NASA/TM–2018–219985

Survey of Methods to Predict Controller Workload for Real-Time Monitoring of Airspace Safety

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August 2018

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August 2018

Acknowledgments

This work was supported by the SMART-NAS project under the Airspace Operations and Safety (AOSP) program within the NASA Aeronautics Research Mission Directorate (ARMD).

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Abstract

The Real Time Safety Monitoring (RTSM) approach allows for assessment and prediction of the safety margin in the National Airspace System (NAS) to help preempt incidents and accidents, rather than having to reactively mitigate them. In RTSM, the NAS is modeled using state variables, and safety metrics are defined in terms of these state variables. The safety metrics have been classified as weather-related, airspace-related, and human-related. Many of the formulated human-related safety metrics need an estimate of the controller workload for their computation. However, this computation is not trivial. Hence, in this report, we perform a literature survey to identify the different factors that enable the computation of controller workload and categorize these factors. Next, we describe studies undertaken to determine a minimal set of factors that provide a correct assessment of controller workload. Lastly, we survey approaches for evaluating how well the selected factors correlate with the controllers' subjective assessment of their workload. Based on this survey, we present factors beneficial to computing and predicting controller workload in real time, and discuss the status of data sources necessary for these computations.

Contents

Chapter 1

Introduction

Aviation risk management requires identifying existing and potential hazards to airspace safety, assessing the risk of those hazards, and finally, mitigating the risks. More mitigation options are available the earlier the situation is understood and a decision is made. Early mitigation may lead not only to more efficient operations, but also to improved safety by enabling the operator to preemptively avoid incidents and accidents. In addition, operating with a positive safety margin allows more latitude for managing unexpected events. In previous work [1, 2], the authors have developed the Real Time Safety Monitoring (RTSM) framework, an automated system to quantify safety in the National Airspace System (NAS), estimate the current level of safety, and predict the future evolution of safety and the occurrence of events that pose an increased risk to flights.

In RTSM, safety is defined by a set of safety metrics that quantify a subset of frequently-occurring and/or important hazards to flight, limited to hazards that can be measured, modeled, and predicted[1] using real-time data. Hazards are categorized into airspace-related hazards, environmental hazards, and human-related hazards. The set of related safety metrics is listed in [3], as human-related safety metrics are typically the most challenging to assess and predict, as the strict privacy policies established by pilot and air traffic controller unions limit available data. In addition, significant variation between humans with respect to the correlations between the task load and their perceived workload makes the computation of workload-related safety metrics difficult.

Since a large number of stakeholders are involved in the management of the national airspace, the safety metrics related to each stakeholder need to be researched individually in order to obtain a comprehensive understanding of all human-related safety hazards. In this work, we focus primarily on enroute air traffic controller (ATC) workload, leaving the study of pilots, traffic managers, and other NAS stakeholders for future work. In today's operations, controllers are responsible for the critical task of maintaining adequate separation between aircraft, and their workload contributes to the assessment of numerous human-related safety metrics. An overloaded controller may lose some amount of situational awareness, overlook a developing unsafe situation, make errors in judgement, become confused, or be unable to cope with a sudden increase in workload. Underworked controllers during a particular shift may become bored and distracted from their primary task, and repetitively being underworked over many shifts may lead to complacency and controller error[2].

[1]The prediction horizon can vary from a few minutes to many hours, depending on the availability of relevant data and models.
[2]https://skybrary.aero/index.php/Controller_Workload

ATC policies are designed to safeguard the airspace against hazards caused by controller workload. One such policy is to divide the airspace into sectors of responsibility, sized according to the capability of a single controller (or a collaborating pair of controllers), expected traffic volume, and expected traffic structure. Moreover, controllers are provided with safety nets and backup teams to support their work. In addition, shift patterns are designed to ensure that controllers can have sufficient rest and to address the different off-duty rest issues for nighttime and daylight duties. Each shift contains appropriate breaks to allow controllers to rest and, if necessary, to recover after periods of high workload. Standard operating procedures (SOPs) properly define handover procedures so that a controller is fully briefed before taking over a position. These policies and SOPs govern all aspects of the controller's job.

Many factors contribute to controller workload, such as staff shortage, equipment malfunction or failure, controller position design, poor Team Resource Management (TRM), and inadequate SOPs. Although these factors contribute to controller stress - a condition experienced when a person perceives that demands exceed the personal and social resources of the individual, they are outside the scope of this report. Instead, we focus on factors that can be measured, estimated, and predicted to provide a quantitative assessment of an individual controller's workload. Operationally, sectors can be combined to maintain at least a minimum workload level. To protect against overload, traffic may be redirected so the workload is slowed or distributed to nearby sectors. These decisions depend on accurate prediction of controller workload. Currently, the Federal Aviation Administration (FAA) determines workload based solely on number of aircraft expected to be in a sector in a one minute period. Each sector has an associated maximum number of aircraft that can be safely managed, known as the Monitor Alert Parameter (MAP) [4]. If predictions show the MAP will be exceeded in any 1-min period, traffic managers reroute aircraft or initiate flow control programs to redistribute the traffic in space or time.

The number of aircraft is a crude approximation of a controller's workload and the FAA has considered modifying it to include additional factors for a more accurate assessment. Various studies have been conducted by the FAA, the National Aeronautics and Space Administration (NASA), associated contractors, and others to identify the factors that influence controller workload. In addition to benefiting current operations, understanding the factors that exceed a controller's capabilities may benefit the next generation air traffic control system in which aircraft self-separation is the norm, with air traffic controllers stepping in only under off-nominal situations. Accurately predicting whether a controller will be able to step in when necessary to assess and manage the situation will be critical for ensuring safety [5].

In this report, we first perform a literature survey to identify the different factors that influence the computation of controller workload and also survey the different formulations available for computing controller workload. While a comprehensive literature survey was done in [6] and [7], in this work we update the findings in these surveys with information presented in more recent literature, and we classify these features based on the approaches used to develop them. A number of authors have also studied the minimum set of factors that must be included for an accurate prediction of workload, and we summarize these factors in this report. Next, based on the survey results, we recommend a set of factors beneficial to assessing and predicting controller workload and discuss the availability of data to compute such features. Finally, we discuss future work where the recommended factors can be utilized to quantitatively explore and evaluate the effect of controller workload on the safety of the NAS.

The report is organized as follows. Chapter 2 presents the results of the literature survey regarding the factors affecting controller workload (Section 2.1), methods used to determine a minimal set of factors that provide a correct assessment of controller workload (Section 2.2), and approaches for evaluating how well the selected factors correlate with the controllers' subjective assessment of their workload (Section 2.3). Chapter 3 presents an analysis of the survey results, beginning with some background on the effects of controller workload on NAS safety and concluding with recommended factors for assessing and predicting workload. Finally, Chapter 4 presents some future directions of research on incorporating controller workload into the RTSM framework.

Chapter 2

Factors Affecting Controller Workload

Numerous researchers have attempted to distill the significant factors that contribute to the cognitive complexity of controlling traffic and could be used to predict controller workload. In Section 2.1, we provide a summary of the proposed factors, organized by the techniques used to identify them. Section 2.2 describes the different approaches employed for determining a minimal set of factors that still provide an accurate assessment of workload. Finally, Section 2.3 reports on studies undertaken to evaluate how well the selected factors correlate with controllers' subjective assessments of their workload.

2.1 Survey of Factors for Predicting Controller Workload

The factors contributing to controller workload have been studied from different vantage points, utilizing methods such as observing controllers to determine their overall tasks, analyzing the complexity of the air traffic and the airspace structure under their responsibility, and relating the air traffic situation to a pattern recognition problem. In this subsection, we describe the various factors or features needed to compute the workload of a controller, organizing the discussion of these factors based on the methods leveraged to derive them.

2.1.1 Task Analysis Methods

Task analysis is the process of observing controllers in action to identify the tasks necessary to achieve safe and expeditious operation of air traffic. The result of such an analysis is a categorization of tasks that contribute to controller's workload and can be used to estimate and predict it. Welch et al. [8, 9] categorized the tasks into four types:

- Background activities
- Inter-sector coordination
- Traffic scanning
- Aircraft separation assurance

The first task, background activities, is assumed to be identical for all sectors and to be a constant fraction of the workload that is arbitrarily set to 0.1, or 10%, of a controller's time. In contrast, the controller's time required for the other three tasks depends on the number of aircraft being controlled. In particular, the workload is computed by estimating the expected rate and mean service times required for transit tasks (i.e., inter-sector coordination required to service aircraft transiting into or out of a controller's sector), recurring tasks (e.g., traffic scanning), and conflict tasks (i.e., provide aircraft separation assurance). The mean service times for transit, recurring, and conflict tasks can be computed from archived data, extracting information such as aircraft handoff duration, time spent looking for potential conflicts, and time required to resolve a conflict. Predicted traffic data can then be used to determine the expected rate for transit, recurring, and conflict tasks. The weighted sum represents the workload intensity, as follows: $G = G_b + \tau_t \lambda_t + \tau_r \lambda_r + \tau_c \lambda_c$, where G_b is the workload of background tasks, τ_t, τ_r, τ_c are the mean service times for transit, recurring, and conflict tasks, respectively, and λ_t, λ_r, λ_c are the rates of transit, recurring, and conflict tasks.

Similarly, Yousefi and Donohue [10] estimate a controller's workload with a weighted sum but partition it using the following four tasks:

- Horizontal movement workload, determined by the number of aircraft in a sector (sector density) and the average flight time
- Conflict detection and resolution workload, determined by the type of conflict and the conflict severity
- Coordination workload, determined by the type of coordination action, e.g., voice call, clearance issuance, and inter- or intra-facility transfer
- Altitude change workload, determined by the type of sector clearance request, i.e., level off, commence climb, and commence descent

Marr and Lindsay [4] decompose a controller's task into more detail and compute workload by accounting for the time required for the following subtasks:

- Entry
- Exit
- Separation
- Delay
- Non-radar arrival
- Non-radar departure
- Scanning
- Coordination
- Transition

Subject matter experts (SME, i.e., expert enroute controllers) expect safety to degrade when the time spent on the sum of each of the tasks for predicted traffic data exceeds a specified percentage of a controller's available time during a selected period (e.g., 15 min). In Marr and Lindsay's work, SMEs recommended that workload in a sector be considered excessive if the sum of time spent on the above tasks exceeds 90% of the controller's available time. In contrast, Schmidt [11] asserts that safety begins to degrade when workload intensity exceeds 80% of a controller's available time.

Additional emphasis is placed on coordination workload by Manning et al. [12]. The authors show that instructional clearances and activity together are a better predictor of workload than either alone, where the activity is significantly correlated with number and duration of all communications, clearances, and frequency changes/courtesies. However, the results of this analysis should be interpreted with caution as the analysis took into account only 40 observations from 4 sectors, and only 4-minute time-segments of data were analyzed. Subsequent analyses using larger data sets could be conducted to obtain more stable results. The authors identified that the most useful measures for evaluating controller workload are:

- Total number of aircraft
- Maximum number of aircraft controlled simultaneously
- Average time the aircraft remain under control
- Average heading/speed/altitude variation
- Average time to accept handoff
- Average time until initiated handoffs are accepted
- Number of radar controller data entries and entry errors
- Number of data controller data entries and entry errors

Interaction with computer systems is considered by Hudgell and Gingell [13]. They present an approach for assessing ATM systems using information processing load (IPL), a combination of workload of all NAS stakeholders, such as controllers, pilots, and computer systems. Some of the factors that contribute to IPL include flight arrival into airspace, interaction detection, resolution planning, resolution implementation, monitoring, other trajectory changes, and coordination with other control agencies.

The above task analysis studies focused primarily on the information to be processed. Hendy et al. [14], describe this as intensity-load. They posit that the load on the human information-processing system results not only from intensity-load but also on the time allowable for making a decision. The ratio of the time necessary to process the required information to the time allowable for making a decision, termed time pressure, determines subjective estimates of workload as well as operator performance.

The previously described workload models focus on enroute controllers. In contrast, Croft[1] describes the factors believed to be increasing the workload of ground controllers, as follows:

- Traffic crossing the takeoff and landing runways

[1] http://aviationweek.com/commercial-aviation/who-charge-safety-amsterdam-schiphol

Table 2.1. Dynamic density features affecting controller workload [15].

Heading Change (N $>$ 15 deg in 2 min) (N = Number of aircraft)	Speed Change (N $>$ 10 kts/0.02 Mach in 2 min)
Altitude Change (N $>$ 750 ft in 2 min)	Conflict Predicted 0-25 nm (N predicted to be in conflict with another aircraft within 0-25 nm at end of 2 min)
Minimum Distance 0-5 nm (N within 0-5 nm to closest aircraft at end of 2 min)	Conflict Predicted 25-40 nm
Minimum Distance 5-10 nm	Conflict Predicted 40-70 nm

- Deviations from procedures to handle the increased traffic load
- Shortage of parking areas
- Large number of daily runway configuration changes, many of which are due to noise restriction agreements

These factors are derived from comments from controllers at Amsterdam Airport Schiphol, one of the busiest airports in Europe.

2.1.2 Air Traffic Complexity Methods

The methods in the previous section derive workload-influencing factors by explicitly analyzing a controller's major tasks. An alternative method for deriving factors focuses only on the traffic characteristics that influence the difficulty of providing aircraft separation assurance to a dynamic set of aircraft, omitting tasks such as communication, scanning, etc.

Dynamic Density

In sociology, dynamic density refers to the combination of population density and the amount of social interaction within that population. Laudeman et al. [15] introduced the concept of dynamic density as a controller workload metric. Their proposed function includes a traffic density term and eight traffic complexity terms, as shown in Table 2.1. Researchers at NASA, the FAA, Wyndemere, and related organizations expanded on the dynamic density concept to characterize the types of interactions that impact controller workload. Zinatullin and Lykens [7] summarize the factors suggested by NASA [5], the FAA, and Wyndemere Inc. [16]. Table 2.2 reproduces their summary. Zinatullin and Lykens also provide a comprehensive description of each factor, including equations on how to compute the factor and required data.

Zhang et al. [17] propose a method similar to dynamic density that forecasts terminal-area congestion through five metrics, as follows:

- Average flow velocity of the aircraft in a controller's area.
- Standard deviation of velocity. Smaller deviations are associated with lower controller workload for anticipating aircraft positions and sequencing aircraft.

Table 2.2. Air traffic complexity features, consolidated list from FAA, NASA, and Wyndemere [5, 7, 16]. Reproduced from [7].

Sector count	Aircraft density	Aircraft density by sector
Convergence recognition index	Separation criticality index	Degrees of freedom index
Coordination task load index 1	Coordination task load index 2	Fraction of flights that are climbing
Fraction of flights that are cruising	Fraction of flights that are descending	Inverse weighted mean of horizontal separation
Inverse weighted mean of vertical separation	Inverse average minimum horizontal separation	Inverse average minimum vertical separation
Inverse of minimum horizontal separation in same vertical neighborhood	Inverse minimum vertical separation in same horizontal neighborhood	Fraction of aircraft with time-to-go to conflict less than 600s
Inverse minimum time to go to conflict with time-to-go to conflict less than 600s	Inverse of smallest time-to-go to conflict for aircraft pairs with time-to-go to conflict less than 600s	Variance of groundspeed
Ration of standard deviation of ground speed to mean of ground speed	Mean conflict resolution difficulty	Number of aircraft with heading change greater than 15 deg
Number of aircraft with speed change greater than 10 knots or 0.002 Mach	Number of aircraft with altitude change greater than 750 ft	Number of aircraft pairs with 3-D Euclidean distance between 0-5 nm
Number of aircraft pairs with 3-D Euclidean distance between 5-10 nm	Number of aircraft pairs with lateral distance between 0-25 nm and vertical separation less than 2000/1000 ft above/below 29000 ft	Number of aircraft pairs with lateral distance between 25-40 nm and vertical separation less than 2000/1000 ft above/below 29000 ft
Number of aircraft pairs with lateral distance between 40-70 nm and vertical separation less than 2000/1000 ft above/below 29000 ft	Number of aircraft pairs with horizontal separation under 8 nm	Convergence angle of conflicting aircraft (average)
Proximity count	Conflict count	Altitude variation
Aircraft heading variation	Number of aircraft close to sector boundary	Aircraft-axis heading variation
Aspect ratio	A measure of the aircraft count	A measure of the aircraft density per sector
A measure of the number of aircraft pairs with less than 8 or 13 nm horizontal distance between them	A measure of the convergence angle for aircraft pairs which are within 13 nm of each other	A measure of the number of aircraft in the neighborhood of an aircraft pair projected to be in conflict
A measure of the number of aircraft pairs which are in conflict with each other and are close to a subsector boundary	Number of aircraft with an altitude change greater than 500 ft per min	Measure of the variation in heading
Measure of the number of aircraft close to a subsector boundary	A measure of airspace structure and the distribution of aircraft within a sector	An alternative measure of airspace structure and the distribution of aircraft within a sector

- Standard deviation of heading angle. This metric reflects the clustering of flight paths. The more dispersed the flight paths, the more difficult it is for controllers to apply structure-based abstractions, as discussed in Section 2.1.2

- Traffic mixing coefficient. This metric reflects the number of aircraft and the mixing degree of different categories of aircraft (i.e., climbing, descending, cruising). The bigger the traffic mixing coefficient, the higher the workload.

- Equivalent airspace occupancy. This metric takes into account the different level of workload associated with each category of aircraft.

Traffic Disorder

Another approach that uses air traffic complexity to predict controller workload is Lee, Feron, and Pritchett's work [18] on visualizing how a given traffic situation responds to disturbances. They consider airspace as a closed-loop control system where the signal of interest is the control activity required to avoid conflicts with a disturbance, such as an entering aircraft. Three types of control activity are considered:

- Sum of the total heading changes over all aircraft inside the sector to maintain a conflict-free situation
- Sum of heading changes due to secondary conflicts
- Number of aircraft that undergo a heading change inside the sector

Delahaye et al. [19,20] also believe that a controller's workload is affected not just by the number of aircraft under control but also by the control actions required from the controller. They measure air traffic complexity by considering the stability of the traffic configuration. Their workload model contains the following factors which measure the disorder of the speed vector field in 3D airspace:

- Density, defined as the level of aggregation of aircraft
- Convergence and divergence of aircraft pairs
- Sensitivity of relative distance to speed and heading changes, using either of the following metrics depending on the operator's objective. In both cases, high sensitivity corresponds to lower workload, since small changes in heading or speed will result in faster conflict resolution.
  - Change of relative distance when small modification is applied to speed and heading of the aircraft involved
  - Conflict duration with the speed and heading modifications

Airspace Structure

The previous studies examine the contribution of the characteristics of air traffic to the cognitive complexity of air traffic control (ATC). The studies of this subsection additionally consider the contribution from the structural design of the airspace.

Histon et al. [21] conducted a series of site visits to ATC facilities to determine the contributors to the complexity of managing traffic. In addition to identifying factors strictly related to the traffic distribution, controllers indicated that the airspace structure within which that traffic operates also contributes to workload. The complete list of factors derived from their study are shown in Table 2.3, duplicated from [21].

To decrease the effort required to maintain situational awareness, Histon et al. report that controllers use structure-based abstractions such as flows, groupings, and critical points. They note that "not including the underlying structural elements on which these abstractions are based may artificially inflate the outputs of any cognitive complexity metrics."

Wei et al. [22] report on the structure-based abstraction concept of grouping traffic to reduce cognitive complexity. As discussed in Section 2.3.1, the authors show that managing traffic segregated by streams

Table 2.3. Airspace-related features derived from ATC site visits. Reproduced from [21]. Items marked with * are related to structural elements.

Airspace Factors	**Traffic Factors**	**Operational Constraints**
Sector dimensions* • Shape, physical size, • Effective "area of regard"	Density of aircraft • Clustering* • Sector-wide	Buffering capacity*
Spatial distribution of airways / Navigational aids*	Aircraft encounters • Number of, • Distance between aircraft, • Relative speed between aircraft, • Location of point of closest approach (near airspace boundary, merge points, etc)*, • Difficulty in identifying, • Sensitivity to controller's actions	Restrictions on available airspace • Presence of convective weather, • Activation of special use airspace, • Aircraft in holding patterns*
Number and position of standard ingress / egress points*	Ranges of aircraft performance • Aircraft types (747, Cessna) • Pilot abilities	Procedural restrictions • Noise abatement procedures* • Traffic management restrictions (e.g., miles-in-trail requirements)
Letters of agreement / Standardized procedures*	Sector transit time*	Communication limitations
Standard flows* • Number of, • Orientation relative to sector shape, • Trajectory complexity, Interactions between flows (crossing points, merges)	Number of aircraft in transition • Altitude, • Heading, • Speed	
Coordination with other controllers* • Point-outs • Hand-offs		

reduces controller workload over managing traffic segregated only by sectors. In their study, a stream is composed of aircraft that have the same engine type, destination airport, and arrival gate.

Gariel, Srivastava, and Feron [23] report on the structure-based abstraction concept of standard flows. They hypothesize that when an aircraft does not conform to standard flight patterns, more attention is required from controllers, thereby increasing workload. They introduce a complexity measure based on Shannon's theory of communication that indicates the disorder with regard to nominal operations. The complexity increases with the number of outliers detected and also with the number of aircraft. Whereas other air traffic complexity approaches require knowledge of the intended trajectory (e.g., via a flight plan) and thus are more applicable to the enroute phase of flight, this method can better handle terminal-area operations in

Table 2.4. Workload model features from treating air traffic management as a pattern recognition / image processing problem [24].

Angular second moment	Contrast	Correlation
Variance	Inverse Difference Method	Sum average
Sum variance	Sum entropy	Entropy
Difference variance	Difference entropy	Difference average

which controllers often vector aircraft off the flight plan, pilots comply with varying urgency with issued directives, and pilots have more leeway in the route flown on a visual approach.

2.1.3 Other Methods

A unique approach to predicting controller workload was taken by Chatterji and Sridhar [24]. They draw an analogy between image processing and traffic pattern recognition and utilize gray-level statistics from image processing to describe a traffic pattern. In their scheme, the aircraft within the traffic pattern are analogous to pixels in the image, while the properties of the aircraft such as their position and velocity are analogous to the gray-level property of the pixels. To determine workload from the traffic pattern statistics, they train a neural network to categorize twelve airspace complexity measures, shown in Table 2.4, into three workload categories (low, medium, high). The complexity measures are derived from second-order statistics and computed from the sum and difference histograms of the positions and velocities of the aircraft.

2.1.4 Weakly Supported Factors

It is informative to also understand features that have been either disproved or not yet proven to be well correlated with increased workload. In this regard, Hagmueller et al. [25] conducted studies to evaluate the human voice as an indicator of workload induced stress. Their results indicate only a weak correlation between stress and voice characteristics, affirming a previous study by EUROCONTROL Experimental Centre.

2.2 Determining a Minimal Set of Predictive Factors

In this subsection, we present some methodologies that can be employed to determine a minimal set of predictive factors.

Riley et al. [26] train a neural network with different sets of complexity measures to determine the ones that perform best at predicting pilots', rather than controllers', assessment of airspace complexity/workload, as the authors stated that pilots retain the primary responsibility for long-term prevention of loss of separation in the operational concept they were investigating. The following complexity measures were found to be most predictive:

- Number of aircraft
- Number of climbing aircraft

- Number of cruising aircraft
- Number of descending aircraft
- Horizontal proximity
- Vertical proximity
- Time until conflict
- Ratio of standard deviation of speed to average speed
- Number of unique alerts ongoing
- Presence/absence of alerting state
- Convergence recognition index, which indicates shallow angle conflicts

Chatterji and Sridhar [24] also train a neural network to determine which subset of 16 dynamic density metrics are most useful for predicting workload. The best predictions occur with the full set of 16 metrics, as follows:

- C_1: Complexity based on aircraft count
- C_2: Complexity measure of aircraft in climb mode
- C_3: Complexity measure of aircraft in level flight
- C_4: Complexity measure of aircraft in descent mode
- C_5: Complexity measure associated with the mean weighted horizontal separation distance
- C_6: Complexity measure associated with the mean weighted vertical separation distance
- C_7: Complexity measure related to the average minimum horizontal separation between aircraft pairs
- C_8: Complexity measure related to the average minimum vertical separation between aircraft pairs
- C_9: Complexity measure based on horizontal separation of aircraft within an altitude band
- C_{10}: Complexity measure based on vertical separation of aircraft within an altitude band
- C_{11}: Complexity measure related to the number of aircraft pairs with positive time-to-go less than equal or equal to Δt, the threshold time at which conflict resolution becomes urgent
- C_{12}: Complexity measure related on the average time-to-go
- C_{13}: Complexity measure based on the smallest time-to-go value from the set of all aircraft pairs that are involved when conflict resolution becomes urgent
- C_{14}: Complexity measure based on variance in the groundspeed
- C_{15}: Complexity measure based on the variance and mean of the groundspeed
- C_{16}: Complexity measure based on the level of conflict resolution difficulty

Table 2.5. Complexity metrics mentioned in [27].

Metric	Definition
NUM	Sector aircraft count
MAP	Monitor/Alert Parameter (operationally defined threshold) SECTVOL Sector Volume, cubic nautical miles (nm^3)
SC	Speed Change; number of aircraft with an airspeed change greater than 10 knots or 0.02 Mach during a 2-minute interval
WACT	A normalized measure of the aircraft count per sector
WDEN	A normalized measure of the aircraft counter per sector
WCLAP	A measure incremented by aircraft pairs with less than 8 nm horizontal distance, and to a lesser extent by pairs with less than 13 nm horizontal distance
WCONVANG	A measure of the convergence angle for aircraft pairs within 13 nm of each other
WCONFLICTNBRS	A measure of the number of aircraft in close proximity to an aircraft pair projected to be in conflict
WCONFBOUND	A measure of the number of aircraft pairs in conflict with each other and close to a subsector boundary
WALC	A measure of the number of aircraft with an altitude change greater than 500 feet per minute
WASP	A measure of the distribution of aircraft relative to sector structure

Masalonis, Callaham, and Wanke [27] assess metrics from previous studies on how well they can support traffic flow management, including whether they can be predicted up to 120 min ahead and their face validity, i.e., how much operational sense a metric makes. They use proportional odds logistic regression to determine the metrics' usefulness for predicting subjective complexity ratings and narrow down 41 metrics to just 12, as shown in Table 2.5. The findings were validated through interviews with traffic management coordinators (TMC) who implement traffic flow initiatives that ultimately affect controller workload. When asked about the desirability of replacing a single dynamic density value with a multivariate value, the TMCs preferred a single number, partially because of familiarity and partially because they feared multiple values could lead to information overload. In an analysis of whether the same set of metrics could be used for different enroute centers, they determined that different factors may contribute to perceived complexity and difficulty in different centers and altitudes.

2.3 Controller Workload Validation Methodologies

In the previous two subsections, we presented factors that can be used to compute and predict controller workload and we described methods to determine the minimal set of such factors that can correctly predict controller workload. In this subsection, we describe some approaches for evaluating how well selected factors correlate with the controllers' subjective assessment of their workload.

2.3.1 Task Analysis

Brooker [28] presents a substantial literature review of applied psychology validation techniques. He concludes that the current techniques need to be improved to provide guidance to next generation ATC systems designers. Until that occurs, systems engineers and operations researchers will continue to use ad hoc validation studies to evaluate prospective ATC systems.

Lee [29] presents a controller-in-the-loop flight simulator experiment used to compare controller workload modeled as linear, nonlinear, and s-curve functions of the number of aircraft to the controllers' subjective scores of the perceived workload. Results suggested the s-curve model to be the best under the tested conditions in which number of aircraft was varied but remained below manageable levels and weather was not considered.

2.3.2 Dynamic Density

Sridhar et al. [30] examine the relationship between airspace complexity and controller workload by assessing how well dynamic density (DD) metrics that consider only the flow conditions in a sector can be predicted. The authors used a trajectory estimator to predict 5 min and 20 min ahead and compared those predictions to the real traffic that occurred. The 5 min predictions were found to be accurate. For the 20 min predictions, missing intent information for several aircraft and not accounting for departure traffic decreased the accuracy, though it still had a high correlation with actual sector controller activity. Hence, it was concluded that dynamic density can be used as a good indicator of controller activity (and workload) up to 20 min ahead. A weighted, linear combination of the following variables were included in the dynamic density formulation in [30], each measured during a sample interval of one minute:

- N: traffic density (number of aircraft)
- NH: number of aircraft with heading change greater than 15 deg
- NS: number of aircraft with speed change greater than 10 kts or 0.002 Mach
- NA: N with altitude change greater than 750 ft
- S5: N with 3D Euclidean distance between 0-5 nm excluding violations
- S10: N with 3D Euclidean distance between 5-10 nm excluding violations
- S25: N with lateral distance between 0-25 nm and vertical separation $<$ 2000/1000 ft above/below 29,000 ft
- S40: N with lateral distance between 25-40 nm and vertical separation $<$ 2000/1000 ft above/below 29,000 ft
- S70: N with lateral distance between 40-70 nm and vertical separation $<$ 2000/1000 ft above/below 29,000 ft

The weights were computed either by regression analysis of activity data or subjective weights from controller survey data.

Wei et al. [22] present a comparison of the workload for conventional sector management versus automation-assisted stream management in which controllers were responsible for merging and spacing and automation was responsible for separation between streams and with terrain. Workload is measured with an adapted version of DD that uses variables relevant to both types of control. As in Sridhar et al.'s work [30], two analyses were conducted, each with a different weighting scheme, either derived by regression analysis or by consulting subject matter experts. It was found that workload was reduced by 18% (using SME-weighted DD equations) or 24% (using regression-weighted DD equations) for the particular data set utilized.

Chatterji et al. [31] evaluate all the ARTCC sectors above 17,000 ft against 15 traffic metrics and 18 sector geometry metrics with the goal of understanding how sectors are currently designed to manage controller workload. The traffic metrics include:

- Maximum number of aircraft
- Maximum number of aircraft in climb
- Maximum number of aircraft in cruise
- Maximum number of aircraft in descent
- Maximum number of jet aircraft
- Maximum number of non-jet aircraft
- Peak conflict count
- Average horizontal separation between aircraft in sector
- Minimum horizontal separation between aircraft in sector
- Average vertical separation between aircraft in sector
- Minimum vertical separation between aircraft in sector
- Average time-to-go to conflict
- Sector average transit time
- Average airspeed
- Variance in airspeed of aircraft

The sector geometry metrics include:

- Number of sectors in centers
- Number of sectors in eight air-traffic control regions
- Sector-type: low, high, or super-high
- Sector volume
- Sector height
- Sector area
- Sector length
- Aspect ratio - length/width
- Principal direction

- Number of subsectors
- Number of navigational aids
- Number of intersections
- Number of airways
- Number of airports
- Number of surrounding sectors
- Special Use Airspace completely inside sector
- Special Use Airspace contained partially
- Distance to closest major airport

Finally, Zhang et al. [17] present a method for evaluating traffic congestion status in terminal areas using a fuzzy C-means clustering algorithm and a method for forecasting traffic congestion status using a support vector machine. Several traffic congestion status evaluation metrics are presented, including:

- Average flow velocity
- Standard deviation of velocity
- Standard deviation of heading angle
- Traffic mixing coefficient
- Equivalent airspace occupancy

2.3.3 Traffic Disorder

Sridhar et al. [32] suggest that to be operationally useful, workload predictions should be available 60-120 min ahead. Because trajectory predictions are imprecise so far in advance, the authors perform a worst-case analysis to determine conditions under which additional aircraft entering a sector would exceed controller workload limits. Their analysis shows that the impact of additional aircraft in a sector is not uniform and depends significantly on the location of the new aircraft in relation with the existing ones. Notably, aircraft entering the interior of a sector (pop-ups) and those entering near boundaries have the worst impact on controller workload, especially if the entering aircraft are close to other aircraft clusters, such as at the intersection of major flows.

Chapter 3

Controller Workload Factors Analysis

Until now, we have presented a summary of factors that have been identified in literature for computing controller workload. In this section, we tie our findings back to our earlier RTSM work on the analysis of safety of the NAS [3]. To this end, we first present the safety metrics that need controller workload as their input. Then, we identify the main factors that were most pervasive in our literature review findings and also comment on the availability of the information needed for quantifying these factors.

3.1 Effects of Controller Workload on NAS Safety

Table 3.1 lists the controller workload safety metric and other RTSM safety metrics from [2] that need controller workload as their input. As indicated in the table, controller workload is a component in the computation of other human-related metrics such as probability of controller error, controller fatigue, probability of fuel exhaustion, and probability of miscommunication. Specifically, the rationale for each related safety metric is as follows:

- Probability of controller error: Excessive controller workload may result in a controller overlooking a developing unsafe situation, making errors in judgement, or becoming confused. Additionally, insufficient workload may result in errors due to, e.g., inattention caused by boredom.
- Controller fatigue: Prolonged periods of maintaining adequate situational awareness and effectively planning for separation of a large number of aircraft with many interdependencies between their routes may lead to increased stress, mental strain, and mental fatigue.
- Probability of fuel exhaustion: A controller experiencing excessive workload may place some aircraft in a hold to allow for additional decision making time. Extended holding could lead to multiple aircraft declaring minimal fuel and requiring expedited routing to the airport, in turn exceeding the allowed airport arrival rate. Note that controller workload is just one link in a potential accident chain. The pilots will be carefully monitoring available fuel and may decide to divert to an alternate if necessary.
- Probability of miscommunication: While managing multiple tasks, an overworked controller may misidentify an improper readback of a clearance. Likewise, a bored and complacent controller may

Table 3.1. Safety metrics that need controller workload as an input.

Safety Metrics	**Inputs**	**Outputs**
Controller workload	controller id, time, services available, aircraft at coordinates, weather at coordinates, airspace complexity, congestion and density, visibility, traffic homogeneity, degree of operational normalcy, approach complexity, communication issues (multiple languages, lack of command in English, multiple frequencies, etc.)	Workload category, e.g., low, medium, high
Probability of controller error	controller id, time, controller workload, controller fatigue, controller observability	Probability in percentage
Controller fatigue	controller id, time, controller workload, number of hours on duty, number of hours of sleep, experience level, days on duty, etc.	Fatigue level, e.g., low, medium, high
Probability of fuel exhaustion	aircraft of interest, time, weather at coordinates, congestion and density, degree of operational normalcy, controller workload, services operation status, airport configuration, avoidance areas at coordinate, departure complexity, wind components, probability of airplane icing, probability of runway contamination, etc.	Probability in percentage
Probability of miscommunication	volume of interest, time, airspace complexity, pilot fatigue, pilot workload, controller workload, controller fatigue, congestion and density, weather at coordinates, degree of operational normalcy, operation type, communication issues (multiple languages, lack of command in English, multiple frequencies, etc.)	Probability in percentage

not be paying adequate attention to the readback and assume that this pilot, like many previous others, correctly understood the clearance.

Note that controller workload is just one component of each of these safety metrics. Many of the other factors for these metrics are challenging to assess and predict in their own right.

Each of the safety metrics listed in Table 3.1 requires a large number of inputs. The availability of data to measure or compute these inputs is imperative to the real-time prediction of these safety metrics. Not all of these inputs are currently available in real-time, such as number of hours on duty, or controller fatigue. Until these inputs become available, metrics may be approximated using user provided or assumed values.

3.2 Recommended Controller Workload Factors

In this report, we focus on the inputs required to compute controller workload. As shown in the previous section, the hypothesis in [2] was that workload is affected by the following: controller id, time of day, {services available, aircraft at coordinates, weather at coordinates, airspace complexity, congestion and density, visibility, traffic homogeneity, degree of operational normalcy, approach complexity}, communication issues (multiple languages, lack of command in English, multiple frequencies, etc.). In the terminology of [2], inputs within braces, e.g., services available, are "helper" metrics that contribute to the computation of other metrics and may also be of interest in their own right. As a result of this survey, we are now able to better define the details of some of the helper metrics, specifically airspace complexity, approach complexity, and congestion and density. In Chapter 2, we surveyed the main factors that previous research has correlated with controller workload. In this section, we list the most prevalent factors that contribute to workload.

The intersection between the factors proposed and validated by the numerous previous studies is quite large and well summarized by Histon et al. [21] Our recommended factors, therefore, begin with their list, reproduced from [21]. To this list, we recommend adding a subset of the remaining factors identified only in a few of the studies, as shown in Table 3.2. First, we recommend additional airspace complexity factors. Next, we include factors defining the workload requirements identified through structured task analyses. Then, we enumerate factors that have been associated with contributing to the workload of ground controllers in particular. Finally, a number of factors were hypothesized to affect controller workload in [2]. The list in [2] was generated from studying accident and incident reports and from the authors' experience as general aviation pilots flying in the system. We believe that some of these factors remain relevant after our study of the literature and thus include them in Table 3.2.

Given that many of the recommended factors have been validated through simulations, it is expected that data is available for their computation. For the factors identified through observation and factors proposed by [2] but not yet validated, the data may not currently be in a digital or accessible form. Whether all of the listed factors are critical could be studied in future research. If the factors are found in validation studies to indeed be beneficial, the data may potentially be provided.

Table 3.2: Recommended factors for computing and predicting controller workload.

Category	**Inputs**	**Data Availability**
Factors documented in Table 2.3 [reproduced from Histon et al. [21]]	Sector dimensions • Shape, physical size • Effective "area of regard"	Yes
	Spatial distribution of airways / Navigational aids	
	Number and position of standard ingress / egress points	
	Letters of agreement / Standardized procedures	
	Standard flows • Number of • Orientation relative to sector shape • Trajectory complexity, Interactions between flows (crossing points, merges)	
	Coordination with other controllers • Point-outs • Hand-offs	
	Density of aircraft • Clustering • Sector-wide	
	Aircraft encounters • Number of • Distance between aircraft • Relative speed between aircraft • Location of point of closest approach (near airspace boundary, merge points, etc.) • Difficulty in identifying • Sensitivity to controller's actions	
	Ranges of aircraft performance • Aircraft types (747, Cesna) • Pilot abilities	

Category	Inputs	Data Availability
	Sector transit time	
	Number of aircraft in transition • Altitude • Heading • Speed	
	Buffering capacity	
	Restrictions on available airspace • Presence of convective weather • Activation of special use airspace • Aircraft in holding patterns	
	Procedural restrictions • Noise abatement procedures • Traffic management restrictions (e.g., miles-in-trail requirements)	
	Communication limitations	
Factors identified by subset of Air Traffic Complexity methods	Number of non-radar arrival and departure aircraft	Yes
	Number of radar controller data entries and entry errors	
	Number of data controller data entries and entry errors	
	Ratio of time necessary to process the required information to the time allowable for making a decision (time pressure)	
	Number of outliers detected wrt standard operations	
	Number of airports	
	Distance to closest major airport	
	Large number of daily runway configuration changes	
Factors identified through Task Analysis	Background activities	These are typically controller specific and could be analyzed *in situ*
	Aircraft separation assurance tasks	
	Traffic scanning	
	Mean service times for transit tasks	
	Mean service times for recurring tasks	
	Mean service times for conflict tasks	
	Rate of transit tasks	
	Rate of recurring tasks	
	Rate of conflict tasks	
Factors specific to ground controller workload	Traffic crossing takeoff and landing runways	Yes
	Deviations from procedures to handle the increased traffic load	
	Shortage of parking areas	
Additional factors identified in Roychoudhury et al. [3]	Services available	Yes
	Visibility	
	Degree of operational normalcy	Partial: Traffic Management Initiatives are available, however, emergency aircraft, etc., may not be readily available
	Communication issues (multiple languages, lack of command in English, multiple frequencies, etc.)	Partial: frequencies in use are available, however, languages used are not readily available
	Controller fatigue	Still in research
	Controller observability	Could be obtained if desired

Chapter 4

Conclusions

This report presents a survey of the different factors that influence the computation of controller workload, presents methods utilized to identify the minimum set of factors that must be included for an accurate prediction of workload, and compiles studies that validate the identified factors. The survey results are summarized into recommended factors to compute workload. The recommended set is composed of (a) factors pervasive in much of the literature, (b) factors resulting from only a subset of surveyed approaches that nevertheless have been shown to be predictive, and (c) factors formerly proposed by the authors that have not otherwise been explored in the literature, but have contributed to incidents and accidents. Additionally, the rationale linking controller workload to other safety metrics is presented.

As part of future work, controller workload for a region of the NAS will be computed using the recommended factors identified in the previous section. Workload will also be predicted with an operationally-useful 120 min lookahead. The computation and prediction results can then be validated with actual human in the loop experiments using approaches similar to those presented in Section 2.3.

Also in future work, methods of assessing and predicting workload and its effects on the safety of the NAS can be studied for other stakeholders of the NAS, such as pilots, ground and ramp controllers, dispatchers, and so on. Maintaining air traffic controller workload within an acceptable range is critical. Being able to assess and predict controller workload has been the holy grail for many years. The survey and recommendations in this report may bring us one step closer to this goal.

Bibliography

1. L. Spirkovska, I. Roychoudhury, M. Daigle, and K. Goebel, “Real time safety monitoring: Concept for supporting safe flight operations,” in *17th AIAA Aviation Technology, Integration, and Operations Conference*, 2017, p. 4494.

2. I. Roychoudhury, L. Spirkovska, M. Daigle, E. Balaban, S. Sankararaman, C. S. Kulkarni, S. Poll, and K. Goebel, “Predicting real-time safety of the national airspace system,” in *AIAA Infotech@ Aerospace*, 2016, p. 2131.

3. I. Roychoudhury, L. Spirkovska, M. Daigle, E. Balaban, S. Sankararaman, C. Kulkarni, S. Poll, and K. Goebel, “Real-time monitoring and prediction of airspace safety,” NASA Ames Research Center, Tech. Rep., 2016.

4. B. Marr and K. Lindsay, “Controller workload-based calculation of monitor alert parameters for en route sectors,” in *15th AIAA Aviation Technology, Integration, and Operations Conference*, 2015, p. 3178.

5. P. H. Kopardekar, A. Schwartz, S. Magyarits, and J. Rhodes, “Airspace complexity measurement: An air traffic control simulation analysis,” *International Journal of Industrial Engineering: Theory, Applications and Practice*, vol. 16, no. 1, pp. 61–70, 2009.

6. A. Majumdar and W. Ochieng, “Factors affecting air traffic controller workload: Multivariate analysis based on simulation modeling of controller workload,” *Transportation Research Record: Journal of the Transportation Research Board*, no. 1788, pp. 58–69, 2002.

7. A. Zinatullin and J. Lykens, “Dynamic density algorithms used by the target generation facility,” Federal Aviation Administration Website. [Available Online].

8. J. Welch, J. Andrews, and J. Post, “Validation of enroute capacity model with peak counts from the us national airspace system,” Massachusetts Institute of Technology Lexington Lincoln Lab, Tech. Rep., 2010.

9. J. D. Welch, J. Y. Cho, N. K. Underhill, and R. A. DeLaura, “Sector workload model for benefits analysis and convective weather capacity prediction,” in *Tenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2013), Chicago, IL*, 2013.

10. A. Yousefi and G. Donohue, “Temporal and spatial distribution of airspace complexity for air traffic controller workload-based sectorization,” in *AIAA 4th aviation technology, integration and operations (ATIO) forum*, 2004, p. 6455.

11. D. K. Schmidt, “Queueing analysis of the air traffic controller’s work load,” Tech. Rep., 1978.

12. C. A. Manning, S. H. Mills, C. M. Fox, E. M. Pfleiderer, and H. J. Mogilka, "Using air traffic control taskload measures and communication events to predict subjective workload," FEDERAL AVIATION ADMINISTRATION OKLAHOMA CITY OK CIVIL AEROMEDICAL INST, Tech. Rep., 2002.

13. A. J. Hudgell and R. Gingell, "Assessing the capacity of novel atm systems," in *4th USA/Europe Air Traffic Management R&D Seminar*, 2001.

14. K. C. Hendy, J. Liao, and P. Milgram, "Combining time and intensity effects in assessing operator information-processing load," *Human Factors*, vol. 39, no. 1, pp. 30–47, 1997.

15. I. V. Laudeman, S. Shelden, R. Branstrom, and C. Brasil, "Dynamic density: An air traffic management metric," 1998.

16. Wyndemere, "An evaluation of air traffic control complexity," NASA Ames Research Center, Tech. Rep. NASA-CR-202457, October 1996.

17. H.-H. Zhang, C.-P. Jiang, and L. Yang, "Forecasting traffic congestion status in terminal areas based on support vector machine," *Advances in Mechanical Engineering*, vol. 8, no. 9, p. 1687814016667384, 2016.

18. K. Lee, E. Feron, and A. Pritchett, "Describing airspace complexity: Airspace response to disturbances," *Journal of Guidance, Control, and Dynamics*, vol. 32, no. 1, pp. 210–222, 2009.

19. D. Delahaye and S. Puechmorel, "Air traffic complexity: towards intrinsic metrics," in *Proceedings of the third USA/Europe Air Traffic Management R & D Seminar*, 2000.

20. S. Athènes, P. Averty, S. Puechmorel, D. Delahaye, and C. Collet, "Atc complexity and controller workload: Trying to bridge the gap," in *Proceedings of the International Conference on HCI in Aeronautics*. AAAI Press Cambridge, MA, 2002, pp. 56–60.

21. J. M. Histon, R. J. Hansman, G. Aigoin, D. Delahaye, and S. Puechmorel, "Introducing structural considerations into complexity metrics," *Air Traffic Control Quarterly*, vol. 10, no. 2, pp. 115–130, 2002.

22. P. Wei, C. Surakitbanharn, S. Landry, and D. Sun, "Workload evaluation of sectorized air traffic control and stream management," in *Integrated Communications, Navigation and Surveillance Conference (ICNS), 2012*. IEEE, 2012, pp. N2–1.

23. M. Gariel, A. N. Srivastava, and E. Feron, "Trajectory clustering and an application to airspace monitoring," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1511–1524, 2011.

24. G. B. Chatterji and B. Sridhar, "Neural network based air traffic controller workload prediction," in *American Control Conference, 1999. Proceedings of the 1999*, vol. 4. IEEE, 1999, pp. 2620–2624.

25. M. Hagmüller, E. Rank, and G. Kubin, "Evaluation of the human voice for indications of workload-induced stress in the aviation environment," in *EEC Note*. Citeseer, 2006.

26. V. Riley, G. Chatterji, W. Johnson, R. Mogford, P. Kopardekar, E. Sieira, M. Landing, and G. Lawton, "Pilot perceptions of airspace complexity - part 2," in *Digital Avionics Systems Conference, 2004. DASC'04. The 23rd*. IEEE, 2004.

27. A. J. Masalonis, M. B. Callaham, and C. R. Wanke, "Dynamic density and complexity metrics for realtime traffic flow management," in *Proceedings of the 5th USA/Europe Air Traffic Management R & D Seminar*, 2003, p. 139.

28. P. Brooker, "Controller workload, airspace capacity and future systems." 2003.

29. P. U. Lee, "A non-linear relationship between controller workload and traffic count," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 49, no. 12. SAGE Publications Sage CA: Los Angeles, CA, 2005, pp. 1129–1133.

30. B. Sridhar, K. S. Sheth, and S. Grabbe, "Airspace complexity and its application in air traffic management," in *2nd USA/Europe Air Traffic Management R&D Seminar*, 1998, pp. 1–6.

31. G. Chatterji, Y. Zheng, and P. Kopardekar, "Analysis of current sectors based on traffic and geometry," in *AIAA Guidance, Navigation and Control Conference and Exhibit*, 2008, p. 7227.

32. B. Sridhar, D. Kulkarni, and K. Sheth, "Impact of uncertainty on the prediction of airspace complexity of congested sectors," *Air Traffic Control Quarterly*, vol. 19, no. 1, pp. 1–21, 2011.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704–0188*

1. REPORT DATE *(DD-MM-YYYY)*
01-08-2018

2. REPORT TYPE
Technical Memorandum

3. DATES COVERED *(From - To)*

4. TITLE AND SUBTITLE
Survey of Methods to Predict Controller Workload for Real-Time Monitoring of Airspace Safety

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Indranil Roychoudhury, Lilly Spirkovska, Molly O'Connor, and Chetan Kulkarni

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
NASA Ames Research Center
Moffet Field, California

8. PERFORMING ORGANIZATION REPORT NUMBER
NASA/TM–2018–219985

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
National Aeronautics and Space Administration
Washington, DC 20546-0001

10. SPONSOR/MONITOR'S ACRONYM(S)
NASA

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
NASA/TM–2018–219985

12. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified-Unlimited
Subject Category 18Distribution: Standard
Availability: NASA CASI (301) 621-0390

13. SUPPLEMENTARY NOTES
An electronic version can be found at http://ntrs.nasa.gov.

14. ABSTRACT
The Real Time Safety Monitoring (RTSM) approach allows for assessment and prediction of the safety margin in the National Airspace System (NAS) to help preempt incidents and accidents, rather than having to reactively mitigate them. In RTSM, the NAS is modeled using state variables, and safety metrics are defined in terms of these state variables. The safety metrics have been classified as weather-related, airspace-related, and human-related. Many of the formulated human-related safety metrics need an estimate of the controller workload for their computation. However, this computation is not trivial. Hence, in this report, we perform a literature survey to identify the different factors that enable the computation of controller workload and categorize these factors. Next, we describe studies undertaken to determine a minimal set of factors that provide a correct assessment of controller workload. Lastly, we survey approaches for evaluating how well the selected factors correlate with the controllers' subjective assessment of their workload. Based on this survey, we present factors beneficial to computing and predicting controller workload in real time, and discuss the status of data sources necessary for these computations.

15. SUBJECT TERMS
System-Wide Safety Assurance Technologies, assurance of flight critical systems, discovery of precursors to safety incidents, assuring safe human-systems integration, prognostic algorithm design for safety assurance

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			STI Help Desk (email: help@sti.nasa.gov)
U	U	U	UU	50	19b. TELEPHONE NUMBER *(Include area code)* (301) 621-0390

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18