Estimation of Maximum-Likelihood Discrete-Choice Models of the Runway Configuration Selection Process

Varun Ramanujam and Hamsa Balakrishnan

Abstract— **The runway configuration is the subset of the runways at an airport that are used for arrivals and departures at any time. Many factors, including weather (wind and visibility), expected arrival and departure demand, environmental considerations such as noise abatement procedures, and coordination of flows with neighboring airports, govern the choice of runway configuration. This paper develops a statistical model to characterize this process using empirical observations. In particular, we demonstrate how a maximum-likelihood discrete-choice model of the runway configuration process can be estimated using aggregate traffic count and other archived data at an airport, that are available over 15 minute intervals. We show that the estimated discrete-choice model not only identifies the influence of various factors in decision-making, but also provides significantly better predictions of runway configuration changes than a baseline model based on the frequency of occurrence of different configurations. The approach is illustrated using data from Newark (EWR) and LaGuardia (LGA) airports.**

I. INTRODUCTION

The runway system at major airports are generally considered to be the primary bottleneck in airport capacity, and consequently, the capacity of the air transportation network [1]. Most major airports are equipped with multiple runways, and at any time, a subset of these runways (and associated traffic directions) are selected to handle arrivals and departures. This choice of the set of runways, known as the airport- or runway configuration, is a critical factor in determining airport capacity. There are no precise rules that dictate the choice of active runways; instead, authorities in the Air Traffic Control Tower (ATCT) consider many factors including weather (wind and visibility), predicted arrival and departure demand, environmental considerations such as noise abatement procedures, and coordination of flows with neighboring airports, in selecting the runway configuration at any time. This paper proposes a statistical model that uses empirical observations to characterize the configuration selection process. In particular, we propose an approach to learn the maximum-likelihood discrete-choice model of configuration selection, and also to infer the air traffic controllers' utility functions in making these decisions.

Several past works have acknowledged the role of runway configuration selection in airport congestion management [2], [3], [4]. Recent research has focused on the development of decision support systems that prescribe the optimal

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sequencing of runway configurations, assuming knowledge of their respective capacities, expected airport demand, and prevailing operating conditions influencing configuration feasibility [5], [6]. This paper takes a complementary approach to the problem of configuration selection: we estimate a maximum-likelihood model of the runway configuration selection process, as well as the factors that influence the utility function of the air traffic controllers, using archived operational data. In short, while past works guide controllers on what runway configurations to select (in order to optimize some predetermined objective such as throughput), this study attempts to model how controllers currently select runway configurations, and their underlying utility functions.

We model the selection of runway configuration as a discrete-choice problem faced by the airport authorities. The utility functions of the different alternatives are represented as functions of the aforementioned factors (wind, demand, etc.) that influence configuration selection. The discrete-choice framework, which has been successfully applied to other applications such as modeling driver lane-changing behavior, enables the estimation of the relationship between influencing factors and the favorability of a configuration, and the prediction of future configuration choices made in response to evolving weather and demand conditions [7], [8].

The rest of this paper briefly describes discrete-choice modeling as well as the proposed methodology for determining the maximum-likelihood discrete-choice model. We then describe the specific application of this approach to the problem of configuration selection. Results from the application of the approach to LaGuardia (LGA) and Newark (EWR) airports are used to demonstrate its ability to predict the runway configuration, given the state of the system in terms of wind, visibility, demand, etc. In this paper, runway configurations are represented in the form 'R1, R2 | R3, R4' where R1 and R2 are the arrival runways, and R3 and R4 are the departure runways.

II. METHODOLOGY

In this section, we briefly describe discrete-choice models, followed by descriptions of the model estimation approach, identification of the utility function that drives runway configuration choice, and the validation techniques applied.

A. Conceptual Framework

Discrete-choice analysis [9] considers problems in which a decision-maker needs to select one option from a finite set of alternatives. It is assumed that the decision-maker chooses the solution that maximizes a utility function that

depends on several influencing factors (known as attributes, and denoted X). The utility function for each alternative is modeled as the sum of an observed component V (which is a linear combination of the influencing factors) and an unobserved component ε represented through error terms. In other words, consider the observation of the nth selection decision. Suppose C_n is the set of alternatives available for the nth choice. Then, the utility of choice $c_i \in C_n$ for selection n is given by

$$V_{in} = \alpha + \beta \cdot X_{in} \quad (1)$$
$$U_{in} = V_{in} + \varepsilon_{in}, \quad (2)$$

Equation (1) reflects the assumption that the utilities are linear functions of the attributes, given by X_{in}, while Equation (2) acknowledges the presence of errors due to factors that are not explicitly modeled or observed. Then, we assume that for the nth observation, the decision-maker selects the alternative $c_j \in C_n$ such that

$$j = \underset{i:c_i \in C_n}{\arg\max} \, U_{in}. \quad (3)$$

The probabilistic distribution assumed for the error terms ε_{in} determines the analytical relation between alternative selection probabilities and the observed component of the utility functions, and hence the type of discrete choice model. For example, if one assumes complete independence in error terms across all alternatives and choice observations, and that the error terms are identically Gumbel distributed, we obtain the popular multinomial logit (MNL) model [9]. The MNL model is a popular choice in many applications due to its analytical tractability, and yields the choice probability expression given by

$$P(c_i|C_n) = \frac{e^{V_{in}}}{\sum_{j:c_j \in C_n} e^{V_{jn}}}. \quad (4)$$

In other words, Equation (4) provides the probability of the nth choice being c_i, given that the set of feasible alternatives was C_i. We note that as the observed component of the utility for alternative c_i (given by V_{in}) increases relative to the utilities of the other alternatives, so does the probability of selecting c_i.

The assumption of independent error terms in the MNL model is potentially too restrictive in the context of runway configuration selection. For instance, let us consider two feasible configurations that contain a common arrival (or departure) runway. This common runway might contribute identical unobserved effects to the configuration utilities, rendering their error terms correlated. To mitigate this shortcoming, we consider advanced versions like the Nested Logit (NL) and Cross-Nested Logit (CNL) models [9]. These model structures permit error correlation within specified subsets of alternatives as illustrated in the nested frameworks shown in Figure 1. Here, four alternatives {alt1, alt2, alt3 and alt4} are grouped into two nests in (a) an exclusive manner (NL representation), and b) an overlapping manner (CNL representation) with alt2 shared between the two nests. We also note that some nests can be singletons. In this

framework, under (a), alt1 and alt2 would have a common component to the error terms, while alt2 and alt3 would have independent errors; under (b), alt2 would have a common component of error with alt1, as well as with alt3 and alt4.
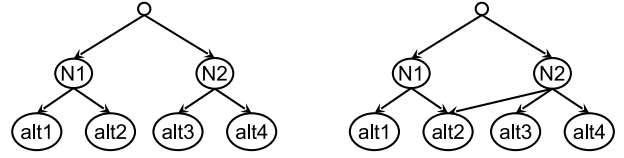

Fig. 1. (a) NL model framework; (b) CNL model framework.

The expressions for alternative probabilities for the NL and CNL models, and their comparisons with the MNL model are described in [9]. For example, the selection probability for alternative alt1 in the NL model (Figure 1 (a)) is given by

$$P(alt1|\{alt1, alt2, alt3, alt4\}) = P(alt1|N1) * P(N1|\{N1, N2\}) \quad (5)$$

where
$$P(alt1|N1) = \frac{e^{\mu_{N1}*V_{alt1}}}{\sum_{j:c_j \in \{alt1,alt2\}} e^{\mu_{N1}*V_j}}, \quad P(N1|\{N1,N2\}) = \frac{e^{V_{N1}}}{e^{V_{N1}}+e^{V_{N2}}}$$
$$V_{N1} = \frac{1}{\mu_{N1}} * \log \sum_{j:c_j \in \{alt1,alt2\}} e^{\mu_{N1}*V_j}, \text{ and similarly for } V_{N2}.$$

Here, the scale parameters μ_{N1} and μ_{N2} provide a measure of the magnitude of error correlation among alternatives within nests N1 and N2 respectively. We investigated the use of all three models (MNL, NL and CNL) for the airport configuration choice problem through appropriate statistical tests.

B. Estimation framework

The model parameters (α, β in Equation (2)), which are the coefficients of the observed influencing factors X_{in} on the alternative utilities U_{in}, are estimated using the maximum-likelihood approach. The likelihood of a given choice observation is simply the probability of selecting the observed choice given the values of the model parameters (α, β) and influencing factors (X_{in}). The likelihood function for an entire dataset of choice observations (say, over N time periods) is the joint probability of observing the sequence of choice decisions recorded, or in other words

$$\mathscr{L}(\alpha,\beta) = P((c_1|C_1) \bigcap .... \bigcap (c_N|C_N)|\alpha,\beta,X) \quad (6)$$

where c_i is the selected alternative, and C_i is the set of available alternatives for i^{th} observation, $i \in 1, 2, .., N$.

We make the additional assumption that the choice observations (at each time) are conditionally independent given the values of the explanatory factors X_{in}. This allows us to express the likelihood function presented in Equation (6) as the product of the likelihood of individual choice observations:

$$\mathscr{L}(\alpha,\beta) = \prod_{i=1}^{N} P(c_i|C_i) \quad (7)$$

where $P(c_i|C_i)$ is given by Equation (4) for the MNL model or Equation (5) for the NL model.

The parameter estimates $(\widehat{\alpha}, \widehat{\beta})$ are those that maximize this likelihood:

$$(\widehat{\alpha}, \widehat{\beta}) = \underset{\alpha, \beta}{\arg\max} \, \mathscr{L}(\alpha, \beta). \qquad (8)$$

Likelihood-maximization is a nonlinear optimization problem. In this study, we used BIOGEME ([10]), a freeware package that specializes in estimating discrete-choice models through customized in-built algorithms.

C. Model specification and structure development

Model specification refers to the exact functional form of the systematic utility component V_{in}, comprising of the observed influencing factors X_{in}. The specification is developed through iterative consideration of candidate factors affecting the choice behavior. Standard hypothesis testing procedures help assess the statistical significance of every new factor considered (Likelihood-ratio test for nested hypothesis testing [9], and Cox composite model test for non-nested hypothesis testing [11], [12]). The structure of a discrete choice logit model refers to the particular correlation structure adopted for the alternative error terms ε_{in}. As mentioned earlier, MNL, NL and CNL models were all considered in this study. Established hypotheses tests (Hausman-McFadden test [13]), help ascertain the statistical validity of structural enhancements offered by the NL or CNL model over the MNL model.

D. Validation

The final step in any empirical model-building process is the evaluation of its predictive capabilities in comparison to a different, typically simpler, model that serves as the base framework. Both the proposed and base models are applied upon a validation dataset, using parameters estimated from a common training dataset, and their predicted probabilities are assessed, through well-defined metrics, for their proximity to the actual observed choices in the validation dataset. The definition of the baseline model is critical to the outcome of the validation task. In this study, we adopt a probabilistic model depicting configuration selection as a Markovian transition process to be the base model [14].

The following section presents the details of the application of the proposed technique to the configuration selection process at LGA and EWR airports, as well as the associated results and inferences.

III. CASE STUDY: LGA AND EWR AIRPORTS

A. Training data set

The training data set comprised of the 15-minute aggregate ASPM records for the year 2006, which provide for each 15 minute interval, the chosen configuration as well as other prevailing airport conditions such as weather, demand, etc. Configuration selection is assumed to occur at every 15-min interval. Operational data for hours from midnight to 6 am were excluded from the data set, since it is apparent from conversations with air traffic controllers that reporting during these periods is more prone to errors. Feasible configurations

for each time period were determined by the set of runways that did not exceed the FAA-specified safety thresholds for tail-winds (5 kn) and cross-winds (30 kn). Observations featuring operation of infeasible runway configurations (most likely reporting errors) were also excluded from the data set.

B. List of candidate influencing factors and expected impact on configuration selection

There are several factors that potentially influence the choice of configuration (from among the feasible options) in any time period. The following factors were explicitly included in the utility functions of the discrete choice model:

- *Inertia:* Configuration changes are a fairly involved procedure, require extensive coordination among the different airport stakeholders, and are thought to cause a loss in airport throughput [5], [6]. For these reasons, the configuration from the previous time interval is likely to be favored pending other considerations, and its utility is therefore expected to increase on account of this inertial factor.
- *Head-wind speeds:* It is hypothesized that higher head-wind speeds are favorable for both arrival and departure operations, and therefore increase the utilities of the respective configurations. In this study, we use a combination of current and forecasted wind conditions as the measure of the influencing factor. In the absence of information on the actual forecast used by airport planners, the observed wind speeds over the immediate future of every time period is used as a reliable proxy.
- *Arrival/departure demand:* During periods of significantly high total (arrival+departure) demand, a high-capacity configuration is likely to be favored. The capacity envelopes for the configurations observed in LGA and EWR were acquired from prior work [15].
- *Noise abatement procedures:* In accordance to FAA procedures, certain runway orientations (and therefore configurations) are to be avoided during applicable time periods. The Standard Operating Procedures (SOPs) for the NY airports identify the overnight hours (10pm-7 am) for activating the noise mitigation measures, and time-specific variables are accordingly defined for the configuration utilities in this study. The pruning of observations between midnight and 6 am from the estimation data set reduced the sample space over which the noise mitigation measure is active; however, we believe that the estimation data set was large enough to compensate for this reduced sample size.
- *Configuration switch proximity:* Configuration changes require increased coordination and disrupt the flow of aircraft on the surface, and authorities might be inclined to minimize the level of effort involved. For example, a configuration change that only requires the addition of a departure or arrival runway may be easier to implement than a change that needs to change the direction of arrival flows entirely. In this study, we equate the type and magnitude of the change to the incident angles between the respective arrival and departure runways

of the preceding and succeeding configurations. We thereby define six distinct possible switch types and study their relative preferability through appropriate categorical variables. For example, the configuration change which results in a 90 deg reorientation of the arrival runway and a 180 deg reorientation of the departure runway is denoted $(90, 180)$.

- *Inter-airport coordination:* In multi-airport terminal-areas such as New York, arrival and departure flows into the different airports must be coordinated. We therefore investigate the effect of JFK's configuration on the concurrent choices for LGA/EWR. We define categorical variables representing interactions between distinct pairs of runway orientations at JFK and at LGA/EWR. Since airport authorities follow runway-specific airspace routes for landing and takeoff operations, the existing interactions among the routes from every pair of runways from the two neighboring airports can be estimated through this set of variables.

C. Estimation of discrete-choice models and utility functions

As explained in the methodological overview, the utility specifications and error structures were developed and statistically verified through a sequence of tests. The details of the resultant models are discussed below.

1) LGA results: The training data set had a total of 17,716 choice observations post-filtering (i.e., data from 17,716 time periods), featuring a total of 10 distinct configuration alternatives. The final model has a NL structure with two alternative nests, grouping configurations with arrival runways 4 and 13 respectively as illustrated in Figure 2. The other configurations are modeled as singleton nests.
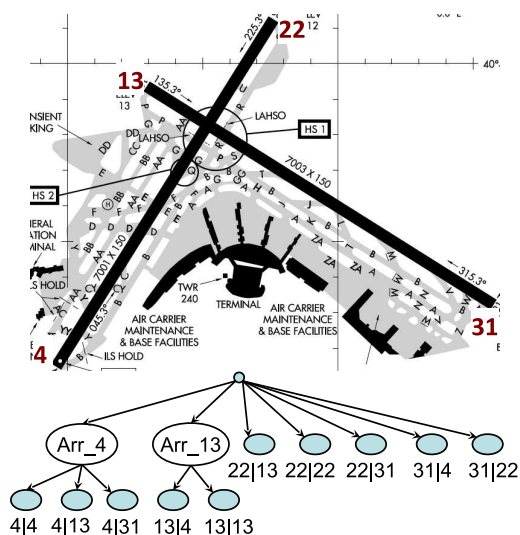

Fig. 2. Layout of LGA, along with the estimated NL structure for LGA configuration selection (for year 2006).

The results of the utility coefficients are tabulated in Table I, along with the corresponding t-statistics in parenthesis. We note that when the absolute value of the t-statistic exceeds

1.96, the estimate of that parameter can be deemed statistically significant. As can be observed, our previously outlined apriori hypotheses are corroborated by the estimation results in the case of inertial effects and headwind speeds. While the tasks of interpreting the estimates for the switch category and the JFK configuration coordination variables are ambiguous due to the lack of clear apriori understanding, we have attempted a comparison with the estimates obtained on application of the same specification on ASPM data from another year. The estimates for these variable types seem to exhibit consistency across the two years, thereby offering credibility to their values.

1. Inertial	
Only for config. from prev. time step (incumbent)	+5.31 (71.6)
2. Headwind speed	
Arrival runway	0.043 (9.2)
Departure runway	0.026 (4.67)
3. Demand	
For crossing runway (high-capacity config)	1.65 (9.25)
4. Noise abatement	
Runway 31 for morning 6-8 am	1.22 (6.3)
Runway 4 for evening 10 pm - 12 am	0.911 (4.1)
Runway 31 for evening 10 pm - 12 am	-0.331 (-1.58)
5. Switch proximity	
Angle of incidence (90,180)	-1.75 (-7.49)
Angle of incidence (180,180)	-1.99 (-4.40)
6. Coordination with JFK	
Departure runways (4@LGA vs 4@JFK)	0.524 (2.1)
Departure runways (13@LGA vs 13@JFK)	-0.404 (-1.37)
Departure runways (13@LGA vs 22@JFK)	-0.586 (-1.68)
Dep. runways (13@LGA vs 31@JFK)	-1.05 (-3.59)
Arrival Runways (22@LGA vs 31@JFK)	-1.22 (-6.71)
Arrival Runways (31@LGA vs 4@JFK)	-0.47 (-2.02)
Departure Runways (31@LGA vs 22@JFK)	0.949 (4.07)

TABLE I

ESTIMATED UTILITY FUNCTIONS (VALUES OF β) FOR THE DISCRETE-CHOICE MODEL OF CONFIGURATION SELECTION AT LGA.

The bar plots in Figure 3 depict how the estimated coefficients translate to configuration choice probabilities. We restrict our discussion to prominent runway configurations: 4|4, 31|31, 4|13, 22|13, 22|31 and 31|4. We construct hypothetical scenarios for illustrating the trade-offs between switch proximity, wind favorability and operational capacity as configuration selection criteria. We assume VFR operating conditions, the simultaneous configuration at JFK to be its most prominent (31R|31L), and a time period with no noise abatement regulations. Within this set of conditions, we consider two demand scenarios, low (demand coefficient not applicable) and high (demand coefficient applicable). Assuming the current incumbent runway configuration at LGA to be 31|31, we examine the relative selection probabilities of the prominent configurations at LGA for wind speeds of 40 kn varyingly aligned along runways 31, 22 and 13 respectively. Firstly, we note that the probabilities presented for non-incumbent configurations are measured relative to each other (i.e, conditioned on the non-selection of the incumbent) to facilitate reasonable comparison. We also append the associated absolute selection probability for the incumbent
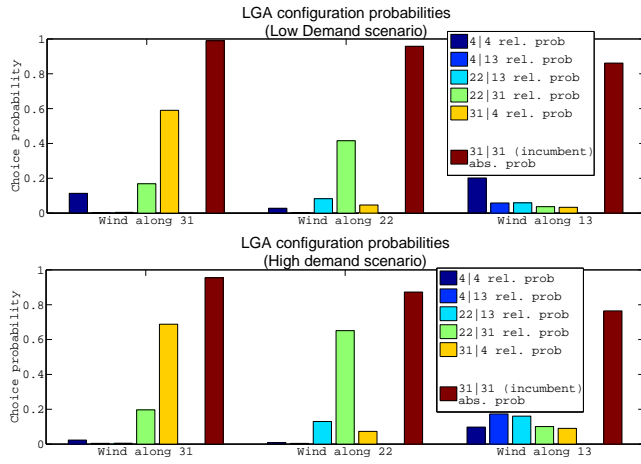
Fig. 3. Relative configuration selection probabilities at LGA for described hypothetical scenarios involving (a) Low demand, and (b) High demand.

configuration. For the low demand scenario (Fig. 3 (a)), we observe that configurations with wind-aligned runways are typically favored among the non-incumbents, with the exception occurring when the wind blows along runway 13. In this scenario, although the non-incumbent configurations 4|13 and 22|13 are 'wind-favorable' through their departure runways, they would both require a less favorable switch (type 4) from the incumbent configuration 31|31, which reduces their desirability. Also, inertia effects ensure the incumbent configuration (31|31) has a high probability of being retained for all three wind directions, although this probability progressively reduces as wind directions become less favorable.

For the high demand scenario (Fig. 3 (b)), configurations with crossing runways (4|13, 22|13, 22|31 and 31|4) dominate among the non-incumbents, while the retention probability for the incumbent also comparatively reduces, highlighting how the increased importance of higher capacity configurations overrides other considerations including switch proximity.

2) EWR results: The training dataset had a total of 23,506 choice observations post filtering, featuring a total of 20 distinct configuration alternatives. The final model had a NL structure with one nest for a well-defined subset of alternatives as depicted in Figure 4. The nest groups together all EWR configuration alternatives with an additional arrival runway. The implication of this nesting is that configurations with an additional arrival runway share commonalities in terms of unobserved factors influencing their preferences.

The results of the utility coefficients are tabulated in Table II, along with the corresponding t-statistics in parenthesis. Once again, we note that when the absolute value of the t-statistic exceeds 1.96, the estimate of that parameter can be deemed statistically significant.

Once again, our stated apriori hypotheses for inertia and wind effects are largely substantiated by the estimation results. Additional wind speed coefficients are introduced to capture effects on the supplementary (extra) runways

1. Inertia	
Only for config. from prev. time step (incumbent)	+4.86 (6.73)
2. Headwind speed	
Primary Arrival runway	0.051 (4.28)
Primary Departure runway	0.04 (2.91)
Extra Arrival runway	0.02 (3.19)
3. Demand	
For parallel runway configuration (when demand exceeds crossing runway config. capacity)	1.042 (7.99)
For configurations with extra arrival runway (when demand exceeds unhindered arrival capacity)	0.447 (3.72)
For configurations with extra departure runway (when demand exceeds parallel runway config. capacity)	2.32 (9.44)
4. Noise abatement	
Runway 11 for morning 6-8 am	-1.7 (-7.38)
Runway 29 for morning 6-8 am	-1.73 (-5.82)
5. Switch type	
Angle of incidence (0,90)	-0.728 (-3.16)
Angle of incidence (90,90)	-1.28 (-2.02)
Angle of incidence (0,180)	-1.91 (-3.29)
Angle of incidence (90,180)	-2.12 (-2.80)
Angle of incidence (180,180)	-0.407 (-3.92)
6. Coordination with JFK	
Dep. Runways (4@EWR vs 31@JFK)	0.826 (2.35)
Dep. Runways (22@EWR vs 4@JFK)	-0.615 (-1.32)
Dep. Runways (22@EWR vs 13@JFK)	-1.14 (-2.35)
Dep. Runways (29@EWR vs 13@JFK)	-0.694 (-2.73)
Arr. Runways (4@EWR vs 22@JFK)	-1.25 (-3.07)
Arr. Runways (11@EWR vs 13@JFK)	0.437 (2.57)
Arr. Runways (11@EWR vs 31@JFK)	0.576 (2.84)
Arr. Runways (22@EWR vs 13@JFK)	1.2 (2.95)
Arr. Runways (22@EWR vs 22@JFK)	-0.94 (-2.63)
Arr. Runways (29@EWR vs 13@JFK)	1.13 (4.08)
Arr. Runways (29@EWR vs 22@JFK)	0.449 (1.66)
Arr. Runways (29@EWR vs 31@JFK)	1.22 (4.17)

TABLE II

ESTIMATED UTILITY FUNCTIONS (VALUES OF β) FOR THE DISCRETE-CHOICE MODEL OF CONFIGURATION SELECTION AT EWR.

independent of the primary runways for configurations featuring more than one arrival or departure runway. Also, the estimates for the switch category and the JFK configuration coordination variables were cross-verified with those obtained for year 2007 to assess their credibility. The estimates for these variable types exhibit reasonable consistency across the two years, thereby corroborating their validity.

For EWR, we graphically demonstrate the trade-offs between switch proximity, demand-capacity inter-relationship and coordination with JFK in configuration selection, as implied by the parameter estimates. As with LGA, we construct hypothetical scenarios controlling for other factors such as wind speed and direction (20 kn along runway 11), visibility conditions (VFR), and noise abatement stipulations (not present). We restrict our attention to the prominent configurations (4R|4L; 4R,11|4L; 4R,29|4L; 22L|22R; 22L,11|22R; 22L|22R,29) and assume 4R|4L to be incumbent configuration. We consider three demand scenarios (when demand exceeds crossing runway configuration capacity, when demand exceeds unhindered (or free) arrival capacity, and when demand exceeds parallel runway config. capacity) each in conjunction with the two most prominent JFK runway configurations: 31R|31L and 13L|13R. As with LGA, we
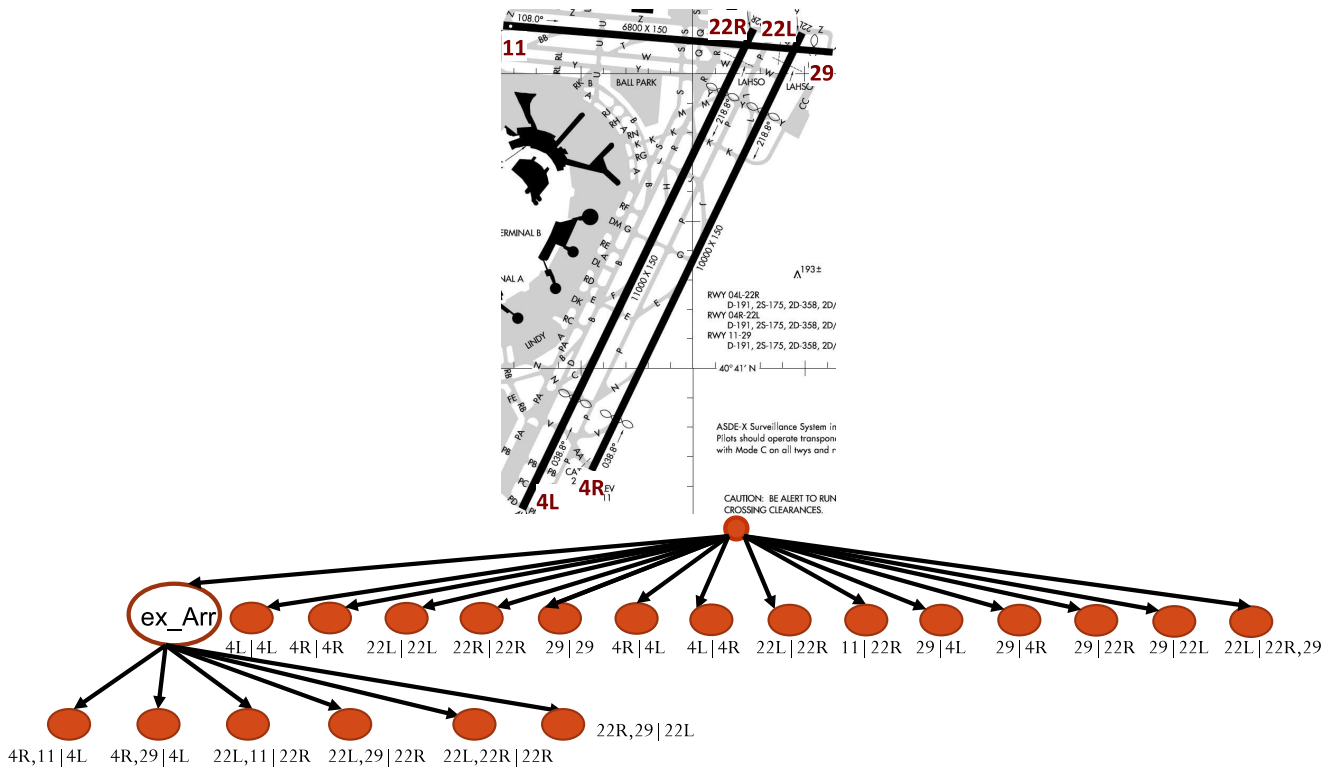
Fig. 4. Layout of EWR, along with the estimated NL structure for EWR configuration selection (for year 2006).

measure the relative selection probabilities for the non-incumbent configurations conditioned on the non-selection of the incumbent.
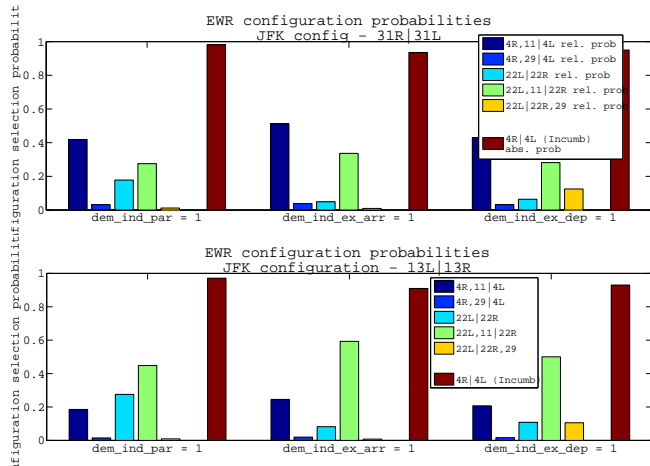

Fig. 5. Relative configuration selection probabilities at EWR for described hypothetical scenarios with JFK configuration as (a) 31R|31L, and (b) 13L|13R.

When JFK is operating 31R|31L (Fig. 5 (a)), we note that configuration 4R,11|4L dominates among the non-incumbents across all demand scenarios, owing to its switching proximity relative to the incumbent as well as favorableness under given JFK configuration (note the positive values of coefficients for *Arr. runways (11@EWR vs 31@JFK)*

and *Dep. runways (4@EWR vs 31@JFK)*). Configuration 22L,11|22R is second-best due to the switching disutility relative to the incumbent (switch angle of incidence (180,180)). Configurations featuring runway 29 are least preferred due to adverse wind direction. Configurations with additional arrival runway (like 4R,11|4L) are more preferable when when demand exceeds unhindered arrival capacity, while configurations with additional departure runway (like 22L|22R,29) are more preferable when demand exceeds parallel runway configuration capacity. When JFK operates 13L|13R (Fig. 5 (b)), the dominant non-incumbent is 22L,11|22R, which is now favored by the JFK configuration (note coefficients for *Arr. runways (22@EWR vs 13@JFK)* and *Arr. runways (11@EWR vs 13@JFK)* are both positive), overriding switch proximity considerations. Also, we note the preference for the configuration with additional departure runway (22L|22R,29) remains suppressed even when demand exceeds parallel runway configuration capacity, since the JFK configuration strongly inhibits it (negative sign for coefficient for *Dep. runways (29@EWR vs 13@JFK)*).

D. Model validation

This section describes the validation of the proposed configuration selection model and its parameter estimates. The validation analysis compares the quality of configuration selection predictions for an external test data set between the estimated discrete choice model and a simpler model (termed base model) respectively. The test set consisted of ASPM data records from 2007 for the study airports, refined using

same filters applied for the training data set (2006 ASPM records). The base model structure is described in the next section, following by a brief discussion of the validation results.

1) Base Model: The use of the discrete choice modeling framework enables the incorporation of relevant influencing attributes like weather conditions, demand, etc. in determination of configuration selection probability. However, a more rudimentary approach might compute explicitly, using available empirical evidence, the probability of a particular configuration being chosen conditional on the configuration in effect in the previous time interval. Such an approach would effectively generate a transition probability matrix Δ, where an element $\Delta(i, j)$ would represent the estimated probability of configuration j being chosen for any time interval t, given that configuration i was active in time interval $t - 1$. Peterson (1992) describes an identical model, based on the Markovian premise, for representing airport capacity dynamics featuring finite capacity states. We replicate his empirical estimation procedure to develop parameter estimates for the base model.

Given $C_t \ \forall t = \{1, 2, ... T\}; C_t \in \{1, ..., N_c\}$, where T is the total number of time intervals, N_c is the total number of possible configurations, and C_t is the configuration selected at time t, then

$$\Delta(i, j) = \frac{\sum_{t=1}^{T} (C_t == j) \wedge (C_{t-1} == i)}{\sum_{t=1}^{T} C_{t-1} == i} \quad \forall i, j \in \{1, .., N_c\}. \quad (9)$$

Note that the above estimation framework implies a discrete choice model (MNL) where the configuration utilities are defined as the aggregation of $N_c - 1$ time-invariant categorical variables, each serving as an indicator of the runway configuration in the previous time-step. Other explanatory factors like weather, demand, etc. are not considered in the base model.

2) Validation Results: In this study, we aggregate predicted configuration probabilities to compare the model predictions to the actual observations. Since typical airport configuration planning horizons are of the order of 3 hours, we consider the predicted probabilities conditioned on the configuration observed 3 hours before, and not the previous 15-min time period.

Suppose obs_c_t denotes the observed configuration for time-step t. The aggregate predicted probability (agg_pr_i) for configuration i is calculated as:

$$agg\_pr_i = \frac{\sum_{t:obs\_c_t=i} P(c_t = i | c_{t-12} = obs\_c_{t-12})}{\sum_{t:obs\_c_t=i} 1} \quad (10)$$

where the prediction probability $P(c_t = i | c_{t-12} = k)$ is computed recursively in the following manner:

$$P(c_t = j | c_{t-12} = k) = \sum_{i=1}^{N_c} P(c_t = j | c_{t-1} = i) P(c_{t-1} = i | c_{t-12} = k)$$

$$P(c_{t-1} = i | c_{t-12} = k) = \sum_{m=1}^{N_c} P(c_{t-1} = i | c_{t-2} = m) P(c_{t-2} = m | c_{t-12} = k)$$

The absolute prediction quality would naturally deteriorate as we increase the length of the look-ahead duration currently

set at 12 (no. of 15 min intervals in 3 hours). However, it should not influence the relative comparison of the prediction qualities of the discrete choice models and their corresponding base models. The aggregate validation measures of this comparison are presented below (Table III for LGA, and Table IV for EWR). The results are partitioned for two disjoint data segments, the first representing observations from time periods that are not within 3 hours of a switch, and the second representing time periods in the temporal vicinity of (i.e., within 3 hours before or after) a switch. We present results for the most frequently used configurations at each airport. The validation tables show the aggregate probability of a runway configuration being correctly predicted, both near and away from configuration switches. We note that the aggregate probabilities in the vicinity of a switch are conditioned on the event of a switch. A perfect prediction mechanism would have an aggregate probability equal to 1.

Outside temporal vicinity of switches			
		Correct prediction	
Config	Frequency	Base	Discrete-Choice
22|13	4403	0.81	0.95
22|31	3725	0.73	0.92
31| 4	2989	0.77	0.90
4|13	2339	0.74	0.91
31|31	1211	0.61	0.70
4| 4	599	0.50	0.69
Within temporal vicinity of switches			
Config	Frequency	Base	Discrete-Choice
31|4	1103	0.48	0.71
22|31	1043	0.50	0.74
22|13	1024	0.55	0.76
4|13	569	0.47	0.58
31|31	403	0.31	0.57
4|4	135	0.31	0.44

TABLE III

VALIDATION RESULTS FOR LGA (AGGREGATE PROBABILITIES OF CORRECT CONFIGURATION PREDICTION FOR 2007 DATASET). NO. OF PARAMETERS IN BASE MODEL = 100; NO. OF PARAMETERS IN DISCRETE-CHOICE MODEL = 36.

The validation results show that the predictions generated by the discrete-choice model are significantly better than those of the base model, in spite of the considerably smaller number of parameters required by the discrete-choice model. This result highlights the richer use of empirical information achieved by the discrete choice model. The fact that the improvement in prediction accuracy is consistent across the two disparate sets of observations (near and away from configuration switches) demonstrates the superiority of the discrete-choice model in predicting the timing of configuration switch as well as the continuation of the incumbent configuration if the prevailing conditions don't motivate a switch. In general, the quality of prediction is lower in the vicinity of configuration switches due to the inertia term biasing predictions towards incumbent configurations. Similarly, we note that the model performs relatively poorly in predicting configurations that are used more infrequently.

	Outside temporal vicinity of switches		
		Correct prediction	
Config	Frequency	Base	Discrete-Choice
22L|22R	6583	0.88	0.87
4R|4L	4173	0.84	0.87
22L,11|22R	1686	0.77	0.94
4R,11|4L	1087	0.74	0.88
4R,29|4L	715	0.74	0.81
31|4	211	0.52	0.16
	Within temporal vicinity of switches		
Config	Frequency	Base	Discrete-Choice
22L|22R	2073	0.70	0.73
4R|4L	1303	0.65	0.73
22L,11|22R	799	0.32	0.76
31|4	573	0.24	0.21
4R,11|4L	505	0.40	0.74
4R,29|4L	336	0.29	0.70

TABLE IV

VALIDATION RESULTS FOR EWR (AGGREGATE PROBABILITIES OF
CORRECT CONFIGURATION PREDICTION FOR 2007 DATASET). NO. OF
PARAMETERS IN BASE MODEL = 400; NO. OF PARAMETERS IN
DISCRETE-CHOICE MODEL = 57.

IV. CONCLUSIONS

Runways are a critical capacity bottleneck in the air transportation system, and runway configuration selection is a key driver of airport capacity. To the best of our knowledge, this paper presented results of the first effort to learn models of the configuration selection process using operational data. The proposed approach estimated a maximum-likelihood discrete-choice model of the configuration choice process. The dependence of the configuration choice upon influencing factors like weather, arrival and departure demand, noise mitigation directives, coordination with neighboring, etc. was identified and quantified. The proposed discrete-choice modeling framework was applied to two major airports in the NY metroplex system, LGA and EWR. The estimated utility functions reinforced many of the a priori expectations regarding the impact of the selected influencing factors. Validation of the proposed model showed that the probability of correct configuration choice prediction was more than 0.8 for the more frequently used configurations, during time periods away from configuration changes. For the most frequently observed configuration at LGA, the probability of correct prediction was 0.95. While the predictive performance deteriorated in the vicinity of switches, the probability of correct prediction was more than 0.7 for the most frequently used configurations at both airports. The validation also showed that although the discrete-choice model required fewer parameters than a baseline Markovian model of configuration change, the former had superior predictive capabilities. The proposed models can be used for the simulation of airport operations, as well as to design and evaluate the benefits of configuration selection decision-support tools.

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