# Controller Workload Models for Generic High-Altitude Airspace


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**Nine controller workload models are evaluated based on their ability to use sector and traffic data to estimate subjective controller workload measurements in generic high-altitude airspace. The evaluation utilized data from a human-in-the-loop simulation involving five recently-retired controllers working on five current high-altitude sectors using tools and procedures appropriate for future generic airspace. Workload models based only on aircraft count and sector capacity estimate controller workload less accurately than models that are a linear combination of 3–17 workload factors. Existing workload models like Dynamic Density and Simplified Dynamic Density achieve errors that are at least 8% lower when their parameters are estimated with training data from this generic high-altitude human-in-the-loop simulation. However, the square of the correlation ($R^2$) values for the Dynamic Density and Simplified Dynamic Density models are at least 0.3 lower in generic high-altitude airspace than in other types of airspace, so these models explain less of the variation in controller workload ratings in generic high-altitude airspace than in other airspaces. A new model referred to as Dynamic Density for generic high-altitude airspace achieves error values that are at least 10% lower than those achieved by any other model in generic high-altitude airspace, but does not achieve $R^2$ values as large as those reported for other models in other types of airspace.**


## I. Introduction

Currently, air traffic controllers are only permitted to control a small number of sectors because current procedures require them to know a significant amount of sector-specific information. In the future, automation and procedures will allow controllers to control any of a large set of "generic" sectors. Due to differences in automation, operations, and controller familiarity, the workload induced by a traffic situation in a sector operated using generic procedures may be different than the workload induced by the same traffic situation in the same sector operated using today's procedures.

Many models for estimating controller workload in current operations have been proposed and evaluated.[1–9] Workload has been studied and modeled in scenarios with various levels of automation, aircraft equipage, and traffic volumes.[10,11] Also, controller acceptability of generic high-altitude airspace has been evaluated with human-in-the-loop simulations.[12] However, workload estimation models have not been evaluated in or developed for generic high-altitude airspace. More precisely, the previous workload research does not exclusively consider airspace sectors that have an altitude floor of 34,000 feet being controlled by


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controllers that are not familiar with the airspace using a particular set of automation that will be available in generic airspace. This set of automation includes controller-pilot data link communications, automated conflict detection, and suggested conflict resolutions.

In this paper, data from a human-in-the-loop simulation of generic high-altitude airspace[13,14] is used to evaluate the ability of existing workload models[7–9,11] to estimate controller workload in generic high-altitude airspace. The parameters in these existing models are estimated with these human-in-the-loop simulation data in an effort to improve the ability of the models to estimate workload for generic high-altitude airspace. In addition, a new workload model is proposed. Its parameters are estimated with these human-in-the-loop data, and its ability to estimate workload in generic high-altitude airspace is evaluated.

The remainder of this paper is structured as follows. The next section discusses previous research on the topic of controller workload modeling and generic high-altitude airspace. The technical approach, including the human-in-the-loop simulation and analyzed workload models, are presented in Section III. Section IV discusses the performance of the workload models and some estimated model parameter values. The paper finishes with conclusions in Section V.

# II. Background

## II.A. Workload Research

In current operations, the number of aircraft in a sector is often used to estimate the workload of the sector controller. However, this model is viewed as inadequate, and there is a significant body of research concerned with developing more sophisticated models. Some approaches involve non-linear estimators or predictors based on approaches like neural networks.[1] Others are multi-dimensional workload estimates with factors selected to enable supervisor decisions about how to reduce workload.[2] Many of the proposed workload metrics are referred to as dynamic density, and they typically generate an estimate from a linear combination of dynamic density factors.[3–6,8,10] Dynamic density factors are workload-inducing characteristics of traffic in a sector, such as aircraft density, the number of ascending or descending aircraft, the variance of aircraft headings, or the number of aircraft near sector boundaries. In some research,[9] the workload factors are theoretically derived by making some assumptions about the nature of air traffic and controller workload.

Most workload models involve some parameters that must be estimated. If the workload model is based on certain assumptions about what causes workload and about air traffic, the parameters may be expressed as analytic functions of the traffic and sector characteristics.[9,15] More commonly, the parameters are estimated by using subjective controller workload estimates, measurements of factor values, and regression techniques.[3,7] Air traffic controllers are asked to control an air traffic situation in a simulator and estimate their workload during the simulation. Factor values are computed from the measurements of airspace and aircraft states during the simulation. For linear workload models, the samples of workload estimates and instantaneous measurements of factor values are used in statistical regression techniques to estimate appropriate parameters.

## II.B. Generic Airspace Research

In the future, automation and procedures may allow appropriately trained controllers to control any of a large set of generic sectors. The primary benefit of this will be that controllers will be able to be deployed in response to system need to a greater extent than they are today.[13,14] Such generic airspace will likely be implemented first in high altitude airspace (34,000 feet and above) because traffic and operations are relatively similar across sectors in this airspace.[12]

# III. Technical Approach

## III.A. Human-in-the-Loop Simulation

A human-in-the-loop simulation of generic high-altitude airspace was conducted in December of 2009 at NASA Ames Research Center.[13,14] The purpose of this simulation was two-fold. The first purpose was to determine whether controllers can acceptably manage unfamiliar sectors when provided with future automation tools and specific sector data. The simulation was designed primarily to achieve this purpose. The second purpose was to "calibrate dynamic density metrics for generic sectors."[13] The objective of this paper is to achieve this second purpose with data from the simulation.

The simulation was conducted in the Crew-Vehicle Systems Research Facility Air Traffic Control Laboratory. This laboratory has air traffic control positions, pseudo-pilot workstations, and a communication system. It uses the Multi Aircraft Control System (MACS) to simulate the Display System Replacement user interface that is currently used by controllers at Federal Aviation Administration (FAA) en route air traffic control facilities.[16] MACS was configured to provide controller-pilot data link communications for all clearances (with voice backup), automated conflict detection, and suggested conflict resolutions.[13] It is assumed that this level of automation will be implemented before generic high-altitude airspace is used operationally. Aside from the main MACS display, each controller workstation had a "Controller Information Tool" (CIT), which was designed to provide information so that controllers unfamiliar with a sector can still control traffic in the sector.[13] The CIT shows a map of the sectors in the simulation and information about them on a 30-inch display. A mouse controls what information is displayed on the CIT. The information available on the CIT includes sector boundaries, altitudes, names, and radio frequencies, Special Use Airspace information, fix and NAVAID locations and names, and major traffic flow locations and information.

In this simulation, sectors 30, 33, and 43 from Oakland Air Route Traffic Control Center (ARTCC) (abbreviated as ZOA) and sectors 42 and 45 from Salt Lake City ARTCC (ZLC) were used to create a fictitious ARTCC referred to as "West High Center," abbreviated as "ZHW." These sectors were modified slightly so that they all had a floor altitude of 34,000 feet. This fictitious ARTCC is shown in figure 1.

The traffic for the two primary simulation scenarios was derived from historical traffic in ZOA and ZLC. The historical traffic was from 9 July 2009 and 21 May 2009, two summer Thursdays with relatively high traffic volume, low delay, and low weather-related delay according to the national statistics in the Operational Network database.[17] Each scenario was 45 minutes to one hour long and designed to start with a low level of workload and build to a moderate level of workload after about 20 minutes.

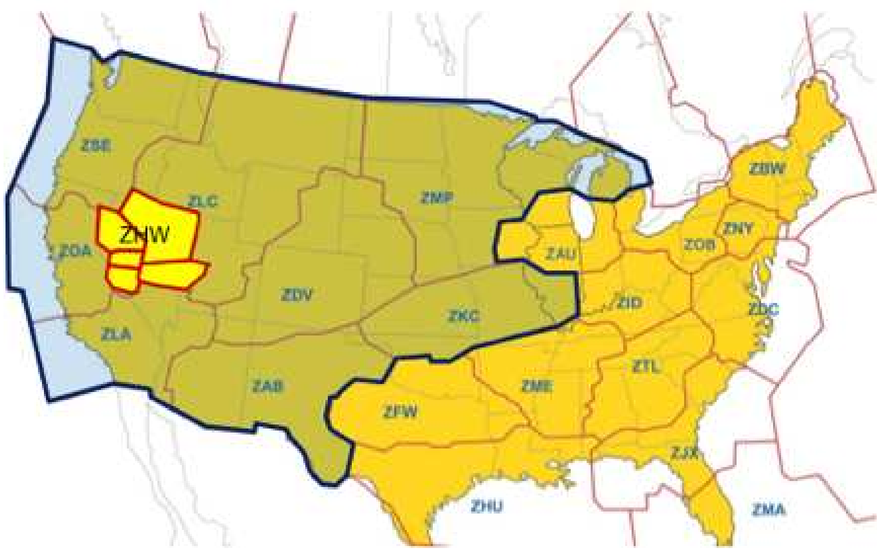



**Figure 1. The sectors in the fictitious West High Center (ZHW) used in the human-in-the-loop simulation[13] are outlined with thick red lines. Current day Centers are outlined with thin lines and labeled with their three-letter abbreviations. The airspace outlined with a dark blue line has been proposed for a national high altitude airspace concept being developed by the FAA.**

Five air traffic controllers who retired less than three years ago from either ZOA or ZLC were recruited for these simulations. The controllers had controlled and were therefore familiar with one or two of the sectors but not the others, allowing for investigations regarding the impact of controller familiarity on workload. Ten data collection simulation runs were conducted, each lasting for 45 minutes to one hour. Each controller worked each of the five sectors with each of the two traffic scenarios exactly once.

At five-minute intervals during the runs, controllers indicated their perceived workload level on an integer scale from 1 (low workload) to 5 (high workload). More precisely, the controllers were instructed that a rating of 1 corresponds to the workload typical in a low volume sector during the night shift. A rating of 5 corresponds to when the controller would normally request the assistance of a second controller (a "D-side assistant"). There were 433 instances where controller workload was sampled, and 331 of those samples were from controllers working unfamiliar sectors. Aircraft state data from the runs was logged every minute during the runs. These data were used to compute the workload factors required by the models discussed in the next section.

## III.B. Workload Models

Nine workload models are analyzed in this paper. The first two, used in current air traffic management operations, are scaled so that their output has the same magnitude as the controller workload ratings in the simulation. Models 3 and 5 are scaled versions of published workload models.[7,8] Four models (numbers 4 and 6-8) use published workload factors[7–9,11] but estimate model parameters with data from this simulation. The ninth model is new, and its factors were selected specifically for generic high-altitude airspace. These models are summarized in Table 1. The intercept column in this table designates whether or not the model includes an intercept term. Lists of the factors in each model are in the appendix.

**Table 1. Workload Models**

| Model Number | Model Name | Number of Factors | Intercept |
|---|---|---|---|
| 1 | Aircraft count (AC) | 1 | No |
| 2 | Aircraft count divided by MAP (AC/MAP) | 1 | No |
| 3 | Dynamic Density (DD)[7] Value | 1 | No |
| 4 | Dynamic Density (DD)[7] Factors | 17 | Yes |
| 5 | Simplified Dynamic Density (SDD)[8] Value | 1 | No |
| 6 | Simplified Dynamic Density (SDD)[8] Factors | 7 | No |
| 7 | Dynamic Density with high automation (DDHA)[11] | 5 | Yes |
| 8 | Schmidt-Welch[9] | 3 | Yes |
| 9 | Dynamic Density for generic high-altitude airspace (DDGHA) | 5 | Yes |

### *III.B.1. Models from Current Air Traffic Management Operations*

The aircraft count (AC) model estimates workload as a scaled version of the aircraft count in the sector. This model is similar to a workload metric commonly used in current operations: the number of aircraft in the sector. This model serves as a baseline.

Aircraft count divided by MAP (AC/MAP) is the second workload model used in current operations. It depends on a sector-specific capacity, measured in number of aircraft, known as the "Monitor Alert Parameter" (MAP). MAP values published in August of 2009 were used for the sectors in this study. When the number of aircraft in a sector exceeds the sector's MAP value, air traffic controller supervisors must evaluate the situation in the sector and determine if any actions must be taken to ensure safe operations in the sector.

### *III.B.2. Scaled Versions of Existing Models*

Two workload models are scaled versions of the workload estimates produced by published workload models. The appropriate scaling factor parameter is estimated as discussed in sub-section III.C. Both of these workload models contain a single workload factor that is a weighted sum of various other workload factors. The parameters in the weighted sum can be found in previous publications.[7,8] The first such model is called Dynamic Density Value (DD Value) and it is computed with the factors and parameters in Table 8 of Ref. 7 (which is reproduced in the appendix). It contains 17 factors and an intercept. The second such model is called Simplified Dynamic Density Value (SDD Value) and it is computed with the factors and parameters in Ref. 8 (available in sub-section IV.A). The published parameters in these models were found based on human-in-the-loop simulation data, but the simulations were of current operations, not of generic high-altitude airspace. The traffic in the simulations used by the SDD Value model exceeded current levels.

#### *III.B.3. Models with Factors from Existing Models*

Four more models are weighted sums of different sets of workload factors. The factors are specified in previous research. The model parameters are estimated with simulation data as described in sub-section III.C.

The workload factors in Ref. 7 are used in model number four, referred to as Dynamic Density Factors (DD Factors). The sixth model is referred to as Simplified Dynamic Density Factors (SDD Factors) and it contains the factors from Ref. 8. The factors in these two models were selected to model controller workload in current operations.

Another workload model called Dynamic Density with high automation (DDHA) is a weighted sum of the five factors specified in Ref. 11 and an intercept term (see appendix for details). The DDHA model was developed to estimate controller workload in airspace similar to generic airspace. Its factors were selected using data from a HITL simulation that was, other than the altitude levels used, similar to the HITL described in sub-section III.A.

The Schmidt-Welch model is model eight. It was proposed in Ref. 9, which in turn was inspired by Ref. 15. The factors in the Schmidt-Welch model were selected to model workload in current operations and can be found in the appendix.

#### *III.B.4. New Model*

A new workload model is proposed and referred to as Dynamic Density for generic high-altitude airspace (DDGHA). This model is a linear combination of a set of workload factors. Many factors are candidates for this model, including all of the factors used in the other models, except for the DD Value and SDD Value factors. These are excluded because they are not actually single factors, but rather combinations of several factors. Factors from other research[18] and factors developed based on expert judgement were also considered. In all, 65 factors were considered for the new model.

The final set of workload factors is determined with training data and a technique referred to as "the lasso" or $\ell_1$-regularization.[19,20] This approach depends on a weight on a regularization term, which was hand-tuned for this application to eliminate most of the 65 candidate factors. The weight on the regularization term was set to 1. The set of five factors is discussed in sub-section IV.B.

### III.C. Parameter Estimation with Linear Regression

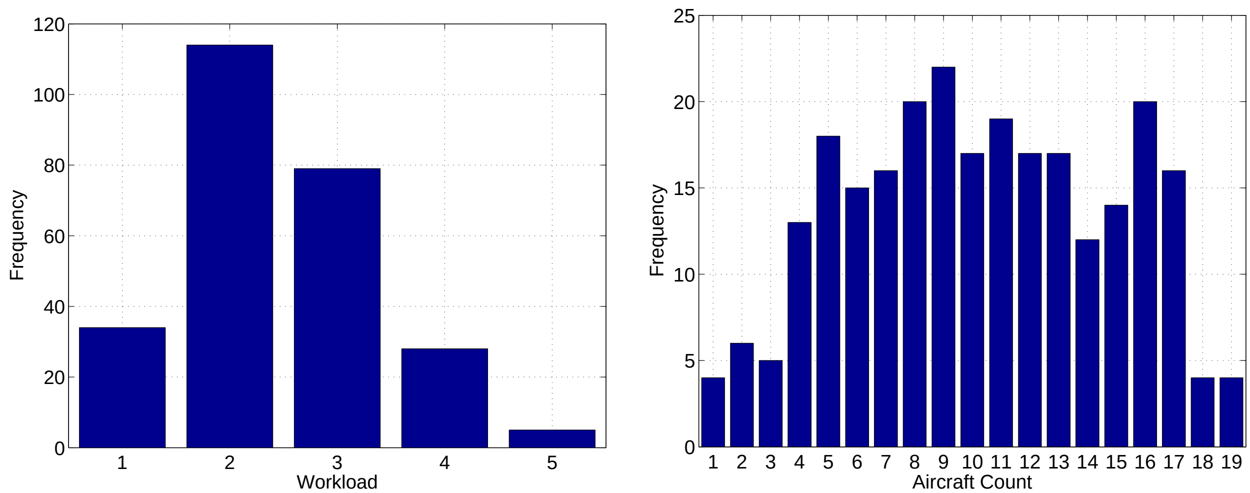
Each controller workload estimate and the corresponding workload factor values make up the available data. Only data from controllers working unfamiliar sectors were used because lower familiarity will be more common in generic airspace. The responses from one of the five controllers were almost always 1 and this controller was deemed to be an outlier. Data from this controller were not used. The remaining data are referred to as the relevant data and contain 259 controller workload measurements and corresponding traffic and sector data. The relevant data were randomly ordered. Cross-validation[19] was used to repeatedly separate the data into training and testing sets.

For each pair of training and testing data sets, the training data were used to estimate the linear model parameters with linear regression. When multiple factors were considered in the same model, the factors' values were normalized so that they all were between zero and one. This common practice ensures that factor magnitudes, which depend on the units of measure used, do not impact statistical analyses. The coefficients in the SDD and DDGHA models were restricted to be positive because workload should increase with each workload factor. This restriction was first used by Klein, Rodgers, and Leiden in Ref. 8. In the case of the DDGHA model, factors were selected using each training data set and $\ell_1$-regularization before linear regression was used to find the appropriate parameters for the selected factors.

## IV. Results

The distribution of workload estimates in the relevant simulation data is shown in figure 2. In the majority of the cases (87%), the workload was estimated to be three or less, so the simulation did not induce many high workload situations.

The distribution of aircraft count values at the time instances when controller workload estimates were recorded is also shown in figure 2. The largest such aircraft count was 19, and at more than half of the times where workload was recorded there were 10 or more aircraft in the sectors. The current MAP values of the sectors in the simulation are 13, 18, 18, 19, and 23 for sectors ZOA 30, ZOA 33, ZOA 43, ZLC 42, and ZLC 45, respectively.




(a) Workload.

(b) Aircraft Count.

**Figure 2. Distribution of (a) workload estimates and (b) aircraft counts at the times that workload estimates were recorded in the simulation runs.**

The relationship between the aircraft count in each sector and the controller workload is shown in the bubble plot in figure 3. In general, larger aircraft counts correspond to higher controller workload levels. There were some exceptions, such as when a controller specified a workload level of four but only two aircraft were present in the sector. In that particular case, two losses of separation had occurred in the sector in the three minutes before the controller workload was recorded. Those losses of separation, not the two aircraft in the sector, were probably the cause of the high workload at that time.

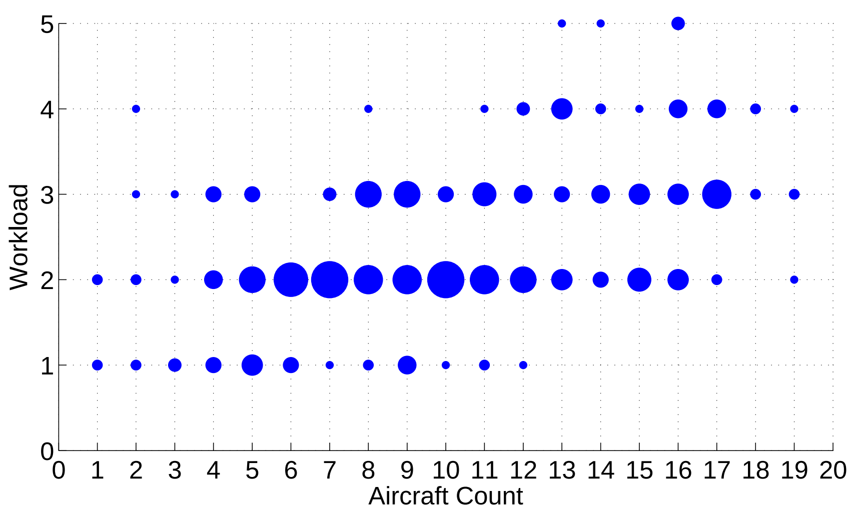



**Figure 3. Bubble plot showing the relationship between aircraft count and controller workload. The area of the marker at each point is proportional to the number of data instances at that point.**

The workload models were evaluated by the root mean squared error (RMSE) and mean absolute error (MAE) they produce in the test data sets. Lower errors indicate more accurate workload estimation models. The models were also evaluated according to the square of the correlation or $R^2$ value in the test data sets. The $R^2$ range is between 0 and 1. Larger $R^2$ values indicate that a higher fraction of the variation in the controller workload in the test data sets is explained by the model. Table 2 shows the performance of the models.

Table 2. **Performance of Workload Metric Models**

| Workload Model | RMSE | MAE | $R^2$ |
|---|---|---|---|
| AC | 0.966 | 0.782 | 0.252 |
| AC/MAP | 0.914 | 0.724 | 0.234 |
| SDD Value | 0.908 | 0.729 | 0.238 |
| SDD Factors | 0.820 | 0.674 | 0.304 |
| DD Value | 1.878 | 1.645 | 0.034 |
| DD Factors | 0.740 | 0.603 | 0.346 |
| DDHA | 0.796 | 0.630 | 0.238 |
| Schmidt-Welch | 0.761 | 0.606 | 0.301 |
| DDGHA | 0.653 | 0.534 | 0.489 |

The workload models based on current operations (AC and AC/MAP) lead to higher RMSE and MAE values and lower $R^2$ values than most other models. The error metric values produced by the workload models based on currently operational workload models (AC and AC/MAP) can be more than 45% larger than the error metric values produced by models with more factors, and the $R^2$ values can be as much as 0.255 lower. This implies that using workload models that are a linear combination of a set of workload factors (all models other than AC and AC/MAP) leads to more accurate workload estimates than models based only on aircraft count or aircraft count divided by MAP. Previous workload research that was not focused on generic high-altitude airspace also reached this conclusion.[7]

The SDD Factors and DD Factors models outperform the SDD Value and DD Value models, respectively, according to all three performance metrics. SDD Factors achieves error metrics that are 8–10% smaller and $R^2$ values that are 0.066 larger than those achieved by SDD Value. DD Value performs worse than any other model, but DD Factors performs better than every model except for DDGHA. DD Value performs poorly partially because it multiplies a sector volume factor by a relatively large and negative parameter that is not properly tuned for the airspace used in this simulation. However, even when this parameter is set to zero, DD Value still performs worse than any other model. These SDD and DD models estimate workload in generic high-altitude airspace more accurately when they are trained with data from generic high-altitude airspace, as would be expected. The SDD parameter estimates are presented in sub-section IV.A.

DDGHA performs better than any other model, which is to be expected because its factors were selected based on generic high-altitude airspace simulation data. The RMSE achieved by DDGHA is at least 12% lower than the RMSE of all other tested models, its MAE is at least 11% lower than the MAE of all other tested models, and its $R^2$ value is at least 0.143 larger than the $R^2$ value of all other tested models.

The performance of these workload models in generic high-altitude airspace is poor relative to the recently published performance of the same models. Figure 4 shows recently published $R^2$ values for the DD,[7] SDD,[8] and DDHA[11] models and the $R^2$ values computed in this paper for the models when operating in generic high-altitude airspace. The $R^2$ values in generic high-altitude airspace are lower than the published values, indicating that the models explain a lower fraction of the variation in controller workload in generic high-altitude airspace than in the airspace simulated in previous research.

There are several possible reasons for this lower performance. Since the performance of the models is being evaluated in different types of airspace, different data sets from different simulations must be used. While these simulations and data sets are similar to the simulation and data set used in this paper, there are several important differences. Different controllers with different skills and perceptions of workload were used in the other simulations, and the data sets used in previous research were not the same size as the data set used here. Also, the previous research used workload scales ranging from 1–7[7,11] and 1–10,[8] whereas in this research, workload was rated on a scale from 1–5. Furthermore, the definitions of what any particular workload rating means may differ between simulations. The previous studies were based on human-in-the-loop simulations of different geographical regions and different traffic patterns. In this research, each workload model is being used to estimate the workload in five different sectors, but in previous studies the models only estimated workload in one,[8] two,[11] or three[7] sectors. However, the performance of the models in generic high-altitude airspace did not improve much when built for fewer sectors rather than all five, so the number of sectors in

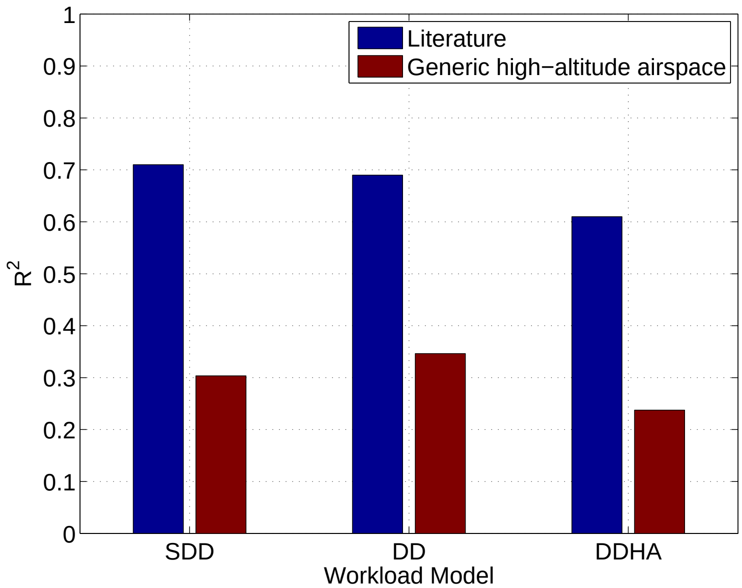



**Figure 4. $R^2$ values for the DD, SDD, and DDHA models published in the literature[7,8,11] and in generic high-altitude airspace.**

the simulation may not be a cause of model performance differences. In the generic high-altitude human-in-the-loop simulation, traffic volumes were approximately at the same level as they are today. In previous research, the traffic volumes varied between 1–1.66 times current levels[8] and 1–3 times current levels.[11] Perhaps a wider range of traffic volumes and correspondingly wider range of workload levels in the data set facilitate more accurate model parameter estimation and better model performance. Finally, the model forms and workload factors that explain workload variations in some airspace may not work well in generic high-altitude airspace due to the differences in controller familiarity with sectors, automation, and sector altitude levels. Further research should be conducted to determine why this lower performance is observed in generic high-altitude airspace and to find metrics that correlate with safe and efficient operations in generic high-altitude airspace. These metrics may be estimates of controller workload, or may be quantifications of the performance of automation involved in generic high-altitude airspace.

### IV.A. SDD Parameters in Generic High-Altitude Airspace

The differences between SDD parameter estimates derived with data from current operations and estimates derived with data from generic high-altitude airspace can give insight into differences between controller workload in these two contexts. The parameters in the SDD Factors model estimated with all the relevant data from the generic high-altitude airspace simulation are shown in Table 3, along with the SDD parameters published in Ref. 8.

The SDD parameter values for generic high-altitude airspace are scaled to be on roughly the same scale as the baseline SDD parameter values by dividing each by the estimate of the amount by which the SDD value must be scaled down to estimate workload measurements on a 1–5 scale. Dividing by this quantity performs the opposite scaling from a 1–5 scale to the SDD scale. Raw SDD values are between 8 and 9 times larger than workload measured on a 1–5 scale.

There are several notable differences between these two sets of parameter values. The aircraft count parameter decreases by more than half when the parameters are estimated with the generic high-altitude airspace simulation data, but the aircraft per volume parameter is almost 75% larger. The proximities and altitude transfers parameters decrease. The boundary transfer parameter decreases so much that it is effectively zero. This change may be the result of a more automated boundary transfer process in generic airspace. The parameters for heading and speed variance decrease slightly and almost double, respectively.

Table 3. SDD Parameters

| Factor | Baseline SDD[8] | Generic High-Altitude SDD |
|---|---|---|
| Aircraft count | 2.20 | 1.06 |
| Proximities | 0.400 | 0.111 |
| Altitude transfers | 0.300 | 0.237 |
| Boundary transfers | 0.500 | 0.000 |
| Aircraft per volume | 30,000 | 52,300 |
| Heading variance | 0.000500 | 0.000485 |
| Speed variance | 0.000500 | 0.000917 |

### IV.B. Dynamic Density for Generic High-Altitude Airspace Model

The factors selected for the new DDGHA model and their corresponding parameter estimates can provide insight into the nature of workload in generic high-altitude airspace. Table 4 shows the workload factors and associated parameter estimates in the DDGHA model.

To generate the factors and parameters in Table 4, all the relevant data were used as training data for the $\ell_1$-regularization factor selection process and subsequent linear regression parameter estimation process. The source workload model that each factor came from is also shown in the table. When each factor value is normalized by dividing it by the largest factor value in the training data set, the linear regression parameter estimation produces the normalized parameters. The normalized parameter values make more apparent the relative contribution of each factor to workload.

Table 4. DDGHA Factors, Sources, and Parameters

| Factor | Source | Parameter | Normalized Parameter |
|---|---|---|---|
| Intercept | | 0.562 | 0.562 |
| Boundary transfers | SDD[8] | 0.00221 | 0.0751 |
| Aircraft per volume | SDD[8] | 4850 | 0.767 |
| Number of aircraft near boundary | DD[7] | 0.124 | 1.05 |
| Aircraft predicted to enter sector within five minutes | Gianazza and Guittet[18] | 0.0778 | 1.79 |
| Aircraft count divided by average dwell time | Schmidt-Welch[9] | 0.196 | 0.339 |

Interestingly, this model does not include aircraft count, which is in most workload models, including those that are used in current operations. It does include aircraft per volume, aircraft predicted to enter the sector within five minutes, and aircraft count divided by average dwell time, which are related to and correlated with aircraft count. DDGHA includes boundary transfers, even though the parameter for this factor was estimated to be zero in SDD (see sub-section IV.A). Assuming that the magnitudes of the normalized parameter values indicate the relative contribution of each factor to the model's workload estimate, the aircraft predicted to enter the sector within five minutes factor contributes the most workload, followed by the number of aircraft near a boundary factor and the aircraft per volume factor.

## V. Conclusions

The ability of nine models to estimate controller workload in generic high-altitude airspace was studied using data from a human-in-the-loop simulation of generic high-altitude airspace. The models were evaluated based on their ability to estimate subjective controller workload measurements using corresponding workload factors computed from sector and traffic data. Workload models that are a linear combination of 3–17 workload factors can estimate controller workload more accurately than workload models based only on aircraft counts or aircraft counts divided by MAP values. Existing workload models achieved RMSE and MAE values that were at least 8% lower when the model parameters were estimated with data from the generic high-altitude airspace simulation. The factors in the DDGHA model were selected with data from the generic high-altitude airspace simulation, and it achieved RMSE and MAE values that were at least 10% lower than those achieved by any other model and an $R^2$ value that was 0.143 larger than the next largest $R^2$ value. The DD, SDD, and DDHA models achieve $R^2$ values in generic high-altitude airspace that were at least 0.3 lower than recently published $R^2$ values for the same models. This relatively poor performance of workload models in generic high-altitude airspace could be the result of several potential causes. Further research should be performed to find predictable metrics that correlate with safe and efficient operations in generic high-altitude airspace. These metrics may explicitly depend on the automation used in generic airspace.

# Appendix

This appendix contains information about the workload models studied in this paper. For a detailed description of a model, consult the cited publications for the model.

The AC model contains just one factor: the instantaneous aircraft count in the sector. The AC/MAP model also only contains one factor: the instantaneous aircraft count in the sector divided by the sector MAP value.

The DD Value model consists of just one factor. This factor is a weighted sum of the 17 factors and intercept shown in Table 5. These factors and the weights in the weighted sum (the parameters) are from Table 8 in Ref. 7. The DD Factors model used the 17 factors in Table 5 and an intercept term with parameters selected with the HITL simulation data.

The SDD Value model consists of just one factor: a weighted sum of the SDD factors in Table 3. The weights in the weighted sum are found in the "Baseline SDD" column of this table; these weights are from Ref. 8. The SDD Factors model uses the seven factors in Table 3 but with parameters selected with the HITL simulation data.

The DDHA model uses the factors in Table 6. These factors are from Ref. 11.

The Schmidt-Welch model consists of the factors in Table 7. These factors are from Refs. 9 and 15.

Finally, the factors and corresponding parameters for the DDGHA model are in Table 4.

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**Table 5. DD Factors and Parameters**

| Factor | Parameter[7] |
|---|---|
| Intercept | 1.2035908 |
| Aircraft count | 0.3157462 |
| Number of aircraft/occupied volume of airspace | 14.131972 |
| Proximity of conflicting aircraft with respect to their separation minima | −0.007039 |
| Sector volume | −0.000267 |
| Number of climbing aircraft | −0.517344 |
| Horizontal proximity measure 3 | −2.575776 |
| Time-to-go to conflict measure 1 | −1.550238 |
| Ratio of standard deviation of speed to average speed | −1.901624 |
| Conflict resolution difficulty based on crossing angle | 3.6584241 |
| Number of aircraft with 3-D Euclidean distance between 0-5 nautical miles excluding violations | −0.406443 |
| Number of aircraft with 3-D Euclidean distance between 5-10 nautical miles excluding violations | −0.151261 |
| The angle of converge between aircraft in a conflict situation | 0.6512409 |
| Count of number of aircraft within a threshold distance of a sector boundary | −1.27544 |
| 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 |
| Number of aircraft with predicted horizontal separation under 8 nmi | 0.4463046 |
| Variance of all aircraft headings in a sector | 0.0039505 |
| Squared difference between heading of each aircraft in a sector and direction of major axis | $-3.01 \times 10^{-07}$ |

**Table 6. DDHA Factors**

| Factor |
|---|
| Intercept |
| Aircraft count |
| Number of conflicts |
| Separation criticality index |
| Degrees of freedom index for aircraft in conflict |

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Table 7. **Schmidt-Welch Factors**

| Factor |
|---|
| Intercept ("Background Workload") |
| Squared aircraft count divided by sector volume ("Conflict Workload") |
| Sector volume ("Recurring workload") |
| Aircraft count divided by average dwell time ("Transition Workload") |

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