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Airspace Complexity Measurement: An Air Traffic Control Simulation Analysis

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This paper describes the results of a dynamic density (DD) human-in-the-loop simulation, as well as the DD model development activity designed to examine complexity measures. DD measures presented at the US/Europe ATM 2003 Seminar were used in the analysis. This study differed from the previous in three main aspects. First, the simulation included Reduced Vertical Separation Minima procedures. Second, the study focused on the Cleveland Air Route Traffic Control Center's airspace where previous study results showed the weakest correlation. Third, the traffic was actively controlled during the simulation, whereas in the previous study, audio/video replays were shown. The results indicated that the DD metric performed better than the aircraft count, which is a current complexity measure. The new DD model performed better than the previous model for Cleveland Center.

Significance: This research identifies airspace complexity factors which are critical to concepts such as airspace design and dynamic airspace configurations and controller workload balancing.

Keywords: Airspace Complexity; Complexity; Dynamic Airspace Configuration; Dynamic Density; Metrics; Monitor Alert Parameter; Air Traffic Control

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1. INTRODUCTION

A number of factors affect air traffic controller workload. These factors include, but are not limited to, potential conflicts, number of hand-offs, heading and speed differences, aircraft proximity to each other and sector boundary, presence of weather, and number of aircraft.[1,2] In the US, the current air traffic management system uses the monitor alert parameter, a threshold based on aircraft count, to measure sector level capacity and air traffic controller workload. It is widely recognized, however, that aircraft count, and hence the monitor alert parameter, has significant shortcomings in its ability to accurately measure and predict sector level complexity.[3,4]

The controller workload is a subjective attribute and is an effect of air traffic complexity. Both the US and Europe aviation communities have been very interested in developing quantifiable metric(s) for air traffic complexity, also known as dynamic density (DD). The term complexity, or dynamic density, is defined as the collective effect of all factors or variables that contribute to sector level air traffic control complexity or difficulty at any given time.[5] This study reports the results of a human-in-the-loop simulation exercise, contributing to the on-going complexity measures development and validation research.

1.1 The Need for Dynamic Density

One of the core elements involving future concepts, such as dynamic airspace configuration and advanced traffic flow management, is the ability to measure and predict complexity. In an operational setting, changes in traffic flows and airspace will be better managed strategically and tactically if an accurate measurement and prediction of complexity for a particular airspace is available, as well as higher levels of automation are proposed for future operations. Should automation degrade and the design calls for a human operator to manage the situation, the measures of complexity are crucial so that human workload limitations are not exceeded.

Complexity measures could be used to determine the areas in which airspace design changes may be necessary. Airspace can be redesigned and examined to ensure that the complexity of the redesigned airspace is same or less than its previous level.

Often when researchers create scenarios for concept or procedural examinations, they need multiple scenarios of similar complexity but not the same scenarios to avoid learning effects. The complexity measures could be used as a yardstick to compare multiple scenarios.

From the research perspective, the use of a DD metric in fast-time simulation models would provide a dynamic indicator of sector capacity and possibly workload. Most current fast-time models use the Monitor Alert Parameter (MAP) as a sector capacity indicator.[6] One problem with using the MAP values is that they are usually generated by the facility that controls the sector and are not always based on objective measures.[7] Although these values can be adjusted dynamically, there is no scientific basis for doing so. A more objective measure would be a DD metric based on the current traffic situation and not on a static MAP value. This would provide a better way to represent potential workload and the ability to dynamically reroute aircraft around saturated airspace.

A number of researchers have studied the topic of air traffic control complexity measurement (Mogford et al., 1995;[2] Laudeman et al., 1999;[8] Sridhar et al., 2000;[9] Chatterji & Sridhar, 2001;[3] Masolonis, 2003; [10] Flynn et al., 2006;[11] Manning & Pfleiderer, 2006.[12]). These efforts largely focused on identifying the quantifiable complexity variables, which were based on the factors that contribute controller workload, using simulation exercises and controller feedback. Their main findings included a number of complexity measures. They, however, were not validated using field data. Therefore, the largest field data collection and validation exercise for complexity measurement and prediction was conducted 1999-2002 by the authors. Researchers collected over 6,400 complexity ratings from controllers and supervisors at four US en route facilities. The study included the review of seventy-two thirty-minute traffic samples from a total of thirty-six high and low sectors. The study included most of the previously identified complexity variables and some additional variables identified by the authors. Researchers conducted an extensive metric development and validation activity with this set of data, which was presented at the 5th USA/Europe ATM 2003 Research and Development (R&D) Seminar.[4] They found that the combination of multiple complexity variables developed by various researchers worked the best in representing the controller workload.

1.2 Motivation for Current Study

The motivation for the current study was threefold. First, the previous data collection and validation effort, which was reported at the 5th USA/Europe ATM2003 R&D Seminar, was performed prior to the implementation of Reduced Vertical Separation Minima (RVSM). Some argue that RVSM procedures may impact the complexity of operations as more altitudes are available for conflict resolution and for setting up traffic flows. Hence, it was thought that some complexity factors might change, therefore, the incorporation of RVSM procedures into a DD study seemed necessary. Second, the DD metric performed differently at different Air Route Traffic Control Centers (ARTCCs) in the previous study. It did not predict the complexity for Cleveland Center’s airspace as compared with the other centers’ airspace. Therefore, a specific focus on Cleveland airspace was warranted. And third, in the previous study, controllers and supervisors observed playbacks of traffic scenarios and provided complexity ratings. The researchers recognized the limitations of this approach and had always planned for another study where controllers would actively control traffic in a real-time simulation environment. In essence, this study could be considered a further validation of the initial study reported in ATM 2003 Seminar.

2. DESCRIPTION OF DD METRICS

In 1999, the FAA William J. Hughes Technical Center (WJHTC), NASA Ames Research Center, and Metron Aviation formed a partnership to research DD. Each organization had its own ideas about what variables contributed to DD, although many similarities existed. The analysis therefore considered all of the proposed variables. A unified DD model (i.e., one containing variables from each organization) performed the best.

For the present study, NASA and the FAA collaborated once again to evaluate the same candidate DD variables that were considered in the previous analysis. This time, however, they used data collected from en route air traffic controllers working live traffic in a simulated environment to establish a more accurate and representative DD model.

A high level description of the proposed variables is provided in the following sections. For detailed formulas, computations, and descriptions of all the metrics, please refer to a review article by Kopardekar.[13]

2.1 WJHTC Metric

Table 1 lists the WJHTC DD variables. More detailed metric descriptions, rationales, and formulas are provided in Kopardekar.[4]

Table 1. WJHTC DD Variables

AD1	Aircraft density 1 - number of aircraft divided by occupied volume of airspace
AD2	Aircraft density 2 - number of aircraft divided by sector volume
CRI	Convergence recognition index – measure of the difficulty of detecting converging aircraft with shallow angles
SCI	Separation criticality index - proximity of conflicting aircraft with respect to their separation minima
DOFI	Degrees of freedom index – based on maneuver options in a conflict situation
CTI1	Coordination taskload index 1 - based on aircraft distance from the sector boundary prior to hand-off
CTI2	Coordination taskload index 2 - different formula based on the same principle as CTI1
SV	Sector volume
AC	Aircraft count

2.2 NASA Metric 1

The NASA-1 metric consisted of 16 variables, which are listed in Table 2. For details of the calculations, readers should refer to Chatterji.[3]

Table 2. NASA Metric 1 Variables

C1	Number of aircraft
C2	Number of climbing aircraft
C3	Number of cruising aircraft
C4	Number of descending aircraft
C5	Horizontal proximity metric 1
C6	Vertical proximity metric 1
C7	Horizontal proximity measure 2
C8	Vertical proximity measure 2
C9	Horizontal proximity measure 3
C10	Vertical proximity measure 3
C11	Time-to-go to conflict measure 1
C12	Time-to-go to conflict measure 2
C13	Time-to-go to conflict measure 3
C14	Variance of speed
C15	Ratio of standard deviation of speed to average speed
C16	Conflict resolution difficulty based on crossing angle

2.3 NASA Metric 2

The NASA-2 metric consisted of 8 variables, which are listed in Table 3. Laudeman et al.[8] and Sridhar et al. describe these variables in detail.[9]

Table 3. NASA Metric 2 Variables

N	Traffic Density
NH	Number of aircraft with Heading Change greater than 15º
NS	Number of aircraft with Speed Change greater than 10 knots or 0.02 Mach
NA	Number of aircraft with Altitude Change greater than 750 feet
S5	Number of aircraft with 3-D Euclidean distance between 0-5 nautical miles excluding violations
S10	Number of aircraft with 3-D Euclidean distance between 5-10 nautical miles excluding violations
S25	Number of aircraft with lateral distance between 0-25 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft
S40	Number of aircraft with lateral distance between 25-40 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft
S70	Number of aircraft with lateral distance between 40-70 nautical miles and vertical separation less than 2000/1000 feet above/below 29000 ft

2.1 Metron Aviation Metric

The Metron metric consisted of 10 variables, listed in Table 4. For further details, refer to Wyndemere.[14]

Table 4. Metron Aviation Variables

WACT	Aircraft count within a sector
WDEN	Aircraft count divided by the usable volume of sector airspace.
WCLAP	Number of aircraft with predicted separation less than a threshold value (e.g., 8 miles) at a particular time.
WCONVANG	The angle of converge between aircraft in a conflict situation
WCONFLICT NBRS	Count of number of other aircraft in close proximity to a potential conflict situation (e.g., within 10 miles laterally and 2000 feet vertically).
WCONF BOUND	Count of predicted conflicts within a threshold distance of a sector boundary (e.g., 10 miles).
WALC	Count of number of altitude changes above a threshold value with the sector.
WHEADVAR	Count of number of bearing changes above a threshold value with the sector.
WBPROX	Count of number of aircraft within a threshold distance of a sector boundary (e.g., 10 miles).
WASP	The squared difference between the heading of each aircraft in a sector and the direction of the major axis of the sector, weighted by the sector aspect ratio.

Table 5 lists 9 additional variables that were used in the study.

Table 4. Additional DD Metrics

NUMHORIZ	Number of aircraft with predicted horizontal separation under 8nm
HDGVARI	Variance of all aircraft headings in a sector
AXISHDG	Squared difference between heading of each aircraft in a sector and direction of major axis
CONVCONF	Average angle of convergence between aircraft in a conflict situation
PROXCOUNT	Number of aircraft in close proximity to a potential conflict situation
CONFCOUNT	Count of predicted conflicts within a threshold distance of a sector boundary
ALTVAR	Variance and mean of all aircraft altitudes in a sector
NUMBNDY	Number of aircraft within a threshold distance of a sector boundary
ASPECT	Major axis length divided by minor axis length of a sector

3. METHOD

The metrics developed by the FAA WJHTC / Titan Systems, NASA Ames Research Center, and Metron Aviation were evaluated in this study. This was the second validation exercise that examined all of the DD metrics using the same common data set to identify their applicability, strengths, and weaknesses.

The DD research activities associated with the current study were performed in three steps. The first step was a data collection effort. It involved selecting traffic samples from actual facility operations, generating simulation scenarios and collecting subjective ratings from controllers on the complexity of those traffic samples in a simulated air traffic control environment.

The second step involved the programming of all the candidate DD variables into the Target Generation Facility (TGF) Data Reduction and Analysis Tool, located at the WJHTC and the generation of DD output/values based on the simulation data.

The third step focused on data analysis and development of an optimal DD metric that included a comparison of the DD output to the complexity ratings and a regression analysis to determine the significant DD metric variables.

3.1 Step 1 – Complexity Rating Data Collection

3.1.1 Participants

During the first step of the DD study, researchers collected System Analysis Recording (SAR) data from Cleveland ARTCC to generate the simulation scenarios. This data source differed from the original study, which used the Enhanced Traffic Management System (ETMS) as the data source.

For the human-in-the-loop simulation, six Certified Professional Controllers (CPCs) and one Operations Supervisor from Cleveland ARTCC served as participants. The CPCs had, on average, eighteen years experience controlling traffic at many facilities, and approximately twelve years experience controlling traffic at Cleveland ARTCC. Fourteen simulation pilots and four ghost controllers also participated in the simulation.

3.1.2 Scenarios

Researchers gathered operational traffic data from three sectors in three areas at Cleveland ARTCC to develop traffic scenarios for the simulation data collection. Table 6 details the sector characteristics, including whether the sector was high or low, and its Monitor Alert Parameter (MAP), or aircraft count threshold.

Table 5. Simulated Cleveland ARTCC Sectors

Sector	Name	Area	High/ Low	MAP Value
04	Mansfield	8	Low	20
48	Ravenna	4	High	14
66	Bellaire	6	High	14

Four traffic scenarios, approximately 75-minutes in length, were developed from the SAR data. Additional traffic was added to the scenarios to ensure levels were 1) high enough to capture a range of complexity and 2) busy across sectors (i.e., not too concentrated in one sector over another). A fifth scenario was also developed that contained off-nominal routing due to weather.

3.1.3 Laboratory and Equipment

The simulation was conducted in the high fidelity Display System Replacement (DSR) Laboratory at the WJHTC. Ten display positions, all equipped with the User Request Evaluation Tool (URET) version 23AC, were utilized during the study (6 test positions, 4 ghost controller positions). The controllers used Voice Switch Communication System (VSCS). The ghost controllers provided hand-offs to and from the surrounding sectors.

Workload Assessment Keypads (WAKs) were installed at each test position as a means of recording complexity ratings during the simulation scenarios. WAKs are electronic keypads containing numerical scales. Participants are prompted to press a button corresponding to workload by buttons that illuminate and an aural tone that activates at specified intervals.

3.1.4 Procedure

Four traffic scenarios were each shown twice during the simulation. The weather scenario was shown only once. CPCs rotated between Radar and Data positions. Controller teams were assigned to sectors in which they were familiar. The CPCs individually provided complexity ratings at 5-minute intervals for each simulation run, including one training run, via the WAKs. They rated complexity on a scale from 1 to 7 where 1 is very low, 4 is moderate, and 7 is very high.

3.2 Step 2 – DD Metric Coding into DRAT

Programmers from the TGF Group at the WJHTC coded the DD variables (provided in Tables 1-5) into the Data Reduction and Analysis Tool (DRAT), which is a JAVA based post-processing simulation data analysis tool. Trajectories and sector geometries used in the human-in-the-loop (HITL) real-time simulation were input into the DRAT software. The DRAT then calculated each DD variables at five minute intervals. During the HITL real-time simulation, controller workload ratings were also collected every five minutes.

3.3Step 3 – Data Analysis & Model Development

For the data analysis and model development portion of the DD study, researchers performed regression analyses of the complexity rating data and DD output to establish weights and significance for the different DD variables. The data set consisted of nine 75-minute runs, resulting in 693 ratings. Some runs resulted in one more rating than other runs depending on the exact time the run concluded. All variables were considered collectively since results from the first study showed that a unified DD metric (i.e., variables across organizations) performed the best. The results of the analysis are discussed in the following sections.

4. RESULTS

4.1 DD Metrics Development

The regression analysis results, reported as R^2 values, are shown in Table 7.

Table 6. Regression Results (R^2 values) for Cleveland ARTCC

	Models	Low Altitude Sectors	High Altitude Sectors	All Sectors
Current Study	DD model	0.64	0.74	0.69
	AC Count based model	0.50	0.44	0.46
Study Reported in 2003	Old DD model	0.40	0.37	0.32
	AC Count based model	0.10	0.05	0.13

Note: R^2 is a coefficient of determination and higher its value, the higher the variance in complexity ratings explained by the model. The maximum value of R^2 is 1.0.

The results indicated the following:

- Both new and old DD metrics represented complexity better than currently used aircraft count.
- The new DD metric more accurately represented complexity ratings for Cleveland ARTCC than the DD metric from the previous study as represented by higher R^2 values.
- The aircraft count based model of the current study had a higher R^2 than the aircraft count based model in the previous study. This could be because of differences in the data quality (i.e., SAR vs. ETSM) and, or,

controllers were actively participating in the simulation rather than observers. This implies that the quality of complexity measurement improves with higher accuracy of data.

The regression equation output for the DD metric is presented in Table 8. The table shows the significant variables and their corresponding weights (estimates), t-values, and p-values. The chosen level of significance was 0.05. Initially, fifty-two variables were entered into a stepwise regression, which eliminated insignificant variables (p > .05). In addition, some predictors were excluded due to multicollinearity which occurs when high intercorrelations exist among the variables. [15] These cases were indicated by high Variance Inflation Factor (VIF) values (VIF > 10), and corresponded to the following variables: C1, WCLAP, WDEN, and AD2. Overall, 35 variables were excluded from the model.

Table 7. Regression Equation Output

Term	Description	Estimate	Std Error	t Ratio	Prob>|t|
Intercept		1.2035908	0.233088	5.16	<.0001
AC	Aircraft count	0.3157462	0.025022	12.62	<.0001
AD1	Number of aircraft/occupied volume of airspace	14.131972	4.977504	2.84	0.0047
SCI	Proximity of conflicting aircraft with respect to their separation minima	-0.007039	0.002824	-2.49	0.0129
SV	Sector volume	-0.000267	4.18E-05	-6.39	<.0001
C2	Number of climbing aircraft	-0.517344	0.136599	-3.79	0.0002
C9	Horizontal proximity measure 3	-2.575776	0.59082	-4.36	<.0001
C11	Time-to-go to conflict measure 1	-1.550238	0.464715	-3.34	0.0009
C15	Ratio of standard deviation of speed to average speed	-1.901624	0.458784	-4.14	<.0001
C16	Conflict resolution difficulty based on crossing angle	3.6584241	1.490403	2.45	0.0144
S5	Number of aircraft with 3-D Euclidean distance between 0-5 nautical miles excluding violations	-0.406443	0.115448	-3.52	0.0005
S10	Number of aircraft with 3-D Euclidean distance between 5-10 nautical miles excluding violations	-0.151261	0.060155	-2.51	0.0122
WCONVANG	The angle of converge between aircraft in a conflict situation	0.6512409	0.125299	5.2	<.0001
WBPROX	Count of number of aircraft within a threshold distance of a sector boundary	-1.27544	0.561373	-2.27	0.0234
WASP	Squared difference between the heading of each aircraft in a sector and the direction of the major axis of the sector, weighted by the sector aspect ratio.	0.0260912	0.002441	10.69	<.0001
NUMHORIZ	Number of aircraft with predicted horizontal separation under 8nm	0.44 63046	0.081356	5.49	<.0001
HDGVARI	Variance of all aircraft headings in a sector	0.0039505	0.001197	3.3	0.001
AXISHDG	Squared difference between heading of each aircraft in a sector and direction of major axis	-3.01E-07	8.56E-08	-3.52	0.0005

The resulting DD model consisted of seventeen variables and accounted for 69% of the variability in the data. Measures of aircraft count and airspace structure were the most significant factors in the model (highest t-values).

One of the motivators of this study was to identify the impact of RVSM on complexity since previous studies were conducted before RVSM was operational. It appears that the RVSM may have impacted the variable termed AD1 (Number of Aircraft/Occupied by Volume of Airspace). In the 2003 study, this variable was not significant. It is plausible that due to RVSM, the aircraft density was higher since higher altitude options are available in the same volume of airspace.

4.2 DD Metrics Testing

4.2.1 Results for Instantaneous DD Model

A performance assessment was conducted using the complete set of data. Figure 1 shows that the DD model followed the complexity ratings better than a model based only on aircraft count. Additionally, the R^2 value was higher for the DD model than the aircraft count based model.

Note: Aircraft Count Model: Rating = .5964075 + 0.3910888*Sector Count, R^2 = 0.46; DD Model: Rating = DD equation, R^2 = 0.69.

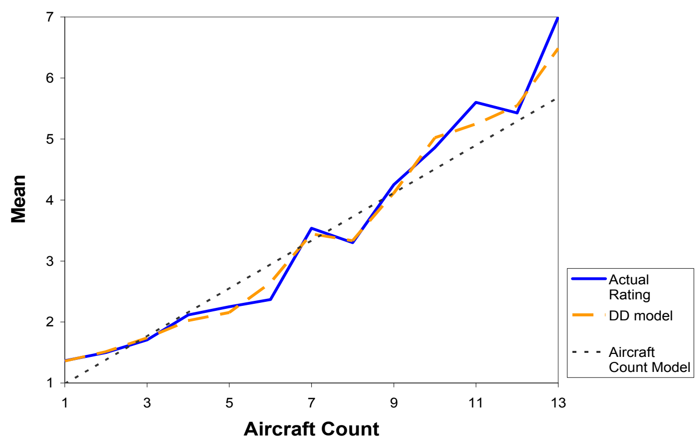

Figure 1. Performance of DD Metric

Table 9 shows the difference between the output of the DD model and the actual complexity ratings. About 94% of the data points were within a 1 unit difference from the actual complexity ratings and about 50% of the data points matched the ratings exactly. Less than 10% of the differences were greater than 2 units.

Table 8. Difference between DD and Complexity Ratings

Value	Percent	Cumulative Percent
-4	0	0
-3	0	0
-2	1.88	1.88
-1	25.97	27.42
0	49.49	78.21
1	18.61	95.81
2	3.32	99.27
3	0.29	99.56
4	0.43	99.99
Total	100	

Figure 2 shows that the mean absolute difference (MAD) between complexity values derived by the DD model and the actual complexity ratings was the lowest when the complexity ratings were closer to 2. The MAD generally increased as the complexity ratings increased. One possible explanation for this is that the data used to build the DD model contained a higher percentage of low complexity ratings and a much smaller percentage of high ratings.

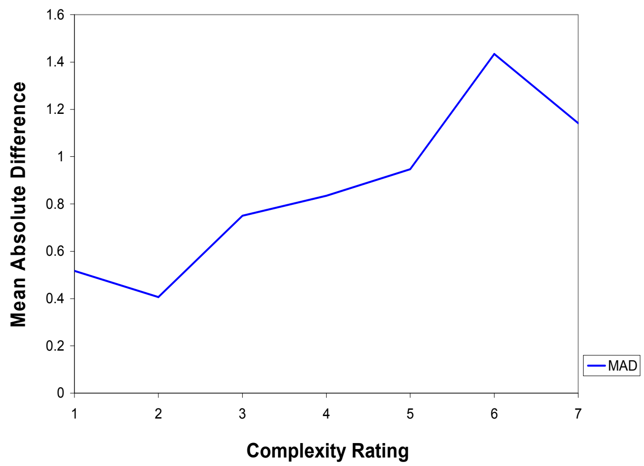

Figure 2. Mean Absolute Difference for Different Complexity Ratings

4.3 Comparison with European Complexity Factors

Flynn et al.[11] indicated that controllers reported that a mix of climbing and descending aircraft, several traffic flows conversing at the same point, traffic bunching, a high number of aircraft and multiple crossing points in the sector were critical complexity factors for Brussels and Hanover sectors. Majumdar et al.[16] reported that the number of aircraft changing altitudes, speed differences, the number of aircraft, the number of surrounding sectors and intersection points contribute to airspace complexity in Europe.

Many complexity factors discovered in the current NASA/FAA study are similar to those that were found in the European studies. To the extent in which a comparison is possible, the European results appear to be consistent with current findings where sector count, fraction of climbing and descending aircraft, and proximity of conflicting aircraft with respect to their separation minima and horizontal proximity were identified as significant complexity factors.

5. OVERALL CONCLUSIONS AND RECOMMENDATIONS

- The DD metric performed better than aircraft count, which is the basis of the presently used complexity gauge.
- In comparison with the previous study, the results show an improved accuracy in the DD model. This could be due to a better source of data (i.e., SAR vs. ETMS), additional significant complexity variables that were not used previously (e.g., HDGVARI, AXISHDG, NUMHORIZ), or the ratings based on controller's direct interaction with the traffic rather than observation of replay.
- The model can be further developed and tested with techniques such as neural networks, genetic algorithms, and non-linear regression.
- Complexity changes with increased levels of automation and the prediction of complexity need to be explored.

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BIOGRAPHICAL SKETCH

Parimal Kopardekar works as the Principal Investigator of the NASA’s NextGen Airspace Project. Prior to this position, he worked as an Associate Principal Investigator of the Dynamic Airspace Configuration research focus area. In the past, he served as a Project Manager of the Strategic Airspace Usage Project and Sub-Project Manager under Advanced Air Transportation Technologies project. Prior to working at NASA, he worked for the FAA where he conducted research and development activities in the area of air traffic management. He has published numerous journal and conference papers in the area of air traffic management. As an adjunct faculty at Rutgers and Drexel Universities, he taught graduate-level courses.

Dr. Kopardekar holds a Ph.D. in Industrial Engineering from the University of Cincinnati (1995), an M.S. in Industrial Engineering from the State University of New York at Buffalo (1992); and a B.E. in Production Engineering from the University of Bombay (1989). He is the recipient of the NASA Ames Honor Award for Engineer of the Year (2003), numerous group awards and two American Institute of Aeronautics Best Paper Awards. He is the author of over 35 publications including technical reports, and journal and conference papers.