A Stochastic Model for Air Traffic Control Radio Channel Utilization

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***Abstract*—This paper offers a stochastic model for radio channel utilization in air traffic control. A log-normal probability distribution for the interaction frequency ('interarrival' times between successive radio interaction), as well as a multivariate joint probability distribution for speech/silence timed sequences have been constructed from over 1300 hours of recorded radio communication. While the density of communication is reflective of the density of traffic, its sequencing and other emerging patterns are also consequences of the controller cognitive processes. Such a model for radio channel utilization is a step toward adjusting automated conflict avoidance and decision support tools to effectively match controller attention patterns and task loading. By tuning the output of automated aids to more closely coincide with flight instructions in a manner easily comprehended and perceived by human controllers, this will help reduce workload, improve situation awareness, and address safety concerns by insuring effective human monitoring and trust of future automated maneuvers. Other applications may be in the use of automated advisory assistants suggesting flight instructions in humanly acceptable, albeit mathematically suboptimal, temporal patterns.**

I. Introduction

By 2025, U.S. air traffic is predicted to increase two- or threefold, reaching gridlock under the current air traffic practices, and similar forecasts of congestion threaten the European skies. It is widely believed that to accommodate this growth a paradigm shift is necessary; one that will alter the current role of air traffic control from management of traffic by default to management by exception - where the majority of the work required to deconflict traffic will be performed by an automated system working in conjunction with a human controller. In fact, most possible future solutions that have been presented involve automated conflict resolution algorithms, with various levels of implementation and control: from systems where the controller retains the ultimate responsibility and decision (Wangermann and Stengel, [1]) to robust fully autonomous free flight systems (Masci et al., [2]). It is reasonable to expect that as we move away from current pratices, the first step in a more automated ATC paradigm will include automation which provides deconfliction suggestions and acts as a decision aid for human controllers. In that environment the roles of the pilots and air traffic controllers remain as they are today and the fixed route structure is largely intact. This paper is aimed at such a context and works toward improving these automated assistants from a cognitive engineering perspective.

While it is clear that the introduction of automation will be required, studies such as those conducted by Parasuraman et al. have revealed that hitherto, increase in automation has not been matched by comparable improvements in performance, and the same is to be expected in the future unless care is taken [3]. Human operators often underutilize or conversely overly rely on automation, and Dzindolet et al. have shown that trust is an important factor in understanding automation reliance decisions [4]. If the desired shift in air traffic management is to take place, it appears critical that the automation put into place be transparent, reliable, and synergetic with its human operator's work practices.

In the present as well as in the future context we are describing, all flight instructions will be issued by the controller and confirmed by the pilot. For this type of automation, which provides conflict resolutions to the controller for approval, several questions regarding communication arise:

- How often should advice be provided?
- How much advice should be provided at any time?

We believe that a step toward answering these questions requires understanding the cadence of controller-pilot communication. The temporal spacing of flight instructions is reflected in communication patterns, and hence the study of communication may provide a valuable means of extrapolating controller work rhythms. By taking into account the customary manner that controllers have of dealing with air traffic management, automation will be less disruptive.

Specifically, an understanding of the temporal spacings in pilot-controller communication is needed in order to adapt the output of such automation to provide maneuver suggestions in a sequence corresponding to the human controller's attention and perception patterns. For a controller assisted by an automatic decision advisor this will help reduce workload and improve situation awareness by respecting the work pattern.

Controller-pilot radio channel utilization is a relatively recent topic of interest and has only been tangentially addressed (cf. literature review by Prinzo and Britton [5]). Radio communication has mostly been a focus of research aimed at analyzing complexity, miscommunication and sources of errors. Burki-Cohen has examined the incidence of the complexity of controller instructions on communication problems and conceptual errors [6]; Prinzo, Hendrix and Hendrix have shown that message complexity is correlated to errors of omission, while message length affected both the production of errors of omission and readback errors [7]; Prinzo and Morrow have elsewhere attempted to improve undertanding by studying the influence of message format and message length [8]; Prinzo has also categorized the communication elements according to their semantic taxonomy and the corresponding distribution of ambiguities or misunderstandings [9].

Rakas and Yin have found that pilot initiated communications at arrival into or departure from a sector are more likely to cause errors then those initiated by controllers, that departures rather than arrivals cause more extensive and significant miscommunications, and suggest that there is less miscommunication in situations when a controller is handling several aircraft simultaneously [10]; Cardosi has conducted similar studies for the purpose of examining communication practices and the relation between complexity and error in the enroute [11] and terminal (tower) [12] environments; Howard's analysis of problematic communication showed that pilot speech contained more errors than the controller one, that higher amounts of information led to increased problematic communication in subsequent interactions, as did linguistic violations of protocol [13].

Straussberger has proposed a model of monotony that considers repetitiveness and uneventfulness, the individual boredom proneness and states at the beginning of the work shift as well as organizational factors to assess monotony with the help of physiological, subjective, and behavioral indicators, in distinction with other states such as fatigue and satiation [14].

Some authors have also explored workload and its relation to voice communication patterns and channel occupancy. Porterfield's work has shown high correlation between the controllers'communication duration and the controllers' subjective workload, hence validating communication duration as a workload measure [15]; Prinzo et al. indicate that hesitation pauses in speech occur in low workload conditions, when the controller has time to think and responds in a cognitive way, as opposed to an automatic way encountered under high traffic load [16]; Bolic et al. have conceived a cognitive utilization metric, meant to capture the ratio of time in which a controller thinks about certain aircraft, and have found this to be correlated with the utilization of the radio channel. Nonetheless in cases when the former exceeds the latter, controllers' and pilots' capacity to conduct voice communications is substantially reduced [17].

However, Manning et al. have shown that the addition of communication to a model of workload does not improve or render more precise its estimates deduced from conventionally measured air traffic control taskload data [18].

By correlating communication data with vector deviations from the assigned flight paths, Yenson and Rakas have developed a controller workload model demonstrating increased efficiency with the use of a mixed voice and datalink system environment that reduces voice channel usage and by extension controller workload [19].

But the preceding papers do not provide the quantitative description of pilot-controller interaction that would allow designers of decision aid automation to integrate information referring to communication. This paper seeks to stochastically model air traffic control and aircraft pilot communication patterns. The ambition of such a model is ultimately that of enhancing air traffic control automation and decision aids by matching the output with pre-existing human controller communication rhythms and attention patterns. It is therefore important to note that our focus is not the direct improvement of the current work practices in air traffic control, but rather the improvement of future automation such that it will feel more natural to the human it is designed to assist under the paradigm shift heralded by NextGen and SESAR. We suggest that the integration of a type of automation cognizant of human idiosyncracies would benefit its acceptance, its intelligibility, and fundamentally the reliance on it.

II. Analysis

The construction of an inter air traffic control - pilot communication model began with the collection of communication data. An analysis in several stages was conducted to identify the statistical distribution of the communicaton parameters.

A total of 1326 hours of radio communication related to Atlanta's Hartsfield-Jackson airport and northeast arrivals has been analyzed. Specifically, these are 344 hours for the TRACON frequency at 127.25 Mhz (north final approach into ATL), 381 hours for the enroute center frequency at 121.35 Mhz, covering sector 49 ('Logen' - represented in Figure 1). Logen is Atlanta's northeast low altitude sector handling all arrival aircraft from the northeast between 11,000 feet up to 23,000 feet), 344 hours for the ATL tower frequency at 119.1 Mhz and 257 hours for the ATL ground frequency at 125.32 MHz.

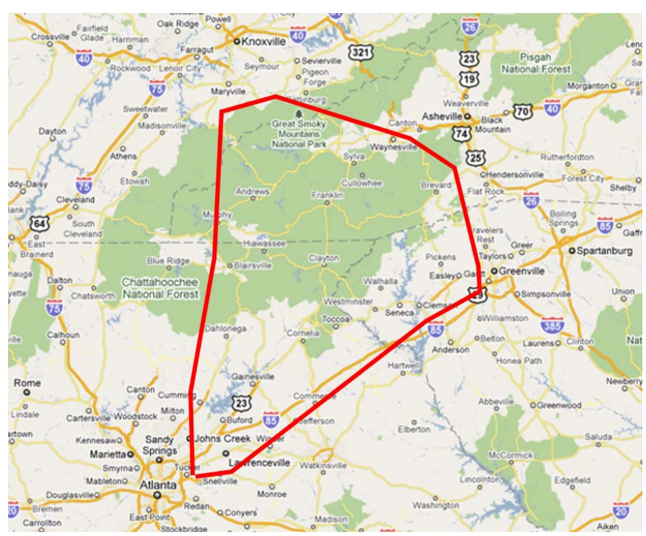


Fig. 1. Atlanta low-altitude sector 49 (Logen) Map data ©2009 Google

For comparison purposes, additional frequencies from New York City's JFK Airport have also been analyzed, over a total of 184 hours. These are : 76 hours for JFK tower broadcasting on 119.1, 123.9, 125.25 MHz, 37 hours for JFK approach (127.4 MHz), 30 hours for JFK final approach (132.4 MHz) and 41 hours for JFK north ground (121.9 MHz).

A Matlab analysis was conducted in three stages; the first stage consisted of detecting sound defined as an average signal intensity surpassing a graphically determined threshold that separated white noise static from coherent speech, over a 0.15 second window. The second stage of the analysis was meant to classify and time conversations and silence periods. A silence period was defined as no noise over 1.5 seconds (in other words no sound detected over 10 window periods), and conversations were then assumed to form the complementary of the silence periods. Shorter periods of silence were assumed to be natural pauses in speech and merged with neighboring conversations. In the final stage, periods of conversation and silence were assembled into histograms to approximate probability distributions for the signal, either with Matlab or with the ExpertFit [20] distribution-fitting software.

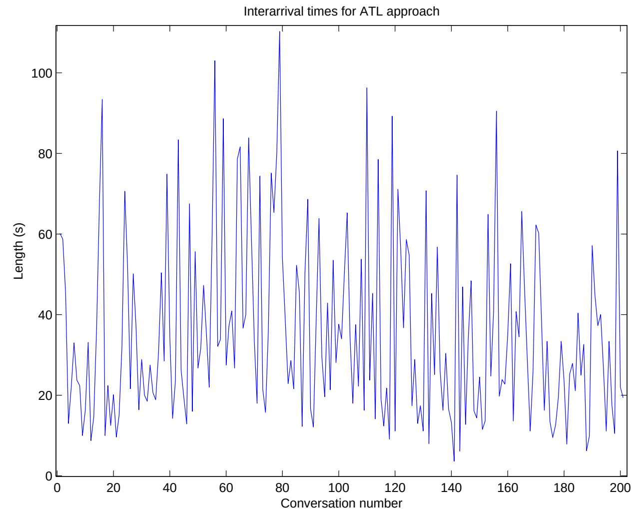
Our choice of silence as the main characteristic was due to its more objective definition. While noise and conversation come in very different and irregular patterns, it was assumed that inter-conversation silence would consist of a continuous lack of coherent signal. The statistical analysis of the channels shows (Table I) varying results for the talk and quiet times balance.

Frequency	Conversations	Talk time	Silence time	Talk ratio
ATL Center	31847	132 h	249 h	35%
ATL Approach	35185	182 h	162 h	53%
ATL Tower	37993	135 h	209 h	39%
ATL Ground	24963	122 h	135 h	47%
JFK Approach	3881	13	24	35%
JFK Final approach	2360	15	15	49%
JFK Tower	7805	24	52	32%
JFK Ground	4819	13	28	33%

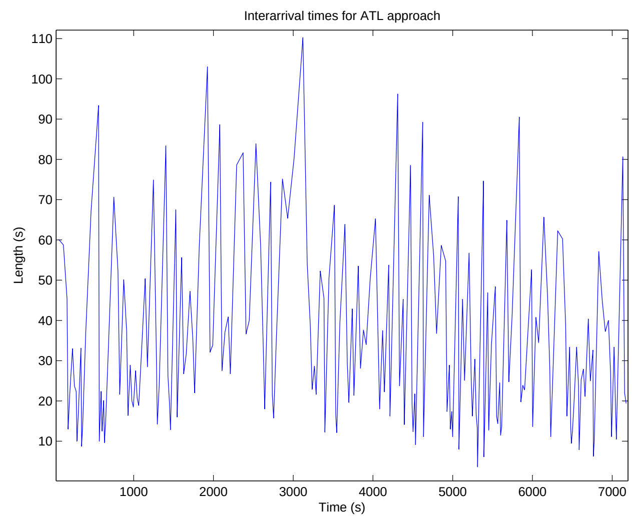
TABLE I
RADIO DATA VOLUME

III. Stochastic model : message interarrival time

The variable we believe would be most useful for integration to decision-aiding output is the 'interarrival time' (cf. plots in Figure 2), defined as the duration between the beginning of one conversation and the beginning of the next (in other words the duration of consecutive 'talk' and 'quiet' times). This interarrival time variable would allow to set a temporal spacing for suggested commands to be established in a way that is coherent with current controller work practices.



(a) By conversation number



(b) By temporal scale

Fig. 2. ATL approach interarrival length

A least square regression was used to classify the data, not providing an exact analytical match. The analysis of communication interarrival time variable is most closely associated with a log-normal probability density distribution (cf. Figures 3 and 4), with a square error below 0.001. The log-normal distribution may also be verified by plotting the logarithm of the variable (cf. Figure 5) which must obey a normal distribution. This result was not expected, as it shows that the communication interarrival is only partially correlated with the aircraft sequencing in entering the sector. Traditionally, under the assumption that these events occur continuously and independently of one another, aircraft entry into a sector has been modeled in simulations by a Poisson process, and consequently the corresponding aircraft interarrival times obey an exponential distribution. As radio communication is highly dependant on aircraft flow input and output, a closer match between communication and flight sequencing was expected.

The repeated and unhomogenous interaction between the controller and some of the aircraft may at least partially account for this distinction. Nonetheless, it is also true that the mathematical fit tests meant to precisely identify a probability distribution for the communication interarrival time remain unconclusive: the chi-square test only yields a p-value of less than 0.01. We believe the unrefined manner of analysis to play some part in this: our definition of the sound detection threshhold and of the temporal analysis windows (chosen to be 0.15 second for sound indentification, 1.5 seconds for silence periods) are inferences and educated assumptions. Only limited empirical verification by audition of the corresponding radio transmissions has been performed at this stage. Insofar, the trend regarding short conversations is confirmed, however it appears that the numerical analysis tends to overestimate longer conversations (over 15 seconds), possibly by assembling several short conversations with distinct aircraft that take place in rapid succession. Refining the numerical method is thus likely to produce results that will come closer to a pure log-normal distribution.

Nonetheless, we find that this distribution offers a solid general model for the communication. As might be expected, the parameters are dependant on the monitored frequency and the corresponding activity. Comparison with the JFK recordings also shows that the convergence of the measured activity toward this distribution is slow, and while a certain uniformity is observed over periods on the order of ten days, that is not the case at the scale of one day. The statistical parameters for the monitored signals are shown in Table II.

Frequency	Median	Mean	Coefficient of variation	Skewness
ATL Center	22	43	2.4	12.7
ATL Approach	26	35	2	25.5
ATL Tower	20	33	1.8	12.4
ATL Ground	22	37	1.4	8
JFK Approach	17	35	4.3	25
JFK Final approach	19	46	6	15.3
JFK Tower	20	36	2.2	13.9
JFK Ground	15	31	1.9	10.6

TABLE II
STATISTICAL PARAMETERS

IV. JOINT PROBABILITY DISTRIBUTION : TALK AND QUIET TIMES

We belive that the question of conditional probability, i.e. that of the interdependance of communication on silence periods, should be investigated. The conclusion that communication patterns follow a log-normal distribution relies on large-scale, historical trends who are inherently imprecise regarding

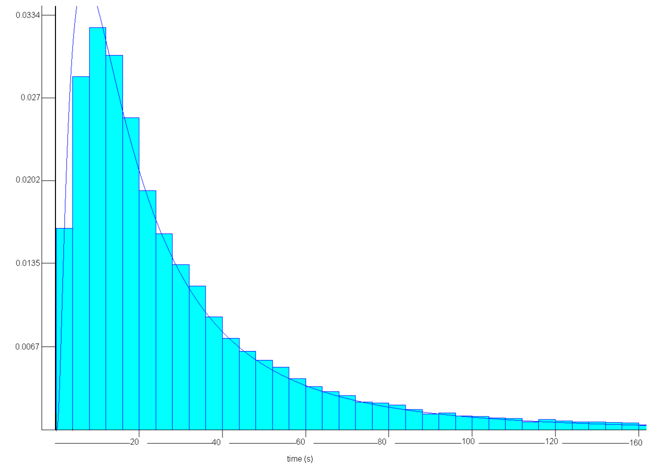
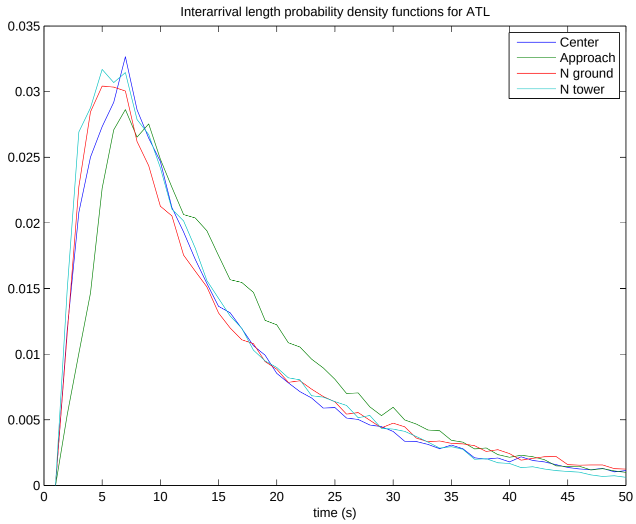


Fig. 3. ATL center interarrival log-normal probability fit

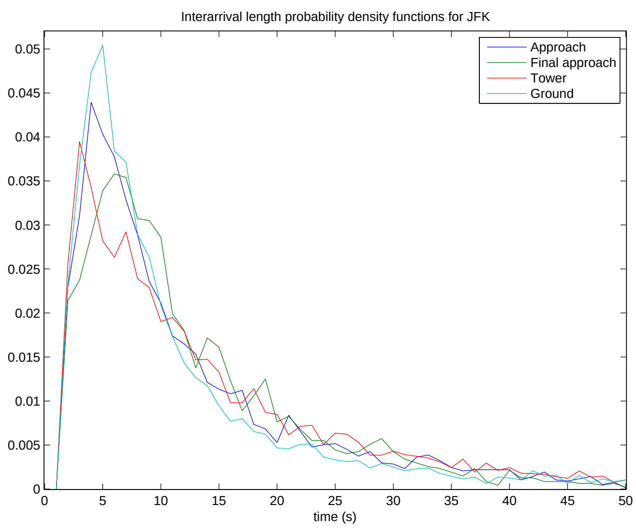
any specific behavior or time period. Either because of extenuating circumstances, judgment calls, personal preferences or experience, a controller would not always apply the communication pattern exactly as predicted and suggested by the automation. It is expected that the work and communication patterns of a controller assisted by decision-aid automation of the kind we are suggesting might stray significantly in the short term from the predicted behavior, i.e. a log-normal distribution, although will respect the long term homogeneity that has been found in this data.

Therefore, in order to account for this variability in communication, a method for dynamic readjustment may prove useful to the automation. That is, the automation may benefit from understanding the conditional probability of communication and silence in order to better calibrate the timing of its advice. Since a balance must be struck between on the one hand respecting historical trends and on the other locally adapting to the changing conditions, adaptability of the automation is the key to reducing controller workload and improving transparency. For that purpose, we have constructed a bivariate joint probability density function for the balance of talk and quiet times, from which any conditional probability may be deduced. The plot in Figure 6 represents $P(talk = X \wedge silence = Y)$.

The conversation length and silence length variables appear to be dependant. A Bayesian gap was calculated, defined by $|P(talk = X \wedge silence = Y) - P(talk = X) * P(silence = Y)|$ (plotted in Figure 8). For independant variables, this must be null. Under the hypothesis that our measurements contain sufficient occurences to approach the total univariate probability distributions for conversation and silence lengths, we have calculated an approximation of $P(talk = X) * P(silence = Y)$ (plotted in Figure 7), and $P(talk = X \wedge silence = Y)$ is given by the histogram method (plotted in Figure 6). For the shorter time spans, a significant gap is clearly visible, amounting to 20% or more (notice the gap value of 0.004 for approximated probability values on the order of 0.015) . These results are consistent throughout the different analyzed

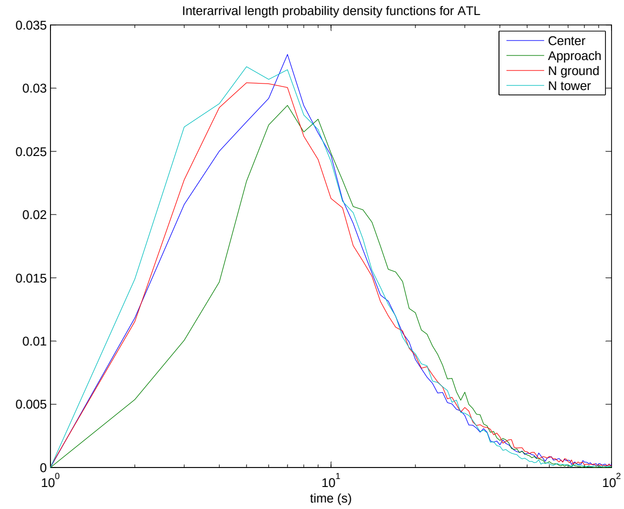


(a) ATL

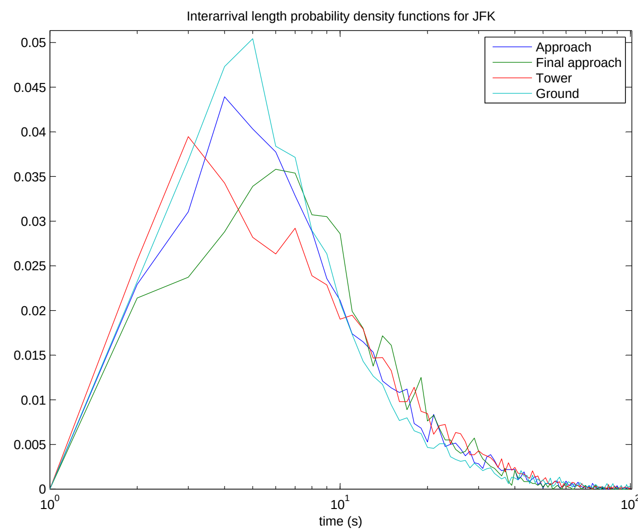


(b) JFK

Fig. 4. Probability density functions



(a) ATL



(b) JFK

Fig. 5. Logarithmic scale probability density functions

frequencies (cf. Annex); the consecutive talking and silence periods are therefore found to be correlated such that the duration of a conversation will influence the subsequent time the controller will remain silent, and reciprocally.

V. Possible Applications and Future Work

As an immediate application, the results presented here allow a more exact modelling of air traffic control interaction with aircraft for simulations that are used in the validation of conflict resolution algorithms and the evaluation of the workload reduction and/or the efficiency increase brought about by these solutions. Further refined, this stochastic model will allow the tuning of decision aids and automation for use in air traffic control settings.

In the future, following a more precise analysis and more extended audition, we expect to gain sufficient insight to refine our definition of silence / speaking and obtain a more precise outline of the communication patterns. We also expect to clarify the influence played by the frequencies' specific use (e.g. approach, ground,...) and to further study the distribution convergence in relation on the total sample size. Another notable direction we are investigating is the relation between communication patterns and the time of day. Furthermore, a major preoccupation remains the correlation between comm-munication against sector geometry, aircraft flow paterns, flight conflict probabilities, weather, and their respective impact on controller workload.

VI. Conclusion

This paper has presented a stochastic model for radio channel utilization in air traffic control. From the analysis of over 1300 hours of radio communication in Atlanta and New York - JFK, a log-normal probability distribution has been identified for the interarrival times between successive radio

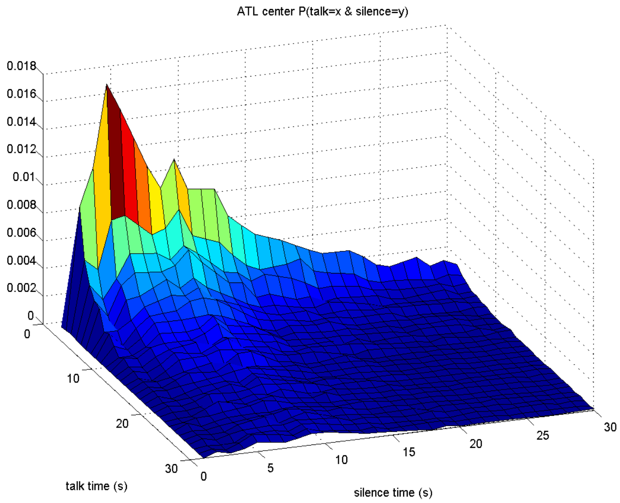


Fig. 6. ATL center measured bivariate probability density

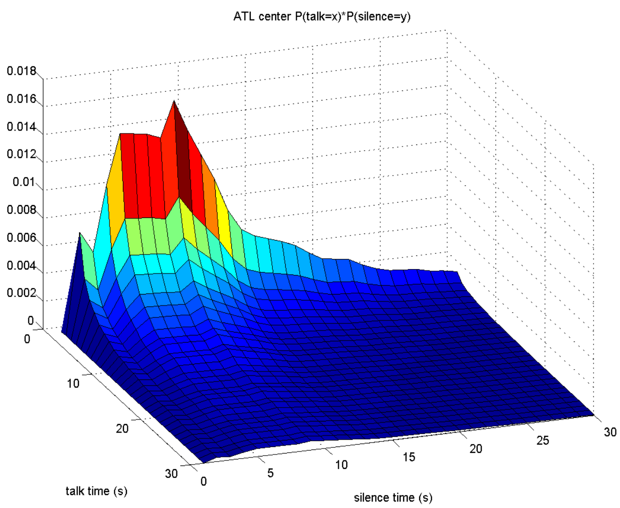


Fig. 7. ATL center approximated bivariate probability density

conversations, and a multivariate joint probability distribution for speech/silence timed sequences has also been constructed. The implementation of such a model for radio communication in future automation is a step toward adjusting automated conflict avoidance and decision support tools to effectively match controller attention patterns and task loading. Under a new paradigm of automation-assisted or automation-controled air traffic management, we believe this to be a direction toward reduced workload, improved situation awareness, and the respect of safety concerns.

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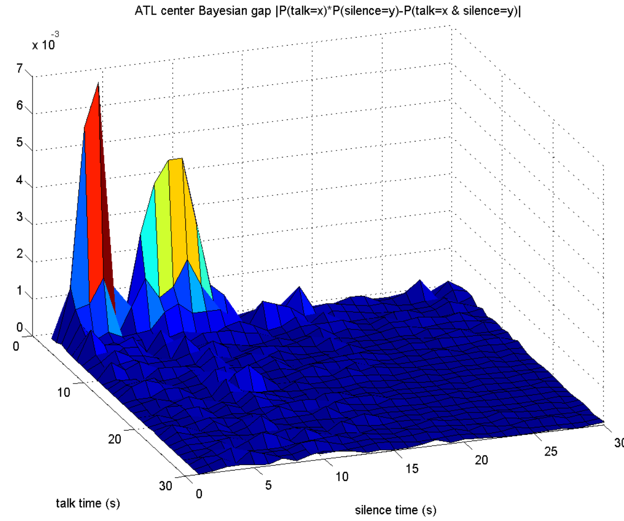

Fig. 8. ATL center Bayesian gap

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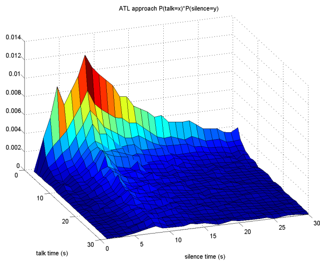
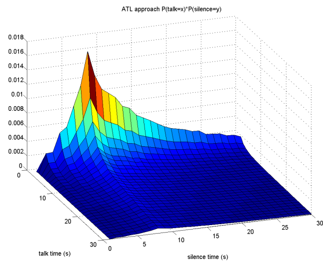
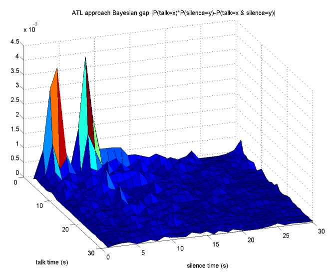
ANNEX: BIVARIATE PROBABILITY DISTRIBUTIONS



(a) Measured

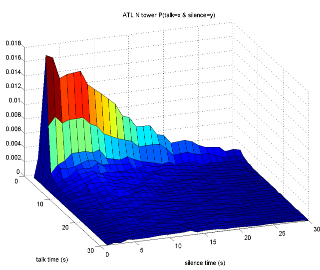


(b) Approximated

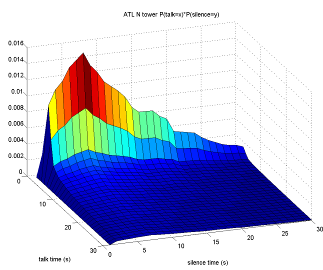


(c) Gap

Fig. 9. ATL approach



(a) Measured



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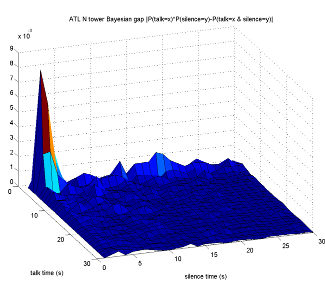
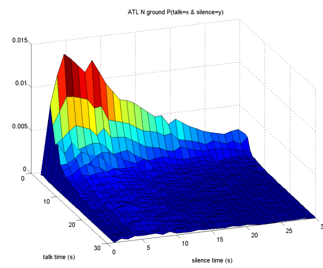
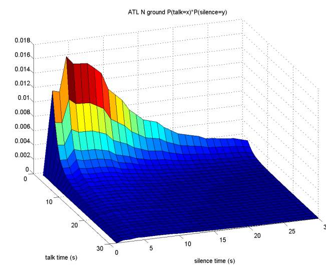


(c) Gap

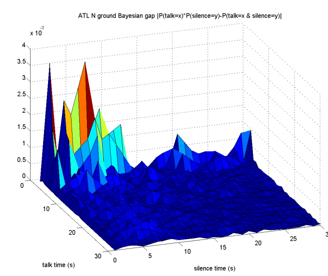
Fig. 10. ATL tower



(a) Measured



(b) Approximated



(c) Gap

Fig. 11. ATL ground