In Search of the Upper Limit to Air Traffic Control Communication

Lu Dai, Yulin Liu, Mark Hansen
Department of Civil and Environmental Engineering
University of California, Berkeley
Berkeley, California
dailu@berkeley.edu
liuyulin101@berkeley.edu
mhansen@ce.berkeley.edu

Abstract— **Communication between pilots and controllers plays an important role in the Air Traffic Control (ATC) process. There have been many studies on the ATC communication analysis but rarely on the suppression of voice activity. A censored regression model with a stochastic right-censored threshold is developed to estimate the relationship between ATC communication voice activities and the ATC operational environment through a wide and representative set of real operational ATC voice recordings. The model estimation result shows that flight operational volume, lead flight operations, time of day, meteorological conditions, visibilities, wind conditions, anomalous flight operations and runway configurations are good indicators of the ATC communication. Lastly, we use the estimated model to simulate the loss percentage of ATC communication. This study has profound implications on further understanding of ATC system capacity, aviation safety and human performance interfacing ATC.**

Keywords-ATC voice communication; frequency congestion, workload, censored regression, human performance

I. INTRODUCTION

In order to increase the Air Traffic Control (ATC) system capacity and enhance airspace safety, Air Navigation Service Providers (ANSPs) have been looking for a way to better understand the operational processes and activities in the ATC system. Communication is central to the ATC process. At present, voice communication via radio is still the primary means for Ground-Air traffic communication. Also, effective radio communication between Air Traffic Controller (ATCO) and pilots has long been recognized as an important element of aviation safety [1]. ATCO's workload has been a topic of numerous studies due to its importance [2]. However, there is little research in the open literature concerning the suppression of ATC communication activity due to frequency congestion or ATCO workload.

From a frequency channel occupancy perspective, a single frequency channel is capable of handling only one ATC communication transmission within a specified time period. In other words, each message between ATCO and pilot requires a certain amount of time to complete. Once the frequency utilization reaches a saturation point, the frequency congestion occurs. Frequency congestion has been identified as "clearly the worst communication problem confronting the aviation system" [4]. It increases the chances that one pilot may accidentally override another, thus requiring the transmission to be repeated, resulting in potential safety issues [3].

From the ATCO's workload perspective, even if the frequency channel is available and free to be used, ATCO cannot work uninterruptedly under pressure. As the number of flights being tuned to a particular frequency channel increases, ATCO cannot transmit messages with all the pilots at any desired time. In order to reduce workload, ATCO usually has to prioritize flights with higher importance (e.g., medical/fuel emergencies) and keep the others waiting, reduce the gap time between two voice messages, or make a tradeoff between information provided and the transmission time [3].

Thus, the ATCO workload and frequency congestion, which suppress the ATC communication voice activities, are important aspects of ATC system capacity. Without this limitation, frequency channel should have been always free to be used - pilots and controllers would be able to transmit messages at any time and receive an immediate reply without any other traffic concern. We refer to the percentage of time a communication channel is utilized in constraint-free environment as the Free Active Rate (FAR) in this study. The percentage utilization that results from the limited capacity, either of the frequency channel or of the controllers' ability to communicate, is called Constrained Active Rate (CAR).

There is little research to investigate the loss of ATC communication voice activity, mainly due to the inaccessibility of the real ATC operational voice recordings. To fill this gap, we utilize a set of ATC audio data to investigate whether, and to what degree, voice communication activity is constrained by limitations in channel or ATCO capacity. We first applied several signal processing algorithms to detect and recognize the ATC communication voice activities. Regression analysis is

performed to understand how those activities relate to different drivers of communication activity.

Most of the literatures in ATC voice recording analysis has been specific to en route communications in attempt to reduce frequency congestion by dividing a saturated ATC sector into two smaller sectors [5][6]. Only a few studies focused on tower controllers [3][7], who use visual observation to instruct aircrafts to land safely or give clearance to departing aircrafts. In this study, we focus on tower controllers at John F. Kennedy International Airport (JFK).

The remainder of this paper is organized as follows: section II describes our data sources and how we preprocess and fuse different datasets. Section III introduces a censored regression model that ascribes CAR with different factors. In section IV, we apply the model estimation results to simulate CAR under different scenarios. Section V offers the conclusion.

II. DATA SOURCES AND PREPROCESSING

A. Data Sources

In this study, we use four different sources of data. The ATC audio dataset, which comes from an audio streaming site (LiveATC.net), provides historical voice communications between controllers and pilots ranging from clearance delivery to approaches. There are four frequency channels available on the website: CAMRN, ROBER, Final and Tower. CAMRN routing over south waypoints and ROBER routing over east waypoints are in the Terminal Radar Approach Control (TRACON) area. TRACON controllers are responsible for avoiding conflict in the airspace and descend the traffic to between 4000 feet and 2000 feet then hand them off to the "Final" controllers. "Final" controllers are supposed to establish proper spacing and assign the traffic to the Tower frequency channel. Tower controllers will make sure the proper separation between every departure flight and arrival flight. For the interests of this study, we focus on the communications from the two tower audio channels at the JFK airport for the final approaches and clearances. While LiveATC provides separate audio tapes for two frequency channels and one tape that recursively merges two tapes (to avoid overlapping audios), we used the later in our study. Although one could argue this may overestimate the communication suppression, we treat it as an appropriate approximation since the runway assignment of a flight — which frequency it would employ — cannot be obtained or inferred from the supporting datasets. The time frame of the data is from March 1st to December 31st in 2017, except five days in October in which recordings were defective.

Our second and third datasets both come from the FAA Aviation System Performance Metrics (ASPM) – ASPM flight level dataset and ASPM airport information dataset. While the former provides detailed information about scheduled/actual departure/ arrival times for individual flights into or out of JFK airport, the latter provides airport information for each quarter hour, including meteorological conditions (i.e., IMC and VMC),

ceiling (in feet), visibility (in statute mile), wind speed (in knots), wind angle (degree), and airport runway configuration. Both datasets are collected at the same time period as the audio dataset.

The fourth dataset — trajectory-based anomaly score — is obtained from Metron Scientific Solution, Inc. (thereafter Metron). 7 anomaly indicators extracted from the 4-d trajectory in the JFK terminal area were used to identify various aspects of the flights that might have safety or efficiency problems: (a) maximum lateral distance (in feet) the flight's track overshoots the Extended Runway Centerline (ERC), (b) angle (in degrees) at which the track intercepts the ERC, (c) speed (in knots) when track intercepts the ERC, (d) glide path angle at intercept (in degrees), (e) long-period altitude tracks and (f) long-period heading tracks. All these anomaly indicator scores were weighted and combined as the Normalcy Score Broker (NSB) for each flight. The NSB are normalized from 0 to 1 by converting to their percentiles, with larger score indicating more anomalous points. A flight scored 0.9 is the 10th percentile anomalies flight in the detection dataset.

The following subsections introduce how we preprocess the four data sources and fuse them together.

B. Voice Activity Detection (VAD)

The first diagram in Figure 1. shows a 150-second sample of a voice clip on April 19, 2017. The sampling rate of the audio is 22,050 Hz, thus each point in the diagram represents the instantaneous signal strength (in Voltage) for 1/22050 second. For the purposes of calculating CAR, we apply a standard spectrum analysis algorithm (i.e., short time Fourier transform)[8] to each 30-minute audio file to find its characteristics such as energy in a time-frequency domain. Algorithm specifics can be found in TABLE I. A 3D representation of the original audio signal – frequency, time and energy – is shown in the second diagram of Figure 1.

TABLE I.   PARAMETER SETTINGS FOR THE SPECTRUM ANALYSIS

Parameter Name (Unit)	Value
Window size (NFFT, frames)	2048
Overlapping Rate	8%
Overlapping window size (frames)	256

After obtaining the spectrogram, we identify time periods when the audio channel is active. To tackle the issue of strong background noise that substantially degrades the accuracy of our identification results, we build up a Voice Activity Detection (VAD) algorithm described in TABLE II. by referring to the work of Pang [9]. Our VAD algorithm can identify the on and off time of each voice speech segment and calculate the CAR over a given period of time.
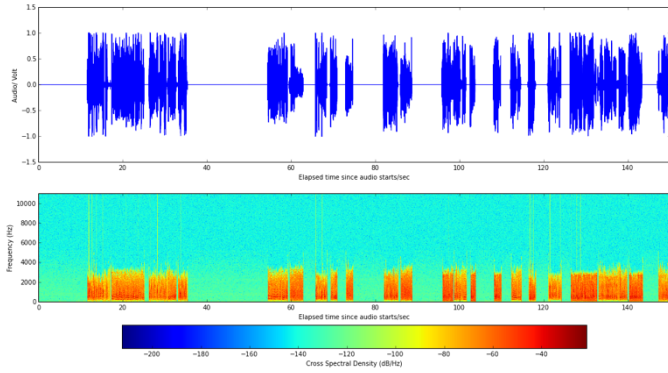
Figure 1. The sinusoid and spectrogram of sample voice signal.

C. Calculating Constrained Active Rate

In this study, we calculate CAR in 5-minute time interval. Other studies in this field also take 4-minute interval prior to real-time flight operation as the modeling unit ([11], [11]). In addition, the voice data are stored every 30 minutes, so that grouping the audio segments into 5-minute time interval can avoid the inconvenience of overlapping two audio recording files, thus improve the calculation efficiency.

TABLE II.   VOICE ACTIVITY DETECTION ALGORITHM

Algorithm 1. Voice Activity Detection
INPUT   The mp3 files of voice data from controller-pilot ATC tower communications at JFK airports.   **PARAMETER**   The number of points in the Moving Average Filter (default: 5)   Voice detection threshold *minE* (default: 0 db./Hz)   Minimum silence gap (default: 0.25 seconds)   Parameters of the spectrum analysis can be found in TABLE I.   **OUTPUT**   The start and end point of voice activity; Constrained Active Rate (CAR)
Step 1 Use the spectrum analysis method to get the power spectrogram, and convert the energy measurements to decibels/Hz. [a]   **Step 2** Divide the spectrum band into two halves: Lower Frequency Band (LFB) ranges from 0 kHz to 5 kHz and the Higher Frequency Band (HFB) is from 5 kHz to 11kHz.   **Step 3** Sum the spectrum energy of each speech window frame in LFB and HFB respectively, and apply the moving average filter to these summed values of each speech window frame.   **Step 4** The filtered spectrum energy in the HFB mainly represents the noise energy, while that in the LFB is dominated by voice pitch and harmonics. Therefore, noise cancellation can be achieved by subtracting the mean of Log noise energy in the HFB from the speech spectrum in the LFB of each speech frame.   **Step 5** Use the threshold *minE* to detect the active periods.   **Step 6** If the duration of non-speech sections is smaller than the minimum silence duration value, we merge the sections to the nearest speech sections.   **Step 7** The start and end time of voice activity is recorded and the active rate of each audio file is calculated and returned.

a. Such conversion involves logarithm operations and may cause negative infinite values, we hereby convert all the negative infinite values to 0

CAR ranges from 0% to 100%. The higher the CAR, the more congested the frequency channel was during that particular 5-minute interval.

D. Preprocessing ASPM Flight Level Data

We extract three types of explanatory variables from the ASPM flight level dataset. First of all, we aggregate the number of arrivals and departures respectively by the wheels-on and wheels-off time for every 5-minute interval corresponding to the time interval of the CAR data. Furthermore, as the flight operation is a key component affecting ATC communication active rate, we also use a set of leading variables of arrivals and departures. To be more specific, for each CAR observation, we use the number of arrivals and departures of the subsequent two 15-minute time intervals as the independent variables. Lastly, to understand how CAR differs in the day time, we use a dummy variable that equals to 1 if the observation time period is between 6 AM to 6 PM local time.

E. ASPM Airport Information Data

Two processes are used to map the CAR data with different weather variables. First, we derive the headwind/ tailwind speed and crosswind speed with respect to the corresponding primary arrival runway configuration. Six most used runway configurations, which account for 80% of observations, are categorized respectively as six dummy variables. Each variable is set to 1 if the JFK airport used the corresponding runway configuration during the observed time period. Second, since the ASPM airport information dataset was recorded every 15 minutes while our CAR data were computed every 5 minutes, we duplicated each ASPM record three times so that it can be matched with the CAR data.

F. Trajectory-based Anomaly Detection Data

We summarized the number of flights in different groups of anomaly scores – $0.6 \leq NSB < 0.7$, $0.7 \leq NSB < 0.8$, $0.8 \leq NSB < 0.9$, $NSB \geq 0.9$, and $NSB < 0.6$ – for every 5 minutes as in the CAR data.

After preprocessing and matching different data sources, our final dataset has a total of 83,280 observations. The summary of variables is presented in TABLE III.

III.   ECONOMETRIC MODEL

A. Censored Regression Model

In search of the upper limit to ATC communication, four histograms of the CAR – March, June, September and December – are shown in Figure 2. , where the vertical lines are the 75th percentile of the data. The histograms are in general skewed to the left, suggesting a right censoring effect, which may result from suppression of voice activity due to frequency congestion or ATCO workload. In other words, limited capacity either of the voice channel or of the controllers and pilots using the channel "squeezes" the usage of the channels, resulting in few observations at high CAR values. On the demand side, especially during the peak hour, high traffic volume tends to

create demand for communications that may strain the voice channel capacity. Weather and wind conditions may also affect communication demand. We seek to understand how the effects of limited channel capacity and communication demand combined to determine the active rate.

TABLE III.   MODEL VARIABLE DESCRIPTION

Variable Code	Variable Description (Units, per 5 minutes)	
Dependent Variable		*Category*
AR	ATC communication active rate (%)	ATC audio
Independent Variable		*Category*
Dep	The number of departures per 5 minutes	Flight operation information
Dep_i	The number of departures in the i-th subsequent 15 minutes ($i = 1,2, ...$)	
Arr	The number of arrivals per 5 minutes	
Arr_i	The number of arrivals in the i-th subsequent 15 minutes ($i = 1,2, ...$)	
Day_dummy	1 if observed period between 6 AM and 6 PM in local time, otherwise 0	
Headwind	Headwind speed (knots)	Airport condition
Tailwind	Tailwind speed (knots)	
Crosswind	Crosswind speed (knots)	
MC_dummy	1 if operations under IMC; 0 if operations under VMC	
Visible	Airport visibility (stature mile)	
Ceiling	Airport ceiling (feet)	
RWY_i_ _dummy	1 if the runway configuration i is used during the observed period, otherwise 0. Airport supplied runway configuration is represented as "arrival | departure).	
Anomalies (j)	The number of anomolous flights in group j. $j \in \{0.6 \leq$ NSB $< 0.7, 0.7 \leq$ NSB $< 0.8, 0.8 \leq$ NSB $< 0.9,$ NSB $\geq 0.9\}$	Flight anomaly detection

Due to the fact that we can only observe CAR in the ATC voice communication, using a naive linear regression will be biased [12]. A censored regression model, which is commonly used when the variable of interest is only observable under certain conditions, is used to estimate the relationship between the suppression of ATC communication and ATC operations under varying weather conditions. Also, Figure 2. suggests that the right censoring threshold is variable, since otherwise we would expect to see a large number observations close to the threshold value. Therefore, we assume that our censored regression model has a normally distributed threshold whose mean and variance are to be estimated. The details of the model will be presented in the next subsection.
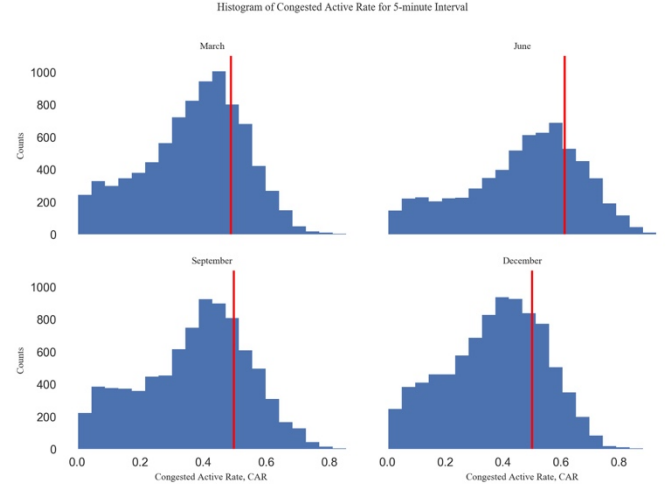

Figure 2.   Histogram of 5-minute Constrained Active Rate.

B. Model Specification

We use CAR, instead of power transformation, as the response variable in the censored regression model since the power parameter is close to 1 in the Box-Cox transformation. Consider our dependent variable y, which is CAR, is the minimal of two normally distributed random variables. Therefore, we can write y as in Equation 1, where $g(X) + \varepsilon_1$ and C_{max} are two Gaussian random variables.

$$y = CAR = \min[g(X) + \varepsilon_1, C_{max}]. \qquad (1)$$

Here we assume $g(X)$ is a linear function of the covariates (e.g., Equation 2), and ε_1 is a Gaussian random variable with zero mean and variance σ_1^2.

$$g(X) = X\underline{\beta}. \qquad (2)$$

The covariates X include variables related to flight operations activity, airport weather condition and flight anomalies described in TABLE III. The active rate predicted by $g(X)$ assumes that the pilots and controllers are able to transmit a message at any time and receive an immediate reply without any other concern. That is to say, there is no right censored limit or ATCO capacity constraint in the communication activity. We assume that the limiting value for C_{max} is a Gaussian random variable with mean μ_2 and variance σ_2^2. Thus:

$$C_{max} = AR_{max} \sim N\ (\mu_2, \sigma_2^2) \qquad (3)$$

The parameters of the C_{max} distribution must be estimated from the data. Lastly, we assume that the correlation coefficient between $g(X)$ and C_{max} is ρ, which also needs to be estimated.

The probability density function (PDF) of y can be derived as in Equation 4 [13], where $\varphi(\cdot)$ and $\Phi(\cdot)$ are respectively the PDF and cumulative distribution function (CDF) of the standard normal distribution. We estimate the value of the parameters $\boldsymbol{\beta}, \sigma_1, \mu_2, \sigma_2, \rho$ simultaneously using maximum likelihood. Notice that $\boldsymbol{\beta}$ estimates the effect of $\mathbf{X}$ on the latent dependent variable $g(\overline{\boldsymbol{X}})$, not the CAR.

$$f(y) = \frac{1}{\sigma_1}\varphi\left(\frac{y-\mu_1}{\sigma_1}\right) \times \Phi\left(\frac{\rho(y-\mu_1)}{\sigma_1\sqrt{1-\rho^2}} - \frac{\rho(y-\mu_2)}{\sigma_2\sqrt{1-\rho^2}}\right) + \frac{1}{\sigma_2}\varphi\left(\frac{y-\mu_2}{\sigma_2}\right) \times \Phi\left(\frac{\rho(y-\mu_2)}{\sigma_2\sqrt{1-\rho^2}} - \frac{\rho(y-\mu_1)}{\sigma_1\sqrt{1-\rho^2}}\right). \quad (4)$$

C. Estimation Result

TABLE IV. shows the estimation results for (1) the linear regression model without considering censoring effect, i.e., $y = g(\boldsymbol{X}) + \varepsilon_1$; (2) a censored regression model, i.e., $y = \min[\,g(\boldsymbol{X}) + \varepsilon_1, C_{max}]$, assuming $\rho = 0$; (3) a full censored regression model considering the correlation coefficient ($\rho \neq 0$).

1) Model selection

Comparing the models, we observe that the OLS regression model without censoring effect has significantly lower log-likelihood than both censored regression models and tend to underestimate the magnitudes of the coefficients. Comparing model II and III, while the majority of the estimates are similar, which matches our expectation, the log likelihood of model III is significantly larger and the results of likelihood ratio test reject the null hypothesis that $\rho = 0$. Therefore, we use model III for the subsequent analysis. The positive correlation suggests that the communication pressure created by a positive FAR residual (or slack resulting from a negative residual) has a concomitant effect on AR_{max}.

2) Right-censored threshold

The estimation result of the right-censored threshold limit is $\mu_2 = AR_{max} = 60.69\%$ and its standard deviation σ_2 is 0.1054. Therefore, the maximum active rate has a probability of 0.95 to be in the interval $[40.03\%, 81.35\%]$. In other words, the value of the FAR at which censoring would occur lies between these two values 95% of the time.

3) ATC operational environment impact

The vast majority of the estimates in TABLE IV. are significant and their signs match our expectation. The leading variables $Dep_{i\geq3}$ and $Arr_{i\geq2}$ are not significant and therefore were omitted from the model. The estimates for variables Ceiling and IMC are also insignificant.

The audio active rate is strongly correlated with the current 5-minute period flight operations and the leading operations up to 30 minutes in the future. And it is noted that the leading effect would decrease and dissipate over time. Higher visibility in statute mile decreases active rate, indicating a good meteorological condition potentially reduces the ATCO's work load.

TABLE IV.   MODEL EMPIRICAL RESULTS

Variable Code	Dependent Variable: *AR* Parameter Estimate [significant level] (Standard Error)		
	Model I: OLS	*Model II: Censored model*	*Model III: Censored model*
ρ	-	-	0.5797*** (0.0248)
μ_2	-	0.7438*** (0.0087)	0.6069*** (0.0037)
Dep	0.0267*** (0.0003)	0.0284*** (0.0004)	0.0296*** (0.0004)
Dep_1	0.0081*** (0.0001)	0.0084*** (0.0002)	0.0084*** (0.0002)
Dep_2	0.0037*** (0.0001)	0.0037*** (0.0002)	0.0036*** (0.0002)
Arr	0.0336*** (0.0004)	0.0355*** (0.0005)	0.0362*** (0.0005)
Arr_1	0.0129*** (0.0002)	0.0135*** (0.0002)	0.0136*** (0.0002)
Arr_2	0.0005** (0.0002)	0.0002 (0.0002)	-
Day_dummy	0.0097*** (0.0009)	0.0078*** (0.0010)	0.0061*** (0.0010)
Headwind	0.0008*** (0.0000)	0.0008*** (0.0001)	0.0009*** (0.0001)
Tailwind	0.0021*** (0.0002)	0.0022*** (0.0002)	0.0022*** (0.0002)
Crosswind	0.0013*** (0.0000)	0.0013*** (0.0001)	0.0014*** (0.0001)
Visible	-0.0014* (0.0002)	-0.0013*** (0.0002)	-0.0014*** (0.0002)
Anomalies (0.6≤ NSB <0.7)	0.0053*** (0.0008)	0.0060*** (0.0009)	0.0068*** (0.0010)
Anomalies (0.7≤ NSB <0.8)	0.0061*** (0.0008)	0.0068*** (0.0009)	0.0075*** (0.0010)
Anomalies (0.8≤ NSB <0.9)	0.0064*** (0.0008)	0.0073*** (0.0009)	0.0084*** (0.0010)
Anomalies (NSB≥ 0.9)	0.0086*** (0.0008)	0.0100*** (0.0009)	0.0112*** (0.0010)
31L, 31R | 31L (45.0%[1])	-0.0496*** (0.0011)	-0.0530*** (0.0012)	-0.0528*** (0.0012)
13L | 13R (13.9%[1])	-0.0303*** (0.0014)	-0.0330*** (0.0015)	-0.0331*** (0.0015)
13L, 22L | 13R (8.4%[1])	-0.0161*** (0.0016)	-0.0149*** (0.0018)	-0.0116*** (0.0019)
22L, 22R | 22R (7.0%[1])	0.0383*** (0.0017)	0.0401*** (0.0018)	0.0407*** (0.0018)
4L, 4R | 4L (4.6%[1])	0.0594*** (0.0019)	0.0615*** (0.0021)	0.0610*** (0.0021)
22L, 22R | 22R, 31L (4.5%[1])	0.0323*** (0.0020)	0.0384*** (0.0023)	0.0460*** (0.0026)
σ_1	-	0.1090*** (0.0003)	0.1082*** (0.0003)
σ_2	-	0.1556*** (0.0036)	0.1054*** (0.0019)
Constant	0.0975*** (0.0020)	0.0926*** (0.0021)	0.0899*** (0.0021)
Observations	83, 280		
Log likelihood	68498.49	68617.76	68872.79

***. Variables are significant at the 0.1% level

**. Variables are significant at the 1% level

*. Variables are significant at the 5% level

1. Frequency of runway configuration in the data

Stronger winds, whether headwind, tailwind or crosswind, lead to more ATC voice activities. Tailwind speed has the strongest impact, probably because it increases the aircraft groundspeed at touchdown and lengthens runway occupancy time. More generally, higher winds, and in particular tailwinds, may increase the amount of voice communication required to maintain separation.

Different runway configurations significantly impact the ATC voice activities. First, we define the runway utilization as the percentage of time that a specific runway configuration is being used in our study period. For example, JFK airport used 31L, 31R as arrival runway and 31L as departure runway about 45% of time during from Match to December in 2017. From TABLE IV. , we observe that the point estimate of the runway configuration fixed effect decreases as the runway utilization increases, which could be explained by the fact that pilots and controllers are more familiar with the frequently-used runway configurations.

Finally, the daytime dummy variable has a significant, positive, effect on the FAR. This could reflect differences in visibility or operating conditions, but further research is required to understand this result.

4) Anomalous flight operation impact

We include four different levels of anomalous arrival counts in the model estimation. They all have positive and significant effects on active rate. Flights with anomalous trajectories appear to require more communication with the tower. If there is one flight in the 10th percentile anomalies group (NSB$\geq$ 0.9), being controlled in the ATC operating system, the pilot-controller communication active rate will increase 1.12% on average relative to a "normal" flight (one with an NSB<0.6). As the level of anomalies rises, the active rate increases from 0.68% to 1.12%, or 2-3 seconds.

To summarize our results, the ATC voice communication active rate increases at heavy traffic, low visibility, strong wind, and trajectory anomalies, especially in the daytime. It also varies with runway configuration.

IV. COMPARISON OF MODEL RESULTS UNDER ATC FREQUENCY CONGESTION

In this section, we first apply Model III to simulate the ATC voice communication active rate for a range of inputs, and then compare these results under different scenarios.

A. Data Simulation

In order to evaluate the model performance, we use the coefficients $\hat{\beta}, \widehat{\mu_2}, \widehat{\sigma_1}, \widehat{\sigma_2}, \hat{\rho}$ in TABLE IV. and original dataset to calculate CAR and FAR. First of all, we randomly draw 40,000 records from our full dataset without replacement. Secondly, for each record, we only keep the independent variables X and calculate $\mu_1 = \widehat{g(X)} = X\widehat{\underline{\beta}}$. Then we draw five sample vectors $Y = [y_1, y_2]$ each with a sample FAR (y_1) and a sample

censored value (y_2) from a multivariate Gaussian distribution with mean $[\mu_1, \mu_2]$ and the covariance matrix $\begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_2\sigma_1 & \sigma_2^2 \end{bmatrix}$.
Lastly, for each record and each sample vector $Y = [y_1, y_2]$, we keep two different values: (a) $\hat{Y} = \min\{y_1, y_2\}$ to represent CAR and (b) $\hat{Y}' = y_1$ to represent FAR. Therefore, we end up generating 200,000 CARs and FARs.
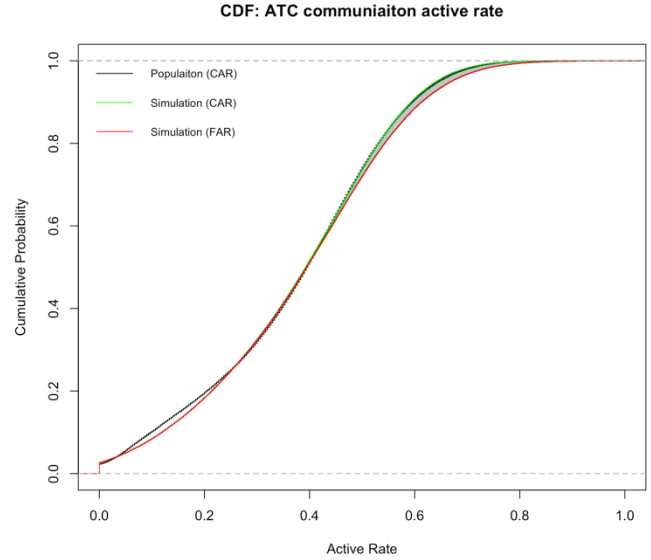

Figure 3. The CDF of Constrained Active Rate and Free Active Rate.

As shown in the Figure 3. , the black curve is the CDF of CAR based directly on the data we observed from the voice recordings. The simulated CDF of CAR, which is the green curve, is more or less similar to the black curve (original dataset). The red curve represents the CDF of the simulated FAR without communication suppression. For low active rates, simulated CAR overlaps with the simulated FAR, and diverges somewhat from the observed CAR. This difference reflects the fact that our model specification allows negative CARs and FARs, and is not of practical importance. At higher active rate values, the observed and simulated CARs are very close, and we observe a small gap between the red FAR curve and the black/green curves. This gap reflects the effect of the channel occupancy constraint on communication. While the FAR assumes that communication is not limited by a maximum active rate, that limitation pushes the CAR distribution to the green curve. The ATCO workload and frequency congestion suppress the ATC communication voice activities, but not that much − the area of gap is small. This can be explained by the estimation result of the correlation coefficient ρ. The positive correlation, 0.58, suggests that the upper limit of ATC voice communication has a significant relation to the communication pressure created by a high FAR. It agrees with the fact that ATCO will increase their

capacity when there is a high demand for pilot-controller communication.

We further quantify the gap between the CAR and FAR. Let $F_{CAR}(y)$, $F_{FAR}(y)$ denote the CDF of CAR and FAR, respectively. The shaded area is the difference in the expectations these two variables and can be calculated as:

$$S_{shaded} = \int_0^1 [F_{CAR}(y) - F_{FAR}(y)]\, dy =$$
$$\int_0^1 \{[1 - F_{FAR}(y)] - [1 - F_{CAR}(y)]\}\, dy = \mathbb{E}_{FAR}(y) -$$
$$\mathbb{E}_{CAR}(y) = 38.17\% - 37.51\% = 0.66\% . \qquad (5)$$

B. Daytime/Nighttime Comparison

We compare the CAR and predicted FAR separately for day time and night time. First, we split the dataset into day time and night time inputs observations on the daytime dummy variable. Then we follow the procedure as described in section IV.A to generate a set of CARs and FARs under day time and night time condition, respectively. Figure 4. presents the distributions of CAR and FAR for daytime operation in blue and red curves, night time operation in black and green curves, respectively. The area between the blue and red curves (daytime) is substantially greater than the area between the black and green curves (nighttime), indicating that communication constraints suppress more voice activity in the busier daytime hours. Numerically, the difference of CAR between daytime and nighttime is 6.14%. And also, we observe amount of observations whose active rate is 0% during the night time and few empty transmissions happen in the daytime because of traffic.
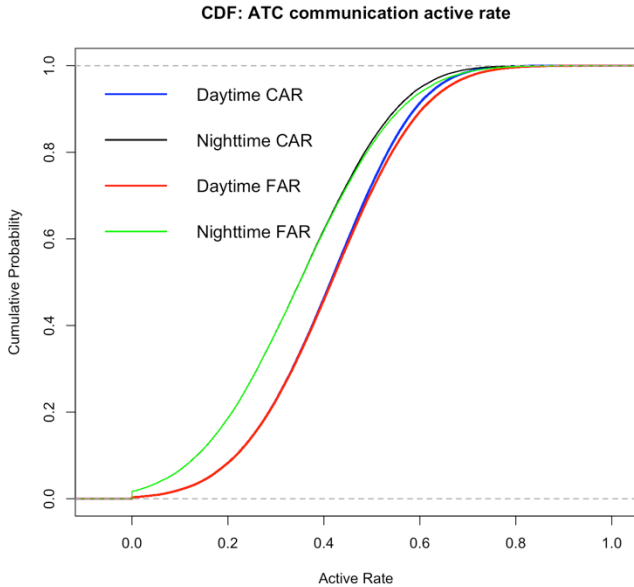

Figure 4.   Daytime and nighttime comparison.

C. Diurnal Variation

Here, we are going to investigate the difference in predicted communication suppression by time of day, along with the impact of flight operational volumes. We apply the same simulation method as above to calculate gap between FAR and CAR in each hour. The number of flight operations per five minutes for each hour are counted by using average value from the same data set. For comparison, these values are plotted against the same timeline with different y-axis in Figure 5. Not surprisingly FAR/CAR gap and flight operations show a similar trend over time. We also observed that there is almost no communication suppression from 0AM to 5 AM due to low traffic.
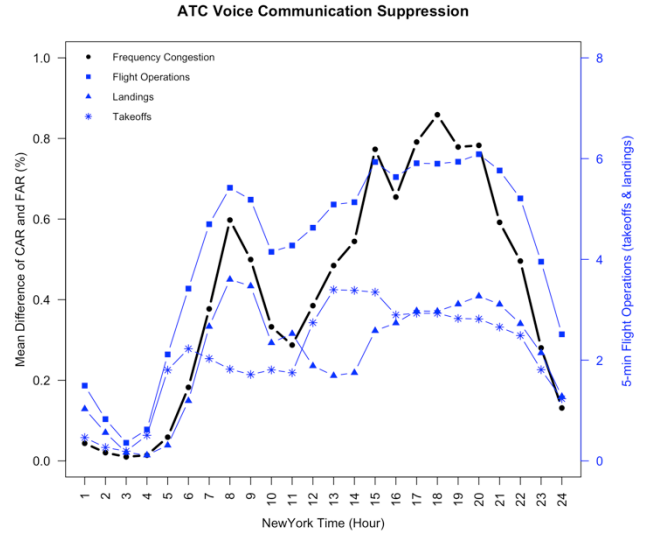

Figure 5.   The frequency congestion and flight operational volume.

V.   Conclusions

This research studies the existence and significance of the suppression of ATC communication voice activity due to frequency congestion or ATCO workload. This study firstly develops an efficient algorithm to detect the voice activity in a large sample of voice recordings under a real ATC operational environment. Using the voice activity data, along with the flight operation information, airport weather condition and anomaly detection results, a censored regression model with a stochastic right-censored threshold is estimated to show the relationship between ATC voice communication and the ATC operational environment. Flight operational volume, lead flight operations, time of day, meteorological conditions, visibilities, wind conditions, anomaly operations and runway configurations have significant impacts on the ATC communication voice activity. The substantial differences in estimation results for the uncensored and censored models strongly suggests the existence of a censoring effect. It suggests that ATCO will intentionally or unintentionally adjust the ATC voice communication active

rate at a manageable and acceptable level when there is heavy demand for communications, probably as a result of his/her workload and/or the amount of activity on the channel.

Through data simulation and comparative analysis, we replicate the distribution. The difference between the simulated distribution of CAR and FAR indicates the loss of communication activity, measured by active rate, that results from an upper limit on the active rate. We find that ATC communication is suppressed by roughly 0.7% in the absence of this limit.

In the future, monitoring CAR and the predicted FAR would allow detecting and predicting the loss of ATC communication activity on a real-time basis. The loss of ATC communication activity could be a helpful indicator to define the "critical points in time". With on-board performance monitoring, we can extend the capability of ATC system once we know where the flight will be at capacity limit and what the ATC operational environment is. A further stage of this study will include the voice data from other frequency channels, more airports and other facilities in the analysis to evaluate how communication suppression varies across the NAS. More research on voice processing—for example speaker recognition so that ATCO and pilot communications can be reliably distinguished—and model specification is needed to assess the validity and reliability of this modeling approach.

ACKNOWLEDGMENT

REFERENCES

[1] I. Barshi and C. Farris, Misunderstandings in ATC Communication. London: Routledge, 2013.

[2] P. Brooker, Controller workload, airspace capacity and future systems. 2003.

[3] K. M. Cardosi, An analysis of tower (local) controller-pilot voice communications (No. DOT-VNTSC-FAA-94-11). John a Volpe National Transportation Systems Center Cambridge MA, 1994.

[4] W. D. Reynard, "The development of the NASA aviation safety reporting system," National Aeronautics and Space Administration, vol. 1114, 1986.

[5] K. M. Cardosi, An analysis of en route controller-pilot voice communications (No. DOT-VNTSC-FAA-93-2). John a Volpe National Transportation Systems Center Cambridge MA, 1993.

[6] D. Morrow, A. Lee, and M. Rodvold, "Analysis of problems in routine controller-pilot communication," The International Journal of Aviation Psychology, 3(4), pp.285-302, October 1993.

[7] J. W. Howard III, "Tower, Am I Cleared to Land?: Problematic Communication in Aviation Discourse," Human communication research, 34(3), pp.370-391, July 2008.

[8] M. Portnoff, "Time-frequency representation of digital signals and systems based on short-time Fourier analysis," IEEE Transactions on Acoustics, Speech, and Signal Processing, 28(1), pp.55-69, February 1980.

[9] J. Pang, "Spectrum energy based voice activity detection," In Computing and Communication Workshop and Conference (CCWC), 2017 IEEE 7th Annual (pp. 1-5). IEEE, January, 2017.

[10] D. H. Porterfield, "Evaluating controller communication time as a measure of workload," The International Journal of Aviation Psychology, 7(2), pp.171-182, April 1997.

[11] C. Manning, C. Fox, E. Pfleiderer, S. Mills and H. Mogilka, "The relationship between air traffic control communication events and measures of controller taskload and workload," Air Traffic Control Quarterly, 10(2), pp.69-83, April 2002.

[12] Y. Ritov, "Estimation in a linear regression model with censored data," The Annals of Statistics, pp.303-328, March 1990.

[13] S. Nadarajah and S. Kotz, "Exact distribution of the max/min of two Gaussian random variables," IEEE Transactions on very large scale integration (VLSI) systems, 16(2), pp.210-212, February 2008.