

Modeling and Analysis of Controller's Taskload in Different Predictability Conditions

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Abstract— This study aims to first develop a successful taskload model which is able to relate the controller's interaction with the radar screen to the dynamical changes in air traffic patterns. Secondly, the study aims to examine whether i4D equipage, as a specific notion of automation, contributes to an improvement in quantification of controller's taskload model. Thirdly, in a more specific approach the study intends to analyze to what extent controllers may or may not benefit from predictable situations at dense traffic conditions when exposed to higher automated airspace environment. The model is applied on 18 data sets featuring different i4D-equipage levels. It compares controllers' taskload for three different scenarios between an en-route and a terminal sector.

Keywords: Human-automation interaction; Air Traffic Controller (ATCO) taskload; airspace complexity; dynamic density

I. INTRODUCTION

During the past 50 years, the results of mathematical models have shown that controllers' workload is being driven by the complexity involved in the airspace environment. Part of this complexity is prompted by the dynamical behavior of traffic patterns. From the results of models describing controller's taskload, it is observed that predictability decreases the complexity [6, 11]. The general idea behind this study is to analyze how a specific notion of predictability influences the controller's taskload. The specific notion in the present study is an automation which enables the aircraft to meet the time constraint set on defined waypoints by the controller in dense traffic conditions. This procedure, based on which the aircraft 3D trajectory is constrained by an additional time factor, is known as 4D trajectory management or initial 4D (i4D).

Today, not all aircraft are equipped with i4D. According to SESAR i4D demonstration plan, those aircraft equipped with i4D have the advantage of managing their speed profile to achieve the Controlled Time of Arrival (CTA) constraint imposed by the controller. Aircraft not equipped with i4D need to be vectored by the controller more frequently to avoid safety concerns. From controller's point of view, management of a mixed-i4D-equipped environment could be a challenge as the normal aircraft needs to be directed based on the constraints

imposed by the i4D-equipped aircraft. On one hand, we know that i4D makes the flight path of an aircraft more predictable for the controller which helps them guide it with less effort. On the other hand, it is observed in the data used for the present study research that in a mixed-i4D-equipped environment the controller cancels the CTA they have previously imposed on an aircraft. Such observations raised two interesting questions:

1. Do the controllers actually benefit from a mixed-i4D equipped environment, having less taskload?
2. Could different levels of i4D equipage affect controllers' taskload to various extents?

In response to the above research questions, this study intends to first investigate the airspace complexity and then model controllers' taskload in a way that it correlates with the complexity of the airspace. Once the successful taskload model has been developed, effects of different automation levels will be analyzed.

In the next section, we will provide a background of the subject. In Section III, the experiment design as the basis for data used in this work is explained. Then in order to have a grasp of the controllers' interaction with the airspace, their activities on the radar screen have been visualized in Section IV. Next in Section V a novel calculation approach is followed and the airspace dynamic density has been quantified using a set of known complexity factors. In Section VI, the approach toward modeling ATCO taskload is introduced. Then in Section VII, the results are presented and ATCO responses to different predictability conditions are analyzed. At last in Section VIII, the main ideas are discussed and possible future work is suggested.

II. BACKGROUND

Complexity within air traffic control (ATC) environment has been defined in [1] as "a measure of the difficulty that a particular traffic situation will present to an air traffic controller". In the same work of [1], workload is explained as "a function of three elements; firstly, the geometrical nature of the air traffic, secondly, the operational procedures and practices used to handle the traffic and thirdly, the

characteristics and behavior of individual controllers (experience, orderliness etc.) ...". The third element of this explanation contains the cognitive workload which by far is proven to be the most difficult task for the mathematicians to formulate [11]. The second element of explanation of [1] of workload, is the basis for measuring controllers' taskload which is the focus of analysis of this work.

To model ATCO taskload, the previous works of [2, 3, 4] have been studied. In 1978, Schmidt put forth the idea that the subjective difficulty of a task to accomplish is highly correlated to the time required to do the task [2]. As a result, "the magnitude of the load" could be obtained by measuring the total time spent on performing a task. In the same work, he further discusses the limitations involved with measuring the time required for performing each task since sometimes the time available to accomplish a task is more or less than the time required to do so. The other limitation he addresses lies in the fact that controller's boredom could affect the task performing duration which makes it difficult to measure the time required for performing tasks. That is because the relationship between type of the task and the boredom associated with it is very difficult to quantify. However, he suggests that the time spent for communicating with the pilot still could be considered as a measure even though it is only a portion of total time required for performing tasks. In line with this concept [3] used the modern Controller Pilot Data Link Communication (CPDLC) data entries and controller-pilot radio communications to measure the taskload [3]. In [4] a macroscopic approach to the workload model is followed and taskload is calculated by splitting the tasks into four different types. They further estimated the required time for accomplishing each task type by making an average over the performed tasks by different controllers in en-route area. The current work mainly relies on the latter work of [4] to quantify taskload mainly because they covered all different tasks that we study.

All of the dynamic density related works have shown that the ATC complexity directly affects ATCO taskload and is the basis of controller subjective workload. To quantify dynamic density, the present work has relied on [5, 6, 7, 8, 9, 3]. In [6], new mathematical formulas have been developed for a set of complexity factors which were observed to have a very dynamic and unpredictable behavior (such as ground speed variance, conflict sensitivity and conflict insensitivity). In [8], a more precise form of formulas of [6] is proposed and by developing a neural network the relationship between complexity factors and the sectors configurations is found. They have further shown which of the complexity factors significantly relate to the workload. In [9], three different automation levels are considered and the effects of a specific type of automation on controller's workload in higher densities are evaluated. In their experiment, the automation has helped the controllers with detecting the conflict in the first level, automatically detecting the conflict in the second level and proposing conflict resolutions in the third level. They have further evaluated the relationship between complexity factors

and the controllers' self-assessment ratings using a linear regression analysis. To calculate the air traffic complexity, we have mainly relied on the work [3, 8]. Similar to all previous works in the literature, a linear regression analysis has been made between the complexity factors and the taskload model.

Compared to the previous related work in the literature [2, 3, 4, 13], three different approaches are followed. Controllers' clicks on the radar screen have been considered as a measure for quantifying taskload. A novel methodology in calculating the airspace complexity factors is developed. Controllers' taskload is analyzed for different i4D-equipped scenarios and the results for an en-route and a terminal sector are discussed. It is worth mentioning that human factors and controllers' characteristics (age, experience etc.) are not considered through the research and will be the scope of a future work.

III. EXPERIMENT DESIGN

In this study, the data for 18 sets of experiments have been analyzed. These experiments are designed and implemented by a team of experts from Air Navigation Services of Sweden (LFV), NORACON, THALES, SESAR JU etc. Each experiment has run for up to 120 minutes and controllers' activities on the radar screen (e.g. mouse clicks etc.) were recorded. In each scenario six licensed air traffic controllers controlled six different sectors covering Stockholm's airport airspace, four of which are en-route sectors. The other two sectors are Terminal Maneuvering Area (TMA) sectors which can be differentiated by east and west direction. Figure 1 shows the airspace studied in the experiment specifying borders for the six sectors (sector 3, sector 4, sector 1, sector 9, sector TMA-W and sector TMA-E).

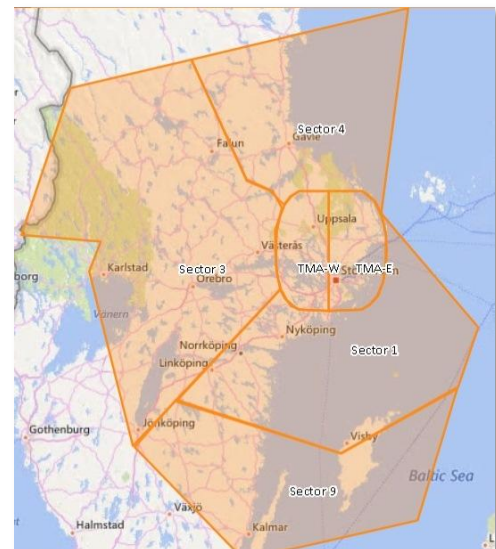


Figure 1. Simplified ATC sectors of Stockholm Airspace¹.

The sector geometry used in the study is the simplified version of the real sectorized airspace. The scenarios were simulated at different times of the day with the controllers being responsible for different sectors in different scenarios. The

¹ Figure is drawn using <http://daim.lfv.se/echarts/>

percentage of the aircraft equipped with i4D varied among different scenarios. Table I shows how many of scenarios were executed with each equipage level.

TABLE I. DISTRIBUTION OF DIFFERENT I4D-EQUIPAGE LEVELS AMONG SCENARIOS.

Number of Scenarios	i4D Equipage Level
7	0% (zero automation level)
8	50%(medium automation level)
3	80% (high automation level)

As can be seen in Table I, in 7 scenarios none of the aircraft were equipped with i4D (zero level of automation) while in 8 of them 50% of the aircraft (medium level of automation) and in 3 of them, 80% of the aircraft (high level of automation) were equipped with i4D. For convenience each scenario is coded with “SCN-(number)-(automation level)” throughout this paper. Only in one scenario (SCN-9-50%) the wind effects were considered. To increase unpredictability of the situation for the controller, in one scenario (SCN-16-50%) the simulation was designed such that the aircraft appeared on the screen with a little time difference.

IV. VISUALIZATION OF ATCO INTERACTION WITH THE AIRSPACE ENVIRONMENT

Due to the nature of air traffic events having relatively fast dynamic changes, various visual representations of the environment were possible. The goal was to reach to a representation out of which the highest possible amount of information about controllers’ interaction could be extracted. Therefore, an algorithm for creating a heat map plot was written in MATLAB to visualize the density of all clicks made on the screen.

Figure 2 illustrates the comparison between the density of clicks among four different scenarios with zero and high automation equipage level. In SCN-8-0% and SCN-12-80% (Figure 2c and 2b), the same controllers were responsible for both sector 3 and TMA-W. But among SCN-5-0% and SCN-15-80% (Figure 2a and 2d), only sector 3 was controlled by the same controller. One can see ATCO mouse interaction with the airspace in sector 3 is in a high contrast with that of other sectors.

In some areas, the controllers clicked for more than 50 times during the whole scenario. Some of these areas are very close to the sector’s borders which could be interpreted as the clicks made for handing over an aircraft to the other controller. However, there are also some dense areas which are far from both sector borders and final approach threshold. In SCN-5-0% and SCN-8-0%, the density of clicks is higher in some areas than in SCN-12-80% and SCN-15-80%. In Figures 2a and 2c, in some areas the number of clicks has reached 120 where in Figures 2b and 2d, it does not exceed a maximum of 60. Even in those scenarios where the same controller was responsible for sector 3 (Figure 2a and 2d) and (Figure 2b and 2c), dissimilarities are very noticeable. Based on such results,

in Section VI the density of controllers’ clicks has been considered as a measure for modeling controllers’ taskload and the model’s effectiveness is evaluated.

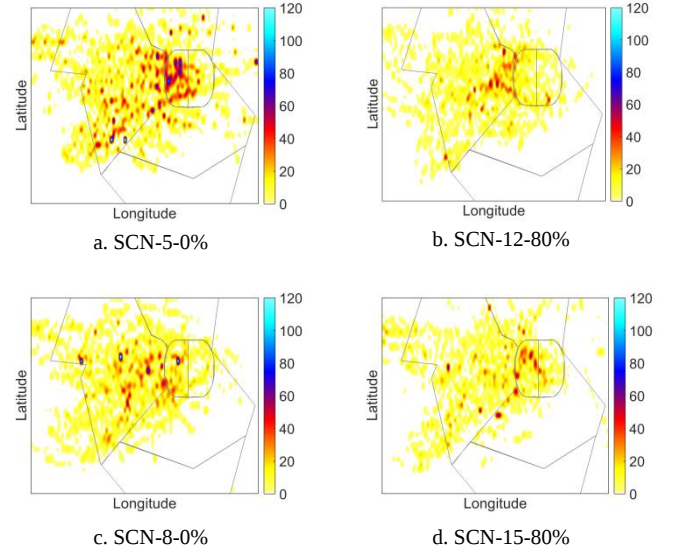


Figure 2. Comparison between controllers’ clicks density in four scenarios with 0%(a and c) and 80%(b and d) i4D-equipage levels.

V. CALCULATION OF AIRSPACE DYNAMICS

This section discusses how the complexity of traffic in a volume of airspace is measured by means of a set of known parameters. The results of the calculations made in this section will be further used in a model to describe controllers’ subjective workload.

In this study, eight complexity factors of [3] have been selected and formulas available in the literature have been used for calculating each factor. For some factors, a formula has been developed based on the definition provided for the corresponding factor in the literature. The developed formulas are explained in [10].

Based on the results of Figure 2, it is presumed that i4D equipage level contributes to explaining taskload. Therefore, we expect to observe an improvement in the taskload model, once i4D equipage level of the aircraft is considered. Therefore, in addition to the eight complexity factors presented in [3], a factor known as i4D equipage has been considered as a representation of the automation level the aircraft is equipped with. These 9 complexity factors are listed in Table II.

Each complexity factor is calculated for every 30-seconds time step of each scenario. Since the aircraft congestion is not distributed homogeneously in the sector, a typical well-known approach suggests a calculation method which splits the sector into equal sized grids [13]. With such approach, the movements of aircraft located near cell boundaries relative to other aircraft are not being considered which is called “the boundary effect”. To reduce boundary effect a number of iterative grid shifts need to be done and the factors need to be recalculated. In this research, in order to avoid boundary effect, a completely different approach has been followed.

Instead of splitting, an algorithm is developed which finds the platoons of aircraft over the whole and spots them.

TABLE II.COMPLEXITY FACTORS CONSIDERED IN THE STUDY.

Parameters	Reference
Variance of Ground Speed	[8]
Number of Aircraft	[5]
Separation Index Horizontal (SIH)	[5]
Number of Descending Aircraft	[5]
Conflict Sensitivity	[8 , 6]
Conflict Insensitivity	[8 , 6]
Vertical Separation	[10]
Horizontal Separation	[10]
i4D Equipage	[10]

Due to non-homogenous dynamic behaviour of aircraft platoons, there will be different number of aircraft groups gathered into clusters with different dimensions. The algorithm searches for the pairs of aircraft that are closer to each other than a certain value (5 nautical miles has been considered in this work).

Then, if two aircraft are closer to a third one, all three will be put in the same cluster. Similarly, if there are four aircraft pairs, all having a common neighbor, a cluster of five aircraft will be formed. Figure 3 illustrates how such clustering is performed.

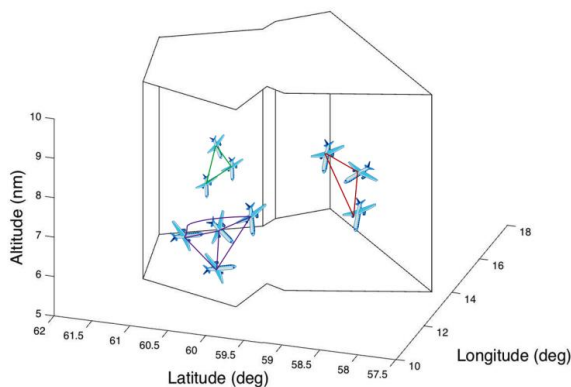


Figure 3. A representation of clustering method used in this work. The size of clusters is specified by the dynamics of aircraft movements relative to each other.

In fact in this approach, it is not the modeler who decides about the dimension of cells. It is the dynamics of aircraft relative status (speed, heading, distance etc.) that defines the clusters' dimensions. In only three of nine complexity factors

the dynamics of aircraft relative status is of concern. Therefore, this calculation method is only used in the calculation of variance of ground speed, conflict sensitivity and conflict insensitivity. A detailed explanation for calculating each complexity factor is presented in [10].

VI. MODELING CONTROLLER'S TASKLOAD

In this work, ATCO taskload has been modeled relying mainly on [3]. Four models have been developed and examined according to the two models developed in [3]. Table III, signifies the key differences between all the six models.

TABLE III. KEY DIFFERENCES BETWEEN THE FOUR MODELS OF OUR STUDY (1-a, 2-a, 1-b AND 2-b) AND THE TWO OF [3] (MODEL A AND MODEL B).

	Non-weighted clicks	Weighted clicks	CPDLC data entries	CPDLC + radio communications
8 Factors	Model 1-a	Model 2-a	Model A	Model B
9 Factors	Model 1-b	Model 2-b		

1. Model 1-a: Non-weighted density of controllers' clicks has been considered as a measure for taskload and 8 factors are used to calculate dynamic density. It is assumed that all clicks were associated with the same amount of ATCO load and i4D equipage does not contribute to airspace complexity.
2. Model 1-b: Non-weighted density of controllers' clicks has been considered as a measure for taskload and 9 factors are used to calculate dynamic density. It is assumed that all clicks were associated with the same amount of ATCO load and i4D equipage does contribute to airspace complexity.
3. Model 2-a: Weighted density of controllers' clicks has been considered as a measure for taskload and 8 factors are used to calculate dynamic density. It is assumed that different types of clicks were associated with different amount of ATCO load and i4D equipage does not contribute to airspace complexity.
4. Model 2-b: Weighted density of controllers' clicks has been considered as a measure for taskload and

9 factors are used to calculate dynamic density. It is assumed that different types of clicks were associated with different amount of ATCO load and i4D equipage does contribute to airspace complexity.

In all models, a linear regression function has been considered to relate the complexity of airspace measured by complexity factors to a parameter describing taskload. The intention was to find a good taskload model by examining to which extent the measured complexity in the airspace correlates with controller's taskload. In each model, a set of parameters have been used to shape the independent variable X and the dependent variable Y. The main difference between the model of [3] and the ones developed in the current work lies in the definition of Y. In [3] controller pilot data link communication (CPDLC) has been first considered as workload measure. Then the workload model has been improved by adding the controller-pilot voice communications to CPDLC activities (Model A). Then, in the next step radio calls durations (frequency occupancy time in 2-minutes time step) and average duration of single calls were calculated and added to CPDLC activities and were considered altogether as the improved taskload model (Model B).

As can be seen in Table III, in models 1-a and 2-a the same 8 complexity factors as the ones presented in [3] has been considered as X, but two different measures has been used to configure taskload. Similarly, in models (1-b and 2-b) the same complexity factors plus i4D equipage (9 factors) are considered as X, but again two different measures has been used for shaping taskload. In models 1-a and 1-b, different types of clicks are assumed to have the same load applied on the controller. But in models 2-a and 2-b, tasks are differentiated and different weights are given to different tasks.

In fact, the goal of developing models 1-b and 2-b was to examine whether automation equipage level could better explain the controllers' taskload while the goal of developing models 1-a and 2-a was to improve taskload model by differentiation between various type of tasks. In models 1-a and 2-a, clicks have been differentiated based on their type and different weights have been assigned to different types of clicks. For example, in SCN-1-50%, there are 56 different tasks. All tasks are classified into four different types based on [4]; background tasks, control tasks, transitioning tasks and recurring tasks. The task classification in each scenario has been performed manually according to the information provided in the log data.

In all scenarios for each 30-seconds time step, the taskload is calculated using the formula presented in [4].

$$Y = \lambda_b \times \tau_b + \lambda_c \times \tau_c + \lambda_t \times \tau_t + \lambda_r \times \tau_r$$

where

τ_b : typical duration of a background task = 2 seconds

τ_c : typical duration of a control task = 50 seconds

τ_t : typical duration of a transitioning task = 10 seconds

τ_r : typical duration of a recurring task = 3 seconds

λ : frequency of tasks in 30 seconds time step

At the end, a dimensionless value is obtained for the taskload for each sector at each time step. Then a linear regression was made between complexity factors and the taskload values using the general form of the formula bellow:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

Because there are different X and Y functions considered in each model, different values for β are expected in each model. Therefore, models are compared to each other on the basis of regression analysis factor R^2 .

VII. RESULTS AND ANALYSIS

The complexity factors were calculated on 18 set of simulations, each taking 90-120 minutes. Each complexity factor as well as the number of clicks and taskload have been calculated over each 30-seconds time step. As a result, a total number of 2077 data points were available for the regression analysis for each sector. Since not enough clicks were made on all sectors in all scenarios, the results for only sector 3 and TMA-W are analyzed. Table IV and Table V compare R^2 between the four taskload models of this work with the two of [3] for sector 3 and TMA-W respectively.

TABLE IV. STATISTICAL COMPARISON BETWEEN FOUR MODELS OF THIS WORK IMPLEMENTED ON SECTOR 3 AND THE TWO OF [3].

Models	A	B	1-a	1-b	2-a	2-b
R^2	0.13	0.16	0.19	0.22	0.62	0.63

TABLE V. STATISTICAL COMPARISON BETWEEN FOUR MODELS OF THIS WORK IMPLEMENTED ON TMA-W AND THE TWO OF [3].

Models	A	B	1-a	1-b	2-a	2-b
R^2	0.13	0.16	0.12	0.12	0.84	0.82

As it is seen from Table IV, R^2 in the model of [3] has improved by 3% while in this work, by going one step forward from clicks to taskload, around 40% improvement in R^2 is achieved. By comparing the R-square between the taskload model 2-a with 2-b, it is seen that i4D equipage does not very much affect complexity of en-route airspace.

As can be seen from Table V, an improvement from clicks to taskload model has resulted in more than 70% increase in correlation factor. By comparing the R-square between the taskload model 2-a of sector 3 with 2-a of TMA-W, one can conclude that the taskload model better correlates with airspace complexity in terminal airspace than in en-route airspace. Both Table IV and V show that i4D equipage does not contribute to a better correlation between airspace complexity and ATCO taskload in both en-route and terminal airspace.

The results of a detailed correlation analysis on the complexity factors presented in [10] have shown that among the selected 8 complexity factors, number of aircraft and number of SIH violations have the highest correlation coefficients (78% and 61% respectively) with the taskload. Number of SIH violations is an index which shows the degree of horizontal proximity of aircraft population in a sector. In order to analyze the effects of automation on controllers' taskload in congested conditions, the graphs for number of SIH violations and taskload are plotted. A comparison between number of SIH violations at different instances gives us a feeling of the degree of congestion while a comparison between taskload values tells us about how controllers reaction to such conditions varied among different scenarios. Figures 4 and 5 depict dynamics of SIH violations and taskload for sector 3 and TMA-W respectively. The results are obtained by implementing model 2-a on SCN-11-0%, SCN-3-50% and SCN-12-80%. In scenarios SCN-3-50% and SCN-12-80, the same controller controlled sector 3. However, different controllers were responsible for TMA-W in the three scenarios.

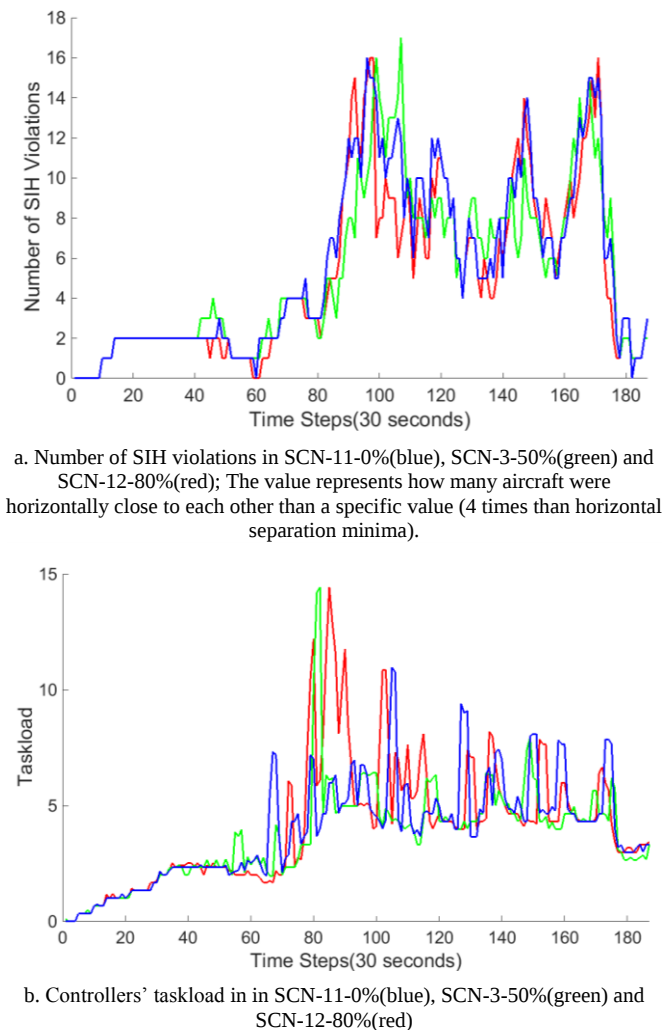


Figure 4. Comparison between SIH violations and controllers' taskload among three different i4D-equipped scenarios in sector 3.

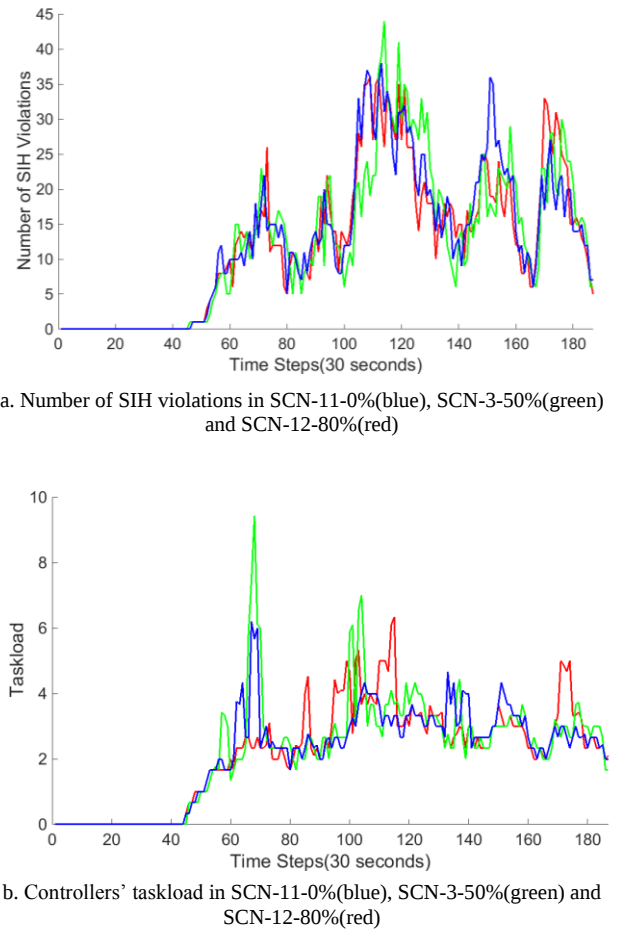


Figure 5. Comparison between SIH violations and controllers' taskload among three different i4D-equipped scenarios in TMA-W.

As can be seen from Figure 4 and 5, although similar patterns are observed in SIH violations, the pattern for controllers' taskload differs a lot among automation scenarios. Figure 4 tells us that even in SCN-3-50% and SCN12-80% where the same controller controlled sector 3, the taskload values differs for similar traffic conditions. For example, Figure 4a shows that around time step 70, the congestion is about to grow to the same degree for both SCN-3-50% and SCN-12-80%. At the same time step, the taskload for SCN-3-50% has risen up to a value higher than that of SCN-12-80%. This indicates that at a specific moment of congestion growth, the same controller experienced less pressure in the scenario where more aircraft were equipped with i4D.

By comparing the taskload between en-route and terminal sector, it is observed that controller responsible for en-route sector on average tolerated higher taskload than the controller responsible for TMA-W.

By comparing Figure 5a with Figure 5b, one can see around time steps 115 and 180, even though SIH violation reaches to a peak with almost the same value for all scenarios, the taskload in SCN-12-80% is much less than in the other two scenarios. This suggests that during denser traffic conditions in TMA

area, the controller had trusted the automation more. This has resulted in ATCO letting more aircraft get closer to each other and therefore utilizing more terminal capacity while tolerating less pressure.

A key point to consider is that in the data there were no three different i4D-equipped scenarios with similar controllers for the two sectors.

Figure 6 compares controller's taskload between sector 3 and TMA-W among three scenarios with 50% of aircraft equipped with i4D. SCN-13-50% is a typical scenario while SCN-16-50% is a scenario in which the aircraft had appeared on controller's screen a little later or sooner than it was planned. SCN-9-50% is a scenario in which wind effects on the aircraft were considered in traffic simulations. The aim of analyzing the results of Figure 6 is to evaluate how other unpredictable factors such as environmental events contribute to controller's taskload.

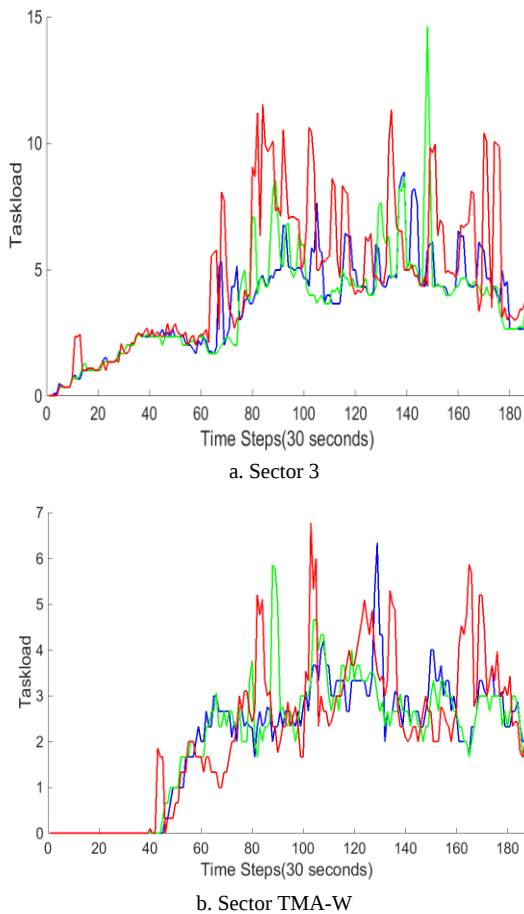


Figure 6. Taskload comparison among three unpredictable conditions with the same automation equipage level; SCN-13-50%(blue) is a typical scenario, in SCN-16-50%(green) aircraft appeared on the screen sooner or later than the controller expected and in SCN-9-50%(red) wind effects were considered.

As can be seen in Figure 6, a considerably large contrast exists between the amounts of taskload the controllers withstood in each scenario. The more unpredictable the situation had

become, the greater and more frequent amount of taskload the controllers confronted.

VIII. DISCUSSION AND CONCLUSION

This work analyzed the effects of unpredictability on controllers' response to handling congested traffic conditions. The work also focused on discovering whether different levels of a specific type of automation influences ATCO taskload. For a set of data, a new calculation approach used to quantify a group of eight complexity factors. The results were analyzed for different scenarios enjoying three different automation levels for one en-route and one terminal sector. Four different workload models were developed and to evaluate the success rate of the models a regression analysis was performed. By comparing the results, it was found that i4D-equipage does not show a strong correlation with complexity. It was observed that for two scenarios with similar en-route traffic patterns controlled by the same controller, in the scenario featuring high automation level, controller underwent less taskload compared to scenarios with medium level. While such conclusion well explains the effects of i4D equipage on taskload it cannot be simply expanded to all automated conditions. In addition, due to the nature of data many important factors such as cognitive load and human factors characteristics are not considered in the model developed in the current study. Thus, the conclusion cannot be generalized to all traffic conditions. Moreover, the effects of environmental factors such as weather conditions on the air traffic patterns are also not considered in the model.

After evaluating the performance of each developed model on each sector, it is concluded that the taskload model explains airspace complexity far better than clicks model. The taskload model developed in this work (model 2-a), showed around 50% and 40% higher success rate in explaining en-route airspace complexity than that of [3] and clicks model (model 1-a). The same model showed around 70% higher success rate in explaining terminal complexity than that of [3] and clicks model. As a result, given the complexity of airspace, the taskload model developed in the present study can explain the ATCO's taskload in terminal sectors far better than that in en-route sectors.

A. Future work

As it was mentioned, the ATCO interaction with the airspace could be more reliably explained if cognitive load were also considered. Despite the difficulty, the literature on human factors have shown that a predictive model for cognitive complexity can be developed based on the known aspects of human cognitive functioning which are attention, decision making, memory and perception [11]. In line with the work of [12], one way to reflect a part of cognitive load is to analyze ATCO's eye gazing movements to obtain an estimation of monitoring load. Figure 7.b and Figure 7.a compares ATCO's eye gazing durations with clicks interaction in SCN-9-50%. As can be seen, there are some areas where ATCO has clicked more frequently and has looked for long while there are also some areas where they have looked at for long but only a few clicks have been made.

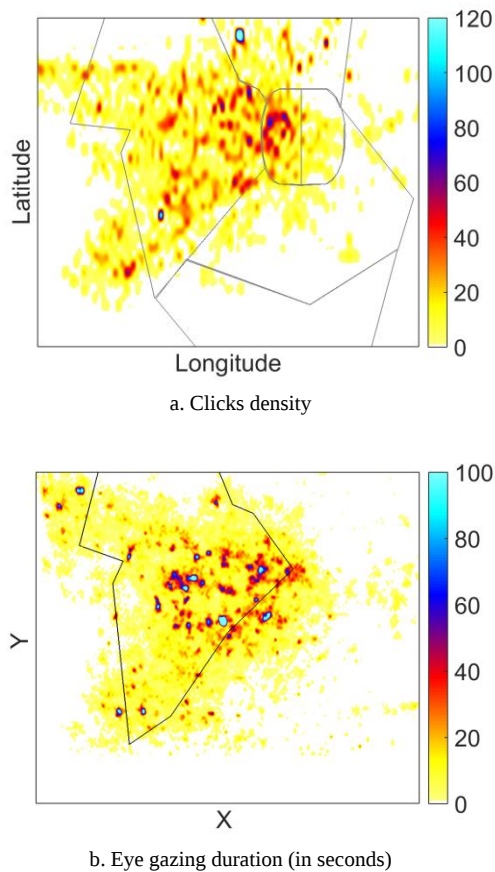


Figure 7. Heat map for density of controller's clicks (top) and controller's eye gazing duration (bottom) for SCN-9-50%.

This approach toward visualization of the data would be very helpful in obtaining a more precise estimation of the time it takes for the controller to perform different types of tasks (e.g. monitoring tasks vs. execution tasks). With such technique, estimating duration of different ATCO tasks as well as quantifying cognitive load will be the focus of a future work.

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