Abstract – Multiple Boeing programs (P-8A, P-8I (India), F-15 Royal Saudi AF, NATO and French AWACS, Wedgetail flight testing and demo activities) have been adversely impacted by FAA spectrum concern of oversaturation of the National Air Space (NAS) in the 1030/1090 MHz frequency utilized for identify friend or foe (IFF)/Traffic Collision Avoidance System (TCAS). Civil Mode S transmissions by far dominate this spectrum, and thus was the focus over other Air Traffic Control Radio Beacon (ATCRB) modes 3, C or military mode 4. In this paper, we present a novel method to quantify relative margin of Mode S transmissions between test locations of Boeing’s interest as compared to dense Northeast traffic corridor near JFK. Assuming that the Northeast corridor operated safely in 2011, our results show that significant margin exists in areas such as Puget Sound area, Charleston, St. Louis and Oklahoma City, even with generous assumptions of increasing air traffic densities. These results provide direct evidence that Boeing can effectively and safely complete test objectives while maintaining the integrity of operations in the national airspace.

Index Terms – 1030/1090 MHz, ADS-B, IFF, TCAS.

I. INTRODUCTION

With the introduction of civilian air traffic management technologies such as Mode S and Automatic Dependent Surveillance-Broadcast (ADS-B) in the continental US (CONUS), the FAA has unprecedented capability to track, identify and receive on-board information from transponder responses at 1090 MHz. Additionally, transponder TCAS communications at 1090 MHz provides real-time proximity warnings to avoid in-air collisions.

However, these functionalities are not without cost. Longer data messaging formats coupled with the ever increasing number of domestic flights has raised concerns within the FAA community regarding additional RF interrogations (at 1030 MHz) and replies (at 1090 MHz), especially those located near international airports. Therefore, FAA has taken a very conservative stance in identifying the level of 1030/1090 MHz transmissions that is deemed safe for all systems to operate without causing interference. Consequently, the Boeing Frequency Management organization has had difficulty obtaining clearance to radiate using 1030/1090 MHz to complete some qualification testing related to Boeing’s Direct Commercial Sale of military, commercial derivative products and possibly commercial airplanes in the future. Alternately, when clearance to operate is granted, it is often very restrictive in scope, requiring long transit time to the designated test locations, which increase the risk of successful test completion, and driving up the cost of delivering products on time and on schedule. MIT Lincoln Laboratories (MIT LL) has published several reports [1] [2] on 1030/1090 MHz congestion, which the FAA cites to validate their position.

As result, multiple Boeing programs (P-8A, P-8I (India), F-15 Royal Saudi AF, NATO and French AWACS, Wedgetail flight testing and demo activities have been adversely impacted by FAA spectrum concern of oversaturation of the NAS in the 1030/1090 MHz frequency [3] utilized for IFF/TCAS collision avoidance systems. The purpose of this paper is to describe a novel method used to analyze 1030/1090 MHz congestion using MIT LL data, and provide results that Boeing can use to quantify its request for testing systems efficiently without significant cost and without causing interference with NAS operation.

Conventional 1030/1090 MHz congestion analysis [4] focused on worst case for one single platform via simulations. In our studies, we propose novel stochastic relative margin analysis. More specifically, we compare flight data between dense Northeast (NE) corridor (i.e., near JFK, LaGuardia and Newark) and Boeing sites where aircraft are either manufactured or modified and require functional testing for delivery or qualification. The sites examined included the Puget Sound area, Charleston, St. Louis and Oklahoma City, but the method could easily be applied to other areas (such as Edwards AFB or PAX River) if the need arose. In particular, we would like to quantify relative operating margins given that flight density is not uniform across CONUS and safe operations are currently being conducted in the dense NE corridor.
The rest of the paper is organized as follows. Section II describes the data we used in our analysis. We then present our analysis in Section III, where we introduce our hypothesis, provide detailed description on simulation analysis approach and corresponding results. The results explore 1090 MHz congestion margins in various CONUS locations of interest from a BCA and BDS perspective. Section IV concludes the paper.

Finally, we would like to point out that the original version of this paper was created via literate programing by using R [5] and R Markdown [6]. As result, all Figures, results in Tables and text along with manuscript itself can be traced and reproduced by readers. However, for this Innovation Quarterly edition, the manuscript was regenerated using Microsoft Word software. Thus, all Figures and numerical results are hard copied in from original manuscript. Please contact authors for the original R markdown documents if readers are interested in reproducing all results directly from raw data sets. The software is Boeing Propriety and requires proper approval by The Boeing Company.

II. AIRPORT RF SPECTRUM ENVIRONMENT DATA

In this section, we describe the data used in our studies. We leverage measurement data collected at JFK described in MIT LL Report [2] as our baseline in our analysis.

In April 2011, MIT LL installed their omnidirectional Thales receiving system at JFK. They also used FAA radar at JFK for simultaneous measurements of aircraft tracks to correlate. They recorded 1030/1090 MHz RF signals for 25 days. Their measurements data are at macro-level instead of observations at individual aircraft. Table 1 summarizes the key characteristics of their data, which requires our model data characteristics to match.

<table>
<thead>
<tr>
<th>MIT LL Data</th>
<th>Match requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal-in-space @ −74 dBm</td>
<td>Proper equivalent range to count aircraft at the other airports.</td>
</tr>
<tr>
<td>Hourly aircraft counts</td>
<td>Need to have same granularity for all the other airports.</td>
</tr>
<tr>
<td>Omnidirectional reception rate and occupancy</td>
<td>All at system macro level, not per aircraft.</td>
</tr>
<tr>
<td>Per-aircraft transmission rate statistics</td>
<td>It can be used as upper bound directly when fewer airplanes than that of JFK present.</td>
</tr>
</tbody>
</table>

Table 1: MIT LL Data Characteristics

In the following, we will describe how we select our data set to match with MIT LL measurement results per Table 1. The threshold of −74 dBm (referred to the signal-in-space) was used by MIT LL to filter their RF recordings for the computation of omnidirectional reception rates. The threshold is also the nominal Minimum Triggering Level (MTL) for a TCAS on an aircraft [2] [7]. In order to align our analysis with this threshold, we need to identify corresponding range within which the received power at antenna is greater or equal to −74 dBm. This is the range we will use to calculate macrolevel occupancy rates for relative margin analysis.

Equation 1 shows calculations for received power:

\[ P_r = P_t + G_t - C_t - L + G_r - C_r \]  

where

- \( P_r \) = received power in dBm
- \( P_t \) = transmission power in dBm
- \( G_t \) = transmitter antenna Gain in dBi
- \( C_t \) = additional cable loss at transmitter in dB
- \( L = 20\log_{10} \frac{4\pi d}{\lambda} \) = free space path loss in dB, in which \( d \) = range and \( \lambda \) = wavelength.
- \( G_r \) = receiver antenna Gain in dBi
- \( C_r \) = additional cable loss at receiver in dB

We use nominal transmitter power 54 dBm at antenna (namely, \( P_t + G_t - C_t \)) as indicated in DO-260B [7] and the same −74 dBm MTL at antenna (namely, \( P_r - G_r + C_r \)). Figure 1 provides the received power and corresponding range. For −74 dBm MTL at the antenna, the corresponding range is 30 nautical miles (nm).

![Figure 1: Radio Range](image_url)

Once we identify the radio range, we need hourly aircraft counts to match the measurement data from MIT LL. We first looked at ASDI dataset available from BR&T ATM group. It has detailed track data for each individual aircraft.
It requires significant effort to abstract that data to the same level of granularity as MIT LL data, namely, hourly total counts above -74 dBm signal-in-space threshold. We then investigated database at FlightAware. It has the same issue of granularity and in addition it also requires license.

Fortunately, we are able to identify flight on time performance data that is openly available from Bureau of Transportation Statistics (BTS) [8]. The hourly total aircraft count within range can be easily obtained from this dataset. We will describe how to use this dataset in Section III in depth. (Reference Appendix A).

We also need to identify which airports are within 30 nm from point of interest and filter out these airports data accordingly from aforementioned BTS dataset. To that end, we use airport location data and planned arrival/departure flight counts from databases maintained by OpenFlights.org [9].

Figure 2 shows airports in JFK, SEA, STL and OKC area. SEA, STL and OKC are candidate test sites for BDS platforms. The area of each red dot is proportional to the total number of distinct planned departure routes for that airport. This figure identifies all airports within 30 nautical miles from airport of interest (e.g., JFK), which are the candidates for being included in the aircraft counts based on BTS dataset. Furthermore, it also provides some level of indication whether those airports are significant in term of contributing to the air traffic. For example, there are two major airports which are within 30 nm from JFK, namely, EWR and LGA. Neither STL nor OKC has any other major airports that are within 30 nm. For SEA, there are a couple of small airports close-by based on number of departure routes. However, when we look at details on number of actual flights, the frequency is so low that including flights from these airports will not have any statistical significance as the total number of flights from these airports are very small.

Similar to Figure 2, Figure 3 shows overview of airports around the potential test sites for BCA platforms, namely, Seattle and Charleston metropolitan areas. It is clear that there are no other major airports in Charleston beside CHS.

Finally, we recognize that BTS dataset only have data for air carrier and it may have missing data since the primary goal of the data set is for measuring airline on-time performance. Therefore, we also compared it with FAA Operations Network (OPSNET) data set (formerly known as Air Traffic Activity System (ATADS)) [10]. OPSNET only has total number of operations on granularity of a day (i.e., no hourly data available). Thus, we cannot compare them directly but we can compare the total over a period of time. Also, FAA OPSNET has totals for air carrier, air taxi and military. This is useful to determine the impacts from air taxi and military aircraft. After careful examination and cross comparison with BTS dataset, we reached the following conclusions and made adjustment accordingly:

- Comparing with air carrier and air taxi, number of military aircraft and other general aviation can be ignored safely due to very low total count. For example, 98.8% of total aircraft are from air carrier and air taxi for SEA in 2014.
- The air taxi in JFK/EWR/LGA is more than any other airports of interests. In fact, EWR has the largest number of air taxi among all airports. Since our analysis is relative margin from JFK/EWR/LGA, we can safely focus on air carrier data only. If large relative margin for an airport of interest exists based on air carrier only comparing with JFK/EWR/LGA, the margin will be even larger if air taxi are included since JFK/EWR/LGA has the largest number of air taxi count.
- BTS data set only has timing data for air carrier and there is small difference when we compare total number of air carrier from BTS with total number of air taxi from FAA OPSNET. Therefore, we calculate the scaling factor such that the total aircraft count from BTS will match with that of FAA OPSNET database. Here we assume that BTS uniformly misses counts on aircraft.
Figure 2: Airports around JFK area and airports around potential test sites for BDS applications
Figure 3: Airports around potential test sites for BCA applications

Figure 4: Example of peak hour arrival and departure distributions at SEA airport with 2014 data
III. RELATIVE MARGIN ANALYSIS AND RESULTS

A. Hypothesis

Our relative margin analysis is based on the key observation that safe operations are currently being conducted in the dense NE corridor (i.e., near JFK, LaGuardia and Newark). Therefore, for any other airport that is in less dense areas, it should be able to increase its load on the 1030/1090 MHz channel safely as long as total number of aircraft within range is less than that of dense NE corridor. This is exactly the hypothesis for our relative margin analysis.

Furthermore, comparing with 1030/1090 MHz channel occupancy of the dense NE corridor, we would like to quantify the relative operating margins for the airports where Boeing can test its products. For example, BCA test locations of interest include Seattle and Charleston. BDS test locations of interest include Seattle, St. Louis and Oklahoma City. While it seems intuitively obvious that 1090 MHz transmissions are lower in Oklahoma City as compared to JFK, it requires vigorous statistical analysis to quantify the relative margin between locations such that we can evaluate the impact of additional hypothetical test flights at each test locations. In the following sections, we will present our analysis in detail and report the corresponding results.

B. Simulation and Analysis

The steps of our statistical analysis on the relative margin can be summarized as following:

1. Compute hourly distribution of aircraft density within 30 nm from any major airport of interest. The rational for using 30 nm is given in Section II.

2. Select reference airport. In our case, we choose JFK. Compute the hourly distribution of aircraft within 30 nm from the reference airport. Since both EWR and LGA are within 30 nm from JFK, the reference hourly distribution is the sum of JFK, EWR and LGA.

3. Measure the reference airport 1030/1090 MHz channel occupancy and per aircraft 1030/1090 MHz message reception distribution. In our analysis, we completely skipped this step as we can fully leverage the results from [2].

4. Perform stochastic simulations to compute the channel occupancy using hourly distribution obtained in step 2. Compare the simulated channel occupancy with measured data from step 3 to scale parameters used in simulations such that the channel occupancy from simulations matches with measurement.

5. Use the same parameters obtained in step 4 for all other airports to compute their channel occupancies via stochastic simulations.

6. Compute the relative margin using the channel occupancies from step 5.

In order to compute the hourly distribution, we use all 365 days data for the year of 2014 from BTS data set as described in Section II. In contrast to [2] in which 25-day data were collected, we use entire year data to include both seasonal and diurnal variations such that we can capture those variations in our simulations. The number of take-offs and landings every hour over a 24-hour period is then used to obtain the distribution. Figure 4 shows examples of hourly distribution for SEA airport. In this example, the histograms for both arrivals and departures at 11:00am and 12:00pm are plotted. We also plot both empirical probability distribution function and Gaussian distribution function with the same mean and standard deviation. At peak hours such as in Figure 4, the Gaussian distribution is a good approximation.

We also compute the hourly distribution for our reference airport JFK area. We compared the yearly total between BTS database and FAA OPSNET database as described in Section II. Figure 5 shows total number of flight operation in the JFK area using FAA OPSNET database. There is modest year-over-year growth for JFK area mainly due to the growth from LGA. We scale the hourly distributions based using FAA OPSNET database for all airports.

Figure 6 shows the final scaled hourly distribution using SEA as example. Clearly, the airport has low utilization activity before 5:00am. The departure flights dominates before 10:00am. During the daytime, the departures and
arrivals are about the same to approach equilibrium. Finally, there are more arrivals during the evening hours, which balanced out more departures during early morning hours. Furthermore, the variance from 1:00am to 5:00am is very low and variance during daytime is high as expected.

After we computed the hourly distribution for all airports, we compare them with that of JFK area. Figure 7 shows the results. Our hourly distribution for JFK/EWR/LGA resembles Figure 10 in [2]. In particular, each day before 5:00am, the number of aircraft around JFK is minimum. The peak hour is in the middle of afternoon. The total number of aircraft at peak hour aligns well between measured data and our constructed distribution.

Figure 7 also clearly shows that number of aircraft in JFK area is much higher than the other airports as we expected. SEA airport is about 30–40% of the total aircraft at
JFK/EWR/LGA. SEA has higher flight density than STL, OKC and CHS. Also note that the busier the airport that higher is the variance.

Once we have the hourly distribution, we can compute number of aircraft within 30 nm that will generate 1030/1090 MHz messages. Since we only know the aircraft distribution with respect to time, we propose a simple method to map it to range. More specifically, we assume that BTS database records departure/arrival time as follows (see top portion in Figure 8):

- Departure time is measured at “Gate departure” when parking brake is released.
- Arrival time is measured at “Parking” when parking brake is set.

![Figure 8: Flight phases and parameter \( t_0 \)](image)

Referring to the bottom part of Figure 8, we define the following for parameters \( t_0 \) departure and \( t_0 \) arrival:

- \( t_0 \) departure is the time interval before \( t \) during which departure flights left the Gate and are still within 30 nm from the airport.
- \( t_0 \) arrival is the time interval after \( t \) during which arrival flights are approaching the Gate and are within 30 nm from the airport.

We could treat both \( t_0 \) departure and \( t_0 \) arrival as random variables and draw samples from their distributions if known. For simplicity, in our analysis, we consider it as a parameter which we can adjust such that the resulting message rate from total number of aircraft will match between simulations and measured data for the reference airport, namely, JFK for our case.

In our simulation, we use the following data based on measurement data from [2]:

- Mode S short messages dominates overall Mode S messages. See Figure 14 in [2]. Therefore, it is clear that we can focus on Mode S short messages. As shown in Figure 7, JFK area has much higher aircraft counts than any other airports. Thus, we can safely ignore messages other than Mode S short messages. This is because we are only interested in relative margin. JFK area will have more uncounted messages than those for any other airports.
- We assume all major airports share the same mix of aircraft as measured in JFK. The Mode S aircraft dominates the overall aircraft at 88%.
- Per aircraft reception rate during daytime is a random variable with mean 14 and 95% interval [10,17]. Note that, this per aircraft reception rate is measured at JFK. The reception at the other airports should be lower due to less density. However, we use the same as conservative approach since we perform relative margin analysis. This conservative assumption provides actual safe margin.

For each of our simulation experiments, the number of departures and arrivals are randomly sampled according to the distribution we computed (examples of such distributions are shown in Figure 4). For each aircraft, the message reception rate is randomly sampled according to [2] as mentioned above. We run 10,000 simulations for each hour during the 24-hour period. The parameters \( t_0 \) departure and \( t_0 \) arrival are adjusted such that the message rate for JFK area matches with Figure 14 in [2]. Once this statistical model of the JFK/LGA/EWR location was verified, we applied similar per-aircraft transmission characteristics, \( t_0 \) departure and \( t_0 \) arrival to other airports. In the following Section, we present the simulation results based on relative margin analysis described above.

Finally, in order to maintain the reproducibility and tractability for documenting the results from our modeling and analysis, we used R Markdown [6] to author this paper. All software code that is required to perform simulation and generate results is embedded within this document. As a result, any reviewers can regenerate this paper and trace all computations right from the document source. This facilitates reproducibility of research, knowledge sharing and reusibility of the software. It also reduces the chances of error when data are updated as all figures and tables are generated each time automatically with latest data.
Figure 9: SEA, STL and OKC vs JFK/EWR/LGA: Timeline Occupancy

Figure 10: SEA and CHS vs JFK/EWR/LGA: Timeline Occupancy
C. Results

The metric used for measuring saturation is timeline occupancy for Mode S in 1090 MHz as defined and measured in [2]. In particular, let $M$ be the number of Mode S messages in 1 second with a threshold of $-74$ dBm and $L$ be fraction of second of time occupied by each Mode S message, the timeline occupancy $\eta$ is defined as following:

$$\eta = M \times L$$

As short Mode S messages dominate the overall 1090 MHz channel, we only need to use short Mode S messages for relative margin analysis. Again, this has built-in safe margin as JFK/EWR/LGA has more long Mode S messages than any of the other airports. Thus, we can use the short Mode S for Equation 2, $L = 64 \times 10^{-6}$, namely, 64 microseconds.

Note that, the use of timeline occupancy $\eta$ as the metrics in relative margin study is novel. There is no prior work in which timeline occupancy $\eta$ is used to compare saturation between airports. Previous research work [4] mainly focused on worst case message rate on a single platform and it only compared with maximum threshold that is limited by hardware/software (e.g., interrupt handling limitations). These methods never looked at the saturation problem from system perspective. We believe that our method fulfilled that gap and it is complementary. The results presented in [2] facilitate the development of our methodology. Our results are complementary and offer system level margin analysis.

<table>
<thead>
<tr>
<th>Airports</th>
<th>Normalized to Seattle peak hour occupancies</th>
</tr>
</thead>
<tbody>
<tr>
<td>JFK/LGA/EWR</td>
<td>2.7</td>
</tr>
<tr>
<td>SEA</td>
<td>1</td>
</tr>
<tr>
<td>STL</td>
<td>0.43</td>
</tr>
<tr>
<td>OKC</td>
<td>0.16</td>
</tr>
<tr>
<td>CHS</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Table 2: Normalized Occupancies Based on SEA Peak Hour Occupancy

Figure 9 and Figure 10 show the timeline occupancy rate comparisons for BDS and BCA test locations respectively. The shaded area represents the variation from the simulation due to the random sampling of hourly arrivals/departures process and random message reception rate per aircraft from its distribution. Both $t_0$ departure and $t_0$ arrival are set to 30 minutes, which yield peak hour occupancy rate $7.6 \pm 1.1\%$. Note that [2] reported maximum peak hour occupancy rate $7.7\%$, which is clearly within our predicted range. All test locations have much less occupancy rate comparing with JFK reference. The OKC has the lowest occupancy rate among potential BDS test locations while CHS has the lowest occupancy rate among potential BCA test locations.
While detailed per hour distributions are given in Figure 9 and Figure 10, we would like to find out the relative ratio at peak hour. To this end, we normalize the Seattle peak hour transponder occupancy and reception rates to 1.0. We compute relative transponder occupancies for other locations as shown in Table 2. The for various CONUS locations of interest from a BCA and BDS perspective. The shaded area represents the variation from the data and simulation.

The sensitivity of transponder occupancy to additional flights was also statistically modeled as illustrated in Figure 11. In this scenario, 5, 10 and 20 test flights per hour are added to the baseline number of flights around SEA area for each hour between 7:00 am to 7:00 pm. That corresponds to 60, 120 and 240 total test flights added during a day. The effect of adding 20 more flights per hour to the SEA corridor is still roughly less than half what is currently experienced in the JFK/LGA/EWR area.

Finally, we would like to compare timeline occupancy results with classic pure Aloha protocol described in detail by Dimitri Bertsekas et al. in [11]. Figure 12 shows the system throughput as function of offered load. The throughput is probability of success, namely, there is no collision at a receiver for a message transmitted in shared medium. The offered load is attempt rate, namely, the expected number of messages transmitted in a time unit. For our case, the offered load is expected number of messages in a 64-microsecond Mode S slot, which is also the probability of timeline occupancy. If we use peak hour timeline occupancy rate measured in [2], i.e., 7.7%, the throughput will be 6.6%. Thus, the success rate with respect to the offered load is 86%. This result is in line with Figure 20 in [2], where percent of 1090 MHz receptions with correct parity verse 1090 MHz reception rate was measured. With 1,200 per second short Mode S at MTL −74 dBm (which is the peak hour rate), Figure 20 in [2] shows about 90% correct parity rate. Note that, the better throughput than pure Aloha is expected since pure Aloha is the simplest wireless random access protocol which is used as the lower bound.

It is also interesting to note that Figure 12 shows the system throughput is maximized when offered load is at 0.5 expected messages per 64-microsecond time unit (which is 50% timeline occupancy). The corresponding throughput is 18%. Thus, the probability of receiving collision free messages with respect to the offered load is 36%. This is not so bad as it reaches 99.999% probability of success after 30 retries. Note that systems like TCAS are designed using retries to ensure the robustness. Since the timeline occupancy is only 7.7% at JFK area, Figure 12 shows traffic density can continue grow even for airports around JFK since 7.7% is far less than maximum achievable throughput when timeline occupancy is at 50%.

**IV. Conclusions**

In this paper, we presented a novel approach to compute relative margin at system level for various systems that utilize 1030/1090 MHz channel. Instead of focusing on saturation of single platform, we quantify relative margin in over-the-air capacity shared by all platforms. Based on our results, it can be safely inferred that less dense air traffic corridors can easily accommodate 1090 MHz transmissions from airborne and ground testing if the additional flights exhibits similar characteristics of air commercial flights. By judiciously managing temporal differences in flight density and interrogator directionality (e.g., away from air corridors of interest) Boeing can effectively and safely complete test objectives while maintaining the integrity of operations in the national airspace.

Subset of the results at very high level was presented to DoD communities [4]. Our methodology and conclusions were well received. Additional collaborations are expected in the near future to resolve the issue about the views on 1030/1090 MHz saturation. Our reproducible analysis can serve that purpose well from technical point of view. To that end, we believe full and detailed documentation of our analysis such as this paper is beneficial.

**APPENDIX**

**A. BTS URL**


User needs to replace the [%d,%d] with year and month. For example, if you need data for January, 2014, the download URL is

ACKNOWLEDGEMENTS

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This publication is dedicated to our late colleague, James Farricker, Boeing Senior Chief Engineer for Networks and Communications and Senior Technical Fellow, (1955-2016).

REFERENCES


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