, we believe that it may perform robustly across major airports. However, further work is needed to complete the capacity-reduction aspect of the framework, and to validate the model’s use in real operations.

V. Implementing the model - Day of operations

In this section, we discuss integration of the model into the FCM framework, for real time operations. As we mentioned earlier, FCM requires probabilistic futures or scenarios of weather impact on airport arrival and departure rates (AARs and ADRs), over a full day forecast horizon. The model that we presented in the preceding discussion is deterministic in nature. For a full day, the model consumes a trajectory of input MCs, wind direction and wind speed, and produces a particular trajectory of hourly runway configuration and nominal capacity. To generate multiple futures for the hourly configurations and nominal capacities, the model requires multiple input trajectories. If the multiple input trajectories capture the uncertainty in the weather conditions, then the multiple trajectories generated by the model would capture the uncertainty in capacity futures.

Integrating our model into the FCM framework requires special consideration on the particular forecast products that may used as inputs to the model. The available choices can be broadly classified as being one of two types of forecasts, a specialized forecast product that are specifically developed for an airport (e.g. Terminal Aerodrome Forecasts or TAFs ), or ensemble forecasts products (e.g. Short Range Ensemble Forecasts or SREFs). There are various advantages and trade-offs for each type of forecasts. For example, TAFs have the required airport-level resolution for our purpose, but are generated manually, and hence do not capture the full-scope of possible weather outcomes. SREFs are computer generated ensemble forecasts that capture a wide range of possible weather outcomes, but do not have optimal resolution. We refer our reader to our previous works for a detailed discussion of the trade-offs between TAFs and SREFs. We have developed our model on the principle that in the longer-term ensemble forecasts with airport-level resolution would be available.

VI. Conclusions

In this work, we presented a modeling framework for predicting AAR/ADR futures for FCM. Our approach differentiates between high- and low-congestion airports. For low-congestion airports, we argued that a simple predictor based on commonly-used configurations is sufficient. For high-congestion airports, we proposed a new multi-stage modeling framework that captures the dependencies between various weather and operational regressors and the airport capacities, at different time-scales. The first step in the model is the prediction of the runway configuration and hence nominal capacities from forecasted MC and wind conditions; this core prediction step was the focus of the paper.

Our core contribution in the paper was an operation-structured prediction model for runway-configuration from available MC and wind forecasts. Once a configuration is predicted, the nominal capacity is determined from average historical capacity for the configuration under the particular MC. We refer to our prediction model as being operation-structured as it leverages operational limits and preferences rather than using a black-box regression.

A. Future Work

Completing the Capacity-Reduction Model. Our predictions for the baseline capacities are based on forecasts of MC and wind conditions. Even for a given runway configuration, MCs may modulate the capacity. Also, convective weather in the terminal area is known to have significant impact on the capacities. Once a baseline capacity is identified, the next steps in our multi-stage prediction model (see Section II) is to determine reductions from the baseline values due to visibility, ceiling forecast and convection. In order to generate the final set of futures for hourly capacity we need to develop a model for deriving reduction from nominal for given visibility, ceiling and convective weather forecast. Anticipated reductions due to visibility and ceiling are tabulated, and some initial literature is available on modeling reductions due to convective weather. However, much remains to be done to develop a comprehensive regression model for capacity reduction. We are currently investigating various deterministic and stochastic approaches, and leave the detailed development to our future work.

Incorporating Further Regressors. The models may be enhanced by using additional regressors, such as time-of-day, scheduled arrivals and departures, and so on. However, care must be taken such that only regressors that can be forecasted with some degree of accuracy should be used as regressors. In our development thus far, we have tried
incorporating one additional regressor, which we term “demand bank”. This regressor labels each hour as being an arrival or a departure bank hour (i.e., an hour with prevailing arrival or departure traffic) based on the historically observed AAR vs. ADR (or actual arrival vs. departure operations). The demand bank can potentially capture any specific operational information that are associated with that time of day and/or provide an idea of expected AAR compared to ADR and so forth. Unfortunately, demand bank definitions using historically observed AAR and ADR proved to be ineffective. In our historical data, each hour was overwhelmingly reported with the exact same AAR and ADR; and so it was impossible to deduce a particular demand bank label for any given hour. Using actual traffic operations to deduce bank labels also proved to be ineffective, because these traffic levels were not significantly predictive of capacities. We are currently seeking ways to refine our definitions of a demand bank as well as investigating other possible regressors for our model.

Anticipatory Predictors and Optimal Runway-Configuration Selection. Our model was motivated by FCM’s need for an airport capacity trajectories, and as a step towards that solution, we presented a prediction model for the most probable runway configuration that would be chosen given a MC and wind forecasts. The operation-structured approach we presented here seeks to encode various operational preferences that decide an airport’s choice of runways. Most significantly, our pilot-reward function captures the head-wind preference.

The prediction model presented here is myopic, in the sense that the prediction at each hour is based only on weather conditions and operational realities at that time. Although the model incorporates memory, it does not capture runway configuration changes based on anticipated future weather conditions. We will pursue development of anticipatory predictors, which may be able to better model human operators’ decision-making process, or allow optimization of runway-configuration selection.

Complimentary to its use as a prediction model, we believe that our approach can provide effective planning tools for airport managers, particularly if an anticipatory model is developed. An understanding of the configuration trajectory that is most likely to be selected given wind and MC forecasts over a full-day horizon can provide airport managers with insights into how their current operational procedures perform, and help in efficient planning.

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