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Dynamic Density: An Air Traffic Management Metric

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Summary

The definition of a metric of air traffic controller workload based on air traffic characteristics is essential to the development of both air traffic management automation and air traffic procedures. Dynamic density is a proposed concept for a metric that includes both traffic density (a count of aircraft in a volume of airspace) and traffic complexity (a measure of the complexity of the air traffic in a volume of airspace). It was hypothesized that a metric that includes terms that capture air traffic complexity will be a better measure of air traffic controller workload than current measures based only on traffic density.

A weighted linear dynamic density function was developed and validated operationally. The proposed dynamic density function includes a traffic density term and eight traffic complexity terms. A unit-weighted dynamic density function was able to account for an average of 22% of the variance in observed controller activity not accounted for by traffic density alone.

A comparative analysis of unit weights, subjective weights, and regression weights for the terms in the dynamic density equation was conducted. The best predictor of controller activity was the dynamic density equation with regression-weighted complexity terms.

Introduction

Providing system flexibility to the user is an important goal in advanced air traffic operations (RTCA, 1995). It is expected that automation to support air traffic management, accompanied by changes in air traffic procedures, will result in increased system flexibility. The development of a metric that predicts controller workload as a function of air traffic characteristics in a volume of airspace is essential to the development of both air traffic management automation and air traffic procedures.

The dynamic density metric proposed here includes both traffic density (a count of aircraft in a volume of airspace) and traffic complexity (a quantitative description of the air traffic complexity in a volume of airspace). The general form of the proposed equation is as follows:

$$DD = \sum_{i=1}^{n} W_i TC_i + TD + CI$$

where DD is dynamic density, TC is the ith traffic complexity factor, W is the ith factor weighting, i is the number of traffic complexity factors, TD is traffic density, and CI is the air traffic controller intent.

It was hypothesized that the proposed metric, which includes air traffic complexity, will be a better measure of air traffic controller workload than current measures based only on traffic density.

The proposed dynamic density metric is likely to be the most useful if it can be implemented in an operational environment where it can be used to provide real time information about the complexity of air traffic. The requirement that the dynamic density measure be computed real time gave rise to the most important constraint in the development of the dynamic density function.

A real-time computation of traffic complexity requires the use of radar track data as input to the dynamic density function. The weakness of this approach is that there is no way to differentiate between similar kinds of radar track data that result from very different kinds of controller intent.

A specific action taken by the air traffic controller could, in general, have several possible motivations and, depending on the motivation of the controller, an observed action could have a range of workload values. For instance, the information that an aircraft is changing altitude can be extracted from radar track data and weighted for its contribution to the traffic complexity in a sector. However, an air traffic controller can have a variety of reasons for issuing a clearance to an aircraft to change its altitude and that variation in intent could result in a variation in the controller workload associated with the observed action.

The dynamic density metric proposed here is designed to capture only the observed changes in the air traffic in a sector as quantified by the TD and TC terms of the dynamic density equation. Identifying and validating values for the controller intent term (CI) in the dynamic

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density equation would be difficult in a controlled experimental setting and virtually impossible in an operational environment. Therefore, the work presented here addresses only the traffic density and traffic complexity terms of the equation. If the dynamic density values derived without intent information can be shown to capture a substantial amount of the variance in observed controller activity, then it is possible that the dynamic density function would be useful without including the controller intent term.

The approach in the development of the proposed dynamic density metric was as follows:

1. Identification of air traffic complexity factors that might meaningfully capture traffic complexity in a volume of airspace and that could be computed from radar track data.
2. Construction of a dynamic density equation that included unit-weighted terms for traffic density and traffic complexity.
3. Validation of the dynamic density equation in an operational environment.
4. Generation of subjective and multiple regression weights for the traffic complexity factors in the dynamic density equation for comparative analysis with the unit-weighted dynamic density equation.

Traffic Factor Selection

The traffic factors included in the dynamic density equation were selected based on an informal interview process with subject matter experts.

Participants

The participants were three currently qualified air traffic controllers from the Oakland Air Route Traffic Control Center (ARTCC) and two former air traffic controllers working on site at Ames Research Center.

Procedure

The air traffic controllers participated in informal interviews in which candidate traffic complexity factors were identified. The choice of factors was constrained by the requirement that the factors be able to be computed in real time using radar track data or information that could be derived from radar track data such as predicted conflicts.

Results

Eight traffic factors were identified as candidates for air traffic complexity factors. The identified factors were of three types: dynamic factors that captured changes such as aircraft speed or heading (factors 1–3); aircraft density factors that captured the variability in the distribution of aircraft in a sector (factors 4 and 5); and conflict factors that captured predictions of aircraft conflicts (factors 6–8).

The two aircraft density variables were essentially the same factor computed for two distance ranges. The thinking was that the impact on the controller might vary as a function of distance and therefore two ranges should be considered. There were three predicted conflict terms identified, as exploring multiple distance ranges was also thought to be important for these terms.

The traffic complexity factors identified were as follows:

1. Heading Change (HC)– The number of aircraft that made a heading change of greater than 15 degrees during a sample interval of two minutes.
2. Speed Change (SC)– The number of aircraft that had a computed airspeed change of greater than 10 knots or 0.02 Mach during a sample interval of two minutes.
3. Altitude Change (AC)– The number of aircraft that made an altitude change of greater than 750 feet during a sample interval of two minutes.
4. Minimum Distance 0–5 n. mi. (MD 5)– The number of aircraft that had a Euclidean distance of 0–5 n. mi. to the closest other aircraft at the end of each two minute sample interval. This measure does not include converging aircraft that are predicted to be in conflict. Predicted conflicts are accounted for in other traffic factors. The Euclidean distance was computed as the shortest distance between two aircraft whose positions were defined by values in the x, y, and z dimensions.
5. Minimum Distance 5–10 n. mi. (MD 10)– The number of aircraft that had a Euclidean distance of 5–10 n. mi. to the closest other aircraft at the end of each two minute sample interval, excluding conflict aircraft.
6. Conflict Predicted 0–25 n. mi. (CP 25)– The number of aircraft predicted to be in conflict with another aircraft whose lateral distance at the end of each two minute sample interval was 0–25 n. mi. The lateral distance was computed as the shortest distance between two aircraft whose positions were defined by values in the x and y dimensions.
7. Conflict Predicted 25–40 n. mi. (CP 40)– The number of aircraft predicted to be in conflict with another aircraft whose lateral distance at the end of each two minute sample interval is 25–40 n. mi.

8. Conflict Predicted 40–70 n. mi. (CP 70)– The number of aircraft predicted to be in conflict with another aircraft whose lateral distance at the end of each two minute sample interval is 40–70 n. mi.

Dynamic Density Function

An a priori decision was made to evaluate a linear combination of traffic density and traffic complexity factors. The dynamic density equation was as follows:

$$\begin{aligned} DD = {} & W_1(HC) + W_2(SC) + W_3(AC) + W_4(MD\ 5) \\ & + W_5(MD\ 10) + W_6(CP\ 25) + W_7(CP\ 40) \\ & + W_8(CP\ 70) + TD \end{aligned}$$

The dynamic density equation was programmed into the Center TRACON Automation System (Erzberger, 1992) as a selectable function with adjustable factor weighting capability. HC, SC, AC, MD 5, and MD 10 values were found using aircraft trajectory information computed from radar track data, flight plan, and weather information. CP 25, CP 40, and CP 70 values were found using the CTAS Conflict Prediction capability (Isaacson and Erzberger, 1997).

The CTAS system was operated in an Air Traffic Management Laboratory at Ames using an air traffic data feed from the Denver ARTCC. Dynamic density was computed using a two minute sample interval for selected air traffic control sectors. The dynamic density function output file included a Zulu time stamp, sector number, dynamic density values, and separate values for each of the traffic complexity factors. The dynamic density output files were used to generate plots of dynamic density as a function of time (fig. 1).

The aircraft count function in figure 1 represents the traffic density in the sector during a four hour period. The dynamic density function represents the traffic density term plus the unit-weighted traffic complexity terms of the dynamic density equation. Where the traffic density function rises slowly at some points in time, the dynamic density function appears to rise more rapidly, suggesting that the dynamic density function might be able to characterize aspects of the air traffic not captured by the traffic density alone. If the two curves had a more nearly identical shape it would be less likely that the added complexity terms would be able to capture traffic complexity information not already captured in the traffic density term.

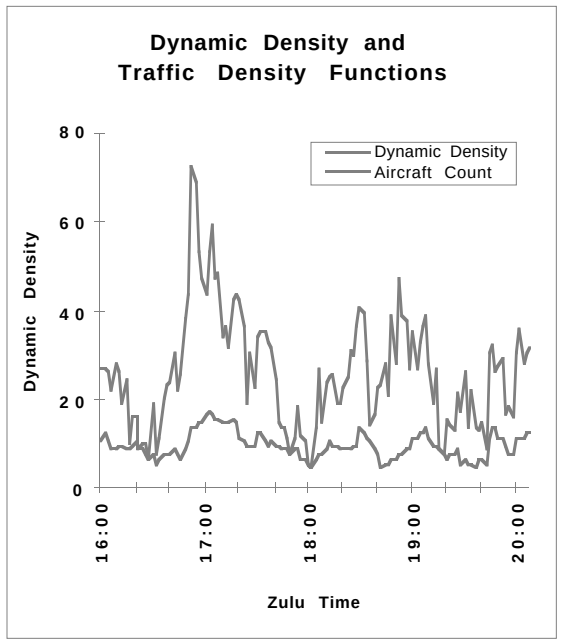

Figure 1. Traffic density and unit-weighted dynamic density functions for four hours of operation recorded at Denver ARTCC Sector 17.

While the difference between the dynamic density and traffic density functions was promising, it was not an adequate demonstration of the usefulness of the added complexity terms in the dynamic density equation. A validation of the equation with operational data was required. An independent measure of observed controller workload was needed to evaluate the relative merits of the dynamic density and air traffic complexity terms and to compute differential weights for the air traffic complexity terms.

What was required was an independent measure of controller workload that could be collected concurrently with dynamic density data. The limitations on the choice of the independent workload measure were (1) that it not interfere in any way with the activity at an operational sector and (2) that it measure only observed actions as opposed to the mental state of the controller. The non-interference requirement was due to the safety concerns related to collecting data in an operational air traffic control facility. As noted earlier, the CI term of the dynamic density equation was not considered in this study. One implication of the elimination of the CI term is the limitation of the workload measure to observable behavior.

Operational Validation

Validation Measure

Observations of air traffic controller activity at the radar (R-side) position of an en route sector was selected as an acceptable independent measure of controller workload as it met both the noninterference and observability criteria.

A representative subset of R-side activities was needed, as it was not feasible to collect real-time observations of every activity performed by the R-side controller. An approach that included the specification of a subset of activities was used in Vortac, Edwards, and Manning (1994) where recorded streams of time-stamped air traffic controller behaviors and communication events were used to examine the actions of individual and paired controller teams. The authors attempted to balance the need to describe "all relevant aspects of controller activities," without the list becoming too large, while still ensuring that each category of behaviors was "mutually exclusive and exhaustive."

An alternative approach would have been to videotape operations and transcribe exhaustive activity counts from the tapes. It is, however, unlikely that video taping would have been allowed on the operational floor of an ARTCC due to the possibility of operational interference. Also, recording a high quality video tape in the darkened environment of an en route center was problematic.

A set of representative activities was selected from a review of past research in the area of air traffic controller workload. A number of activities that have been shown to correlate significantly with air traffic controller workload have been identified in studies of controller activity (Buckley et al., 1983; Stein, 1985; Mogford et al., 1995).

Buckley et al. (1983) found an average of 16% of the variance in workload was accounted for by predicted aircraft conflicts and 13% by communication factors. Mogford et al. (1995) found 28% of the variance in sector complexity was captured by predicted conflicts and 38% by frequency congestion. Stein (1985) found that regression of local aircraft density, heading change, and outbound hand-off on workload produced a multiple $R^2 = 0.73$.

From the variables identified, eight air traffic controller activities were selected for use in the dynamic density metric validation study. The selected activities included radio communications activities and radar scope related activities.

1. Zoom In/Out– Controller changes the radar scope field of view. Typically the controller will zoom out and then return the field of view to its normal setting. This constitutes a single event.
2. Trend Line– Manipulation of a single trend line, or a global change to all displayed trend lines. Typically, the controller will extend a single aircraft's trend line, assess the aircraft trajectory, and then remove the trend line. This constitutes a single event.
3. Conflict– Flight Data Blocks (FDB) of two aircraft flash, indicating a potential conflict. This is a timed event. The first key press starts the timer. When the conflict stops flashing, the second key press stops the timer.
4. Route Line– Controller displays an aircraft filed route of flight. This constitutes a single event.
5. Minimum Separation Ring– Activation of a minimum separation ring. This is a timed event. The first key press starts the timer. When the minimum separation ring is deactivated by the controller, the second key press stops the timer.
6. ATC Communication– Any controller-initiated communication with an aircraft, together with the aircraft response. This constitutes a single event.
7. Say Again– A controller who misses a communication will issue a sectorwide communication, "aircraft calling center, say again." This constitutes a single event and is not also recorded as an ATC Communication.
8. Pilot Communication– Any pilot-initiated communication with the controller together with the controller response. This constitutes a single event.
9. Incorrect Readback– Any aircrew error in reading back ATC instructions. This constitutes a single event.

Dynamic Density Validation Study

Participants

The participants were air traffic controllers who were observed while performing their normally assigned duties at the R-side position of Sectors 9, 16, 17, and 28 of the Denver ARTCC.

Activity Observation Data Collection

Activity observations were recorded on laptop computers by single observers sitting immediately behind and to the side of the R-side controller at the sector. A total of four observers were used in the study. Observers collected activity observations with the Activity Catalog Tool

(ACT). The ACT is a tool designed to assist in the collection of activity observations (Segal and Andre, 1993) and is shown in figure 2. The ACT output files included time stamps that could be synchronized with dynamic density file time stamps and activity labels. A count of activity events recorded during each two minute sample interval was used as the controller workload measure. Communications were recorded by pairs (e.g., aircraft to controller and controller response) but were counted as two communications for the purposes of the workload analysis.

Figure 2. Activity Catalog Tool for collection of workload observations.

Observer Reliability

Observer reliability was assessed using a percentage agreement method (Shaughnessy, 1994). Observer agreement was established with observational data collected at Sector 33 of the Oakland ARTCC prior to the study at the Denver ARTCC. Sector 33 was chosen because it is one of the busiest sectors in the Oakland ARTCC airspace. Observer reliability was established in a pairwise process in six 45 minute data collection sessions. The inter-observer percent agreement ranged from 84.9 to 95.9 across all pairs for all data collection periods. The matrix of observer percent agreement values is shown in table 1.

Table 1. Pairwise observer percent agreement values for the four observers who collected activity observation data.

	1	2	3	4
Observer 1		92.8	92.3	95.9
Observer 2			93.8	84.9
Observer 3				86.8

Procedure

The CTAS system with conflict detection functionality was installed on the operational floor of the Denver ARTCC where it was configured to compute dynamic density values for Sectors 9, 16, 17, and 28 at two minute sample intervals for the duration of each data collection period. The conflict probe parameters were set to predict conflicts at a lateral separation of 10 miles or less and vertical separation of less than 2000 feet above FL 290 and less than 1000 feet below FL 290 with a 20 minute time horizon.

Air traffic controller activity observations and dynamic density data were collected concurrently in eighteen 0.5–2 hour data collection periods for a total of 24.5 hours on Sectors 9, 16, 17, and 28 at the Denver ARTCC. Sectors 9, 16, 17, and 28 are high altitude sectors that generally contain a mix of arrival, departure, and overflight traffic. The data were collected during the morning and evening high traffic periods. A sample of unit-weighted dynamic density data, traffic density data, and activity count data is shown in figure 3.

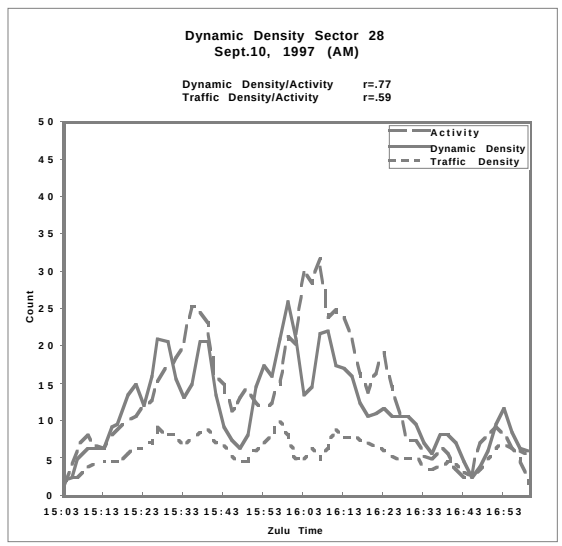

Figure 3. Sample of unit-weighted dynamic density, traffic density, and activity observation data collected at Denver ARTCC Sector 28.

Results

The correlation (Pearson r) and variance (r^2) values for dynamic density with activity (DD/ACT) and traffic density with activity (TD/ACT) were computed for the unit-weighted data collected during each of the data collection periods and are shown in table 2.

Table 2. Correlation and variance values computed from unit-weighted dynamic density, traffic density, and observed activity data collected during each of the 18 data collection periods.

Period	Sector	DD/ACT		TD/ACT	
		r	r^2	r	r^2
1	16	0.83	0.68	0.77	0.60
2	17	0.35	0.12	0.29	0.08
3	28	0.77	0.60	0.59	0.35
4	16	0.79	0.62	0.61	0.37
5	28	0.72	0.52	0.65	0.43
6	16	0.63	0.40	0.55	0.30
7	17	0.79	0.63	0.69	0.48
8	16	0.72	0.52	0.32	0.10
9	17	0.45	0.20	0.49	0.24
10	28	0.67	0.45	0.16	0.03
11	16	0.80	0.64	0.73	0.53
13	28	0.77	0.59	0.73	0.53
14	9	0.95	0.90	0.89	0.79
15	9	0.64	0.40	0.37	0.14
16	9	0.64	0.41	0.28	0.08
17	9	0.86	0.75	0.68	0.48
18	9	0.60	0.36	0.21	0.04

Dynamic density correlated more highly with observed controller activity than did traffic density for 17 of the 18 data collection periods. There were also four collection periods (8, 10, 16, and 18) during which traffic density had little correlation with activity, whereas dynamic density had moderate to high correlation. These data are promising, as they indicate a robustness of the traffic complexity terms in their ability to capture added variance in controller activity across different sectors and times.

The data were collapsed across sector and collection period, and correlation and variance values were computed for the full data set as follows:

$$\text{mean } r_{(ACT/DD)} = 0.74 \qquad r^2_{(ACT/DD)} = 0.55$$

$$\text{mean } r_{(ACT/TD)} = 0.57 \qquad r^2_{(ACT/TD)} = 0.33$$

The dynamic density equation with unit-weighted traffic complexity factors was able to account for an average of 55% of the variance in controller activity, where the traffic density term alone accounted for an average of 33% of the variance in controller activity.

While the correlational analyses were able to show that the set of complexity terms appeared to contribute substantially to the variance in controller activity accounted for by dynamic density, it was not clear that all eight of the complexity terms accounted for equal amounts of the total variance. It was also unclear whether any of the complexity terms were redundant. A traffic complexity term intercorrelation matrix was computed to identify shared variance or redundancy among the terms (table 3). Ideally, the terms would be roughly orthogonal and thus have minimal intercorrelations. The traffic complexity terms all had very low intercorrelations with the exception

Table 3. Intercorrelation matrix of traffic complexity values.

	CP 25	CP 40	CP 70	CA	CH	MD 10	MD 5	CS
CP25	1.0	0.083	0.269	0.074	0.179	0.053	0.102	0.114
CP 40		1.0	0.052	0.069	0.033	0.109	0.027	0.036
CP 70			1.0	0.019	0.099	0.074	0.089	0.102
CA				1.0	0.171	0.033	0.084	0.502
CH					1.0	0.171	0.172	0.189
MD 10						1.0	0.257	0.150
MD 5							1.0	0.165
CS								1.0

of the Altitude and Speed Change terms for which r = 0.502. Some intercorrelation was expected for these two terms, as an altitude change is often accompanied by a speed change.

Traffic Factor Weighting

Multiple Regression Weighting Analysis

A multiple regression analysis was conducted to determine whether there was justification for differentially weighting each term in the dynamic density equation. A split-half multiple regression analysis was conducted in which half the data set was used to identify regression weights and the other half was used to test the identified regression weights. The database of activity observations and dynamic density values included 729 cases, of which 364 were used to compute regression weights and 365 were used to test the regression weights.

Factor weights were computed in a multiple regression analysis in which traffic density and all the traffic complexity factors were forced into the equation. The dynamic density factors, the computed normalized weights (B), and the statistical significance (Sig T) of each factor weight are shown in table 4. The B weights are normalized with a mean of zero and a standard deviation of 1. The statistical significance of each weight was computed with a T test that compared the mean of the computed weight with a zero mean.

The heading change term (HC) received the highest weight, which can be explained by the fact that there was significant arrival traffic in all the sectors that were observed. The headings on these aircraft changed as they were vectored to their arrival gates, thus contributing significantly to the heading change term.

Two of the conflict prediction terms (CP 40, CP 70) also received substantial weights. The weights on these two terms were the same (1.85), suggesting that dividing the conflict space by current range of aircraft might not have been necessary.

One measure of the local density (MD 10) of aircraft in portions of the sector also received a significant weight. If the local densities occur near sector boundaries, the communication counts are likely to increase, as all the closely clumped aircraft are likely to be checking in and out of the sector at the same time thus increasing communication counts for those sample intervals.

Two terms in the regression equation had weights that were approaching the accepted 0.05 significance level: number of aircraft changing altitude (AC) with 0.08 and number of aircraft with current distance to closest other aircraft of 0–5 n. mi. (MD 5) with 0.07. Typically, the inclusion of extra terms whose weighting might be low or redundant is of less concern than the loss of terms that might carry important portions of the variance. Therefore, the two terms AC and MD 5 were provisionally included in the equation, pending further studies that might more clearly include or exclude them.

Table 4. Regression factor weights with statistical significance values.

Traffic density	Regression		
	B	T	Sig T
	0.79	5.79	0.00
Traffic factors	**Regression**		
	B	T	Sig T
HC	2.17	3.06	0.00
SC	0.15	0.34	0.73
AC	0.88	1.78	0.08
MD 5	1.02	1.84	0.07
MD 10	1.18	3.94	0.00
CP 25	0.10	0.14	0.89
CP 40	1.85	2.59	0.01
CP 70	1.85	2.85	0.00

The two factors whose computed regression weights were small and substantially nonsignificant were the count of aircraft changing speed (SC) and the count of aircraft in conflict with a current range less than 25 n. mi. (CP 25). These two terms were removed from the equation that was used to compute dynamic density.

It is possible that the low weighting of the speed factor is an artifact of the types of sectors that were analyzed. This term might capture a significant amount of the variance in observed activity in a low altitude sector with a large proportion of arrival traffic. There are typically a high percentage of aircraft changing speed in arrival sectors as they slow down for final approach to an airport. The generalization of this and the other factor weights to different types of airspace is, in any event, an empirical question that remains to be answered.

The nonsignificance of the conflict prediction term for a current range of 0–25 n. mi. is possibly the result of its relatively low base rate, as two converging aircraft are relatively unlikely to close to less than 25 n. mi. of each other in an airspace in which all aircraft are under radar control.

The final form of the dynamic density equation with multiple regression weights was as follows:

$$\begin{aligned} DD = {} & 2.17(HC) + 1.85(CP\ 40) + 1.85(CP\ 70) \\ & + 1.02(MD\ 5) + 1.18(MD\ 10) + 0.88(AC) \\ & + 0.79(TD) \end{aligned}$$

Subjective Weighting Analysis

An alternative approach to the use of regression weights is the use of subjective weights collected from survey data. The use of subjective weights addresses the possibility that air traffic controllers might be able to provide more accurate weights for traffic complexity terms when asked explicitly than can be obtained by the observational methods used above.

Survey data were collected to provide differential weighting values for the eight traffic complexity factors. The traffic density term was assumed to have a weighting of 1.0. The traffic complexity factor weightings were collected for individual aircraft present in an en route sector. For factors such as MD 5 and CP 25 where two aircraft are involved, the weighting was applied separately to each of the aircraft involved.

Participants

The participants were 65 currently qualified air traffic controllers from the Oakland ARTCC.

Procedure

Each participant filled out a survey form in which he or she was asked to give ratings for each of the eight traffic complexity factors. Survey forms were provided to the air traffic controllers through the National Air Traffic Controllers Association (NATCA) office of the Oakland ARTCC. Traffic complexity factor weighting values were collected using a Likert scale, with minimum and maximum values defined as follows:

- Workload (1) is the amount of work required to accept and then hand off a single aircraft that requires no additional controller services during a period of average traffic level in a sector that you normally work.
- Workload (5) is the amount of work required to provide services to the most demanding nonemergency user that you encounter during a period of average traffic level in a sector that you normally work.

Results

The mean and standard deviation of the subjective weighting values computed for the eight traffic factors are shown in table 5. The relatively high standard deviation values (e.g., CP 70 mean = 2.11, standard deviation = 1.02) suggest that the mean subjective weight values contain so much individual variation that they are not likely to provide robust results when used in the dynamic density equation.

Table 5. Subjective traffic factor weight mean and standard deviations. Regression factor weights with statistical significance values.

Traffic density					
	Subjective		Regression		
	Mean	SD	B	T	Sig T
	1.0	0.00	0.79	5.79	0.00
Traffic factors					
	Subjective		Regression		
	Mean	SD	B	T	Sig T
HC	2.40	0.88	2.17	3.06	0.00
SC	2.45	0.92	0.15	0.34	0.73
AC	2.94	0.98	0.88	1.78	0.08
MD 5	2.45	1.23	1.02	1.84	0.07
MD 10	1.83	0.99	1.18	3.94	0.00
CP 25	4.00	1.09	0.10	0.14	0.89
CP 40	3.00	1.06	1.85	2.59	0.01
CP 70	2.11	1.02	1.85	2.85	0.00

The dynamic density equation with subjective weights was as follows:

$$\begin{aligned} DD = {} & 2.40(HC) + 2.45(SC) + 2.94(AC) + 2.45(MD\ 5) \\ & + 1.83(MD\ 10) + 4.00(CP\ 25) + 3.00(CP\ 40) \\ & + 2.11(CP\ 70) + 1.00(TD) \end{aligned}$$

Comparative Analysis of Subjective and Regression Weights

Dynamic density values were computed for the 365 test cases using the normalized regression weights, the subjective weights, and unit-weighted traffic complexity factors in the dynamic density equation.

The correlations of observed air traffic controller activity with dynamic density values computed with unit-weighted traffic complexity factor values, subjectively weighted traffic complexity factor values, and regression-weighted traffic factor values were as follows:

$$r_{(\text{Activity/DD unit weighted})} = 0.67$$

$$r_{(\text{Activity/DD Subjective Weights})} = 0.65$$

$$r_{(\text{Activity/DD Regression Weights})} = 0.71$$

The dynamic density equation using factor weights computed from the multiple regression analysis was the strongest predictor of observed air traffic controller activity. The variance in observed activity accounted for by the multiple regression dynamic density equation was 0.50, or 50%, on average. The implication here is that 50% of the variance is not accounted for by the dynamic density equation.

One of the likely possibilities for controller behavior that was not captured by the dynamic density equation was communication related to pilot requests for ride reports. During poor weather conditions, it was common for virtually every aircraft to request a ride report upon entering a sector. The added communication load for the controller was not reflected in any of the dynamic density terms since it did not result in changes that were reflected in the radar track data.

Conclusions

The correlation of dynamic density with observed controller activity was consistently higher than correlations of traffic density with observed controller activity across the various data collection periods. These data support the conclusion that the traffic complexity terms of the dynamic density equation are robust in their ability to capture more of the variance in controller activity than the traffic density term alone.

When the data were collapsed across sector and collection period, the overall unit-weighted dynamic density factors accounted for 22% of the variance in observed controller activity that was not accounted for by traffic density alone. These data support the hypothesis that the eight proposed traffic factors (or some subset of these factors) can better account for increased controller workload due to complexity in sector traffic.

The multiple regression dynamic density equation was a better predictor of controller activity than the subjectively weighted dynamic density equation. The multiple regression equation was able to account for 50% of the total variance in air traffic controller activity in the set of test cases, suggesting that the dynamic density equation has some generalizability across operational conditions.

The multiple regression analysis identified statistically significant weights for four of the eight proposed traffic factors, with two additional factors approaching significance. It would be premature, however, to remove any of the proposed traffic complexity terms from consideration until the proposed dynamic density equation has been tested in a variety of operational settings.

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The definition of a metric of air traffic controller workload based on air traffic characteristics is essential to the development of both air traffic management automation and air traffic procedures. Dynamic density is a proposed concept for a metric that includes both traffic density (a count of aircraft in a volume of airspace) and traffic complexity (a measure of the complexity of the air traffic in a volume of airspace). It was hypothesized that a metric that includes terms that capture air traffic complexity will be a better measure of air traffic controller workload than current measures based only on traffic density.

A weighted linear dynamic density function was developed and validated operationally. The proposed dynamic density function includes a traffic density term and eight traffic complexity terms. A unit-weighted dynamic density function was able to account for an average of 22% of the variance in observed controller activity not accounted for by traffic density alone.

A comparative analysis of unit weights, subjective weights, and regression weights for the terms in the dynamic density equation was conducted. The best predictor of controller activity was the dynamic density equation with regression-weighted complexity terms.

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