Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2022) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

34th Conference of the European Association for Aviation Psychology

Toward a more transparent and explainable conflict resolution algorithm for air traffic controllers

Christophe Hurter[a]*, Augustin Degas[a], Arnaud Guibert[a], Nicolas Durand[a], Ana Ferreira[c], Nicola Cavagnetto [c], Mir Riyanul Islam[b], Shaibal Barua[b], Mobyen Uddin Ahmed[b], Shahina Begum[b], Stefano Bonelli[c], Giulia Cartocci[c], Gianluca Di Flumeri[d], Gianluca Borghini[d], Pietro Aricó[d], Fabio Babiloni[d]

[a]*Ecole Nationale de l'aviation Civile, 7 Avenue Edouard Belin, Toulouse, France*
[b]*Artificial Intelligence and Intelligent Systems Research Group, School of Innovation, Design and Engineering, Mälardalen University, Högskoleplan 1, 722 20 Västerås, Sweden*
[c]*Deep Blue s.r.l., Via Manin 53, 00185 Rome, Italy*
[d]*Department of Molecular Medicine, Sapienza University of Rome, Piazzale Aldo Moro 5, Rome, Italy*

Abstract

Recently, Artificial intelligence (AI) algorithms have received increasable interest in various application domains including in Air Transportation Management (ATM). Different AI in particular Machine Learning (ML) algorithms are used to provide decision support in autonomous decision-making tasks in the ATM domain e.g., predicting air transportation traffic and optimizing traffic flows. However, most of the time these automated systems are not accepted or trusted by the intended users as the decisions provided by AI are often opaque, non-intuitive and not understandable by human operators. Safety is the major pillar to air traffic management, and no black box process can be inserted in a decision-making process when human life is involved. To address this challenge related to transparency of the automated system in the ATM domain, we investigated AI methods in predicting air transportation traffic conflict and optimizing traffic flows based on the domain of Explainable Artificial Intelligence (XAI). Here, AI models' explainability in terms of understanding a decision i.e., post hoc interpretability and understanding how the model works i.e., transparency can be provided for air traffic controllers. In this paper, we report our research directions and our findings to support better decision making with AI algorithm with extended transparency.

* Corresponding author. Tel.: +33 (0) 5 62 25 96 27.
E-mail address: christophe.hurter@enac.fr

2352-1465

Keywords: Artificial Intelligence, Air Traffic Control, Genetic Algorithm, Algorithm Transparency, Explainable AI

1. Introduction

Recently, Artificial intelligence (AI) algorithms have received increasable interest in various application domains including Air Transportation Management (ATM). However, most of the time these automated systems are not accepted or trusted by the intended users as the decisions provided by AI are often opaque, non-intuitive, and not understandable by human operators. Safety is the major pillar of air traffic management, and no black box process can be inserted in a decision-making process when human life is involved. To address this challenge related to transparency of the automated system in the ATM domain, we investigated AI methods for detection and resolving air transportation traffic conflict based on the domain of Explainable Artificial Intelligence (XAI). We developed and assessed one AI model's explainability in terms of understanding for air traffic controllers. As such, the Artimation project investigates how much transparent algorithms can help Air Traffic Controllers (ATCo) to better understand and accept solutions proposed by machines in the context of conflict resolution. We based our investigation on the recently identified need for more transparency and explainable algorithm for life-critical systems like the aeronautic one (Degas et al., 2022). Such transparency is today provided by the mean of data visualization to ensure communication between the machine and the user. The machine needs to provide insights supporting the algorithm rational, while the user needs to retrieve in a non-ambiguous way the provided information. Data visualization has a long history (Card et al. 1999) and has proven to leverage user ability for reasoning and to support decision-making. Processing aircraft trajectories, as part of data processing, has some specificity while belonging to spatial-temporal data reasoning (Bach et al. 2017). For example, interactive systems can be used (Hurter et al., 2009) or static data visualization can help to retrieve valuable information like conflicts, complexity, and unexpected information like the wind (Hurter et al. 2014). Such data communication can also operate with data-driven techniques which have shown many advantages in terms of data understanding, memorization, and sharing (Riche et al. 2018). In our conducted research we use these data presentation techniques to explain the rational of a confit resolution algorithm based on a genetic algorithm (Durand Nicolas and Gotteland, 2006).

In short, a Genetic Algorithm (GA) is a population and evolutionary-based Meta-Heuristic. This means that a GA tries to iteratively improve candidate solutions according to some predefined criteria. In our conflict resolution case, a candidate solution for the GA is a set of trajectories, some modified, some not. The trajectories can be modified by using turning point maneuvers. Candidate solutions forming the population are evaluated in function of three criteria: the duration of the conflicts, if any; the length of the trajectories; and the number of orders one ATCO must give to implement this candidate solution. Once the GA has evaluated all candidate solutions in the population, it selects a set of candidate solutions, mostly the bests, but also other candidate solutions to better explore the solution space. The algorithm then applies a set of mutation and crossover operations to enhance the population and possibly converge toward one of the optimal solutions (Durand Nicolas and Gotteland, 2006).

In this paper, we report our result when assessing different levels of explanation to ATCo extracted from our conflict resolution genetic algorithm. To do so, we define three levels of explanation: Black Box, where only the selected solution is presented, Heat Map, where a corpus of potential solutions is displayed thanks to a density map, Story Telling, where data-driven storytelling technique is applied to convey the explication of the proposed solution.

To assess these three levels of explanation, we conducted an experimentation with 9 ATCo for a one-hour simulation with moving aircraft which creates conflicts over time. After running the experiment, ATCo answered questions through questionnaires to capture their feedback. We also conducted semi-structured interviews to extract fine-grained details. We process these quantitative and qualitative results and summarized them. Our paper contributes to a better understanding of the user needs for more transparent and explainable algorithms in the specific domain of conflict resolution.

2. Data Driven Transparency presentation

As previously explained, our GA algorithm explored the possible solution for a given conflicting situation between aircraft and extracted one solution which is qualified as the "best" one with the given optimization criteria (number of actions, length of the trajectory, etc.). To provide explanations for the proposed solution, we developed three different types of data presentation which are detailed in the following paragraphs.

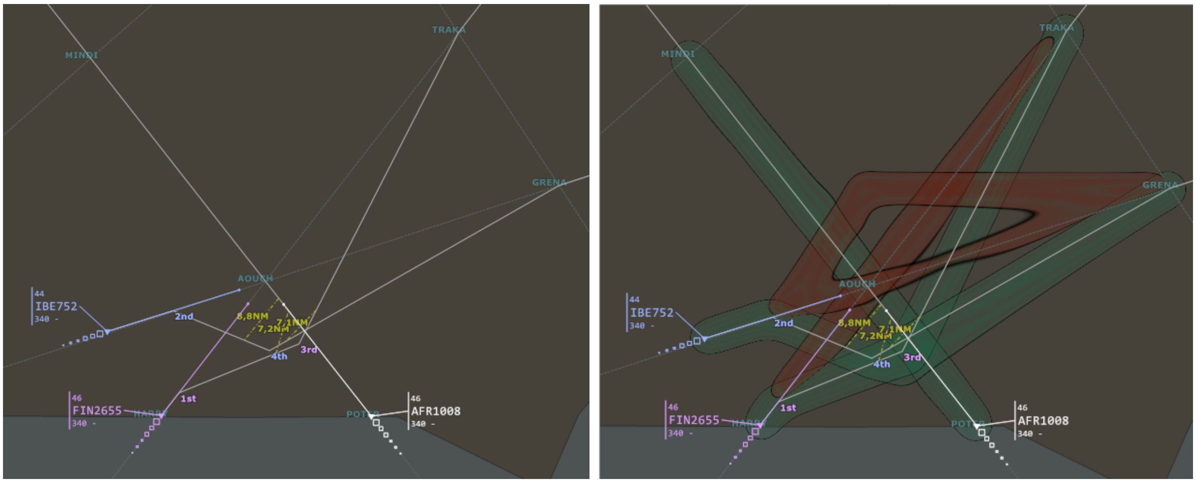

Figure 1: Blackbox visualization the solution proposed by the Genetic Algorithm (left), Heatmap visualization the solution proposed by the Genetic Algorithm (right). Green areas show the contour of possible solutions, while the red area shows the location of conflicting trajectories.

Black box: This visualization is a simple as possible and only displays the proposed solution by the GA algorithm, enhanced by instructions to proceed (see Figure 1):

Airplane trajectories are colored differently. The minimal distance between airplanes is computed and displayed in yellow. The control orders that must be given by the ATCO to the different airplanes are placed along the trajectory, as well as their ordering (1^{st}, 2^{nd}. …, M^{n}). This data presentation is not an explanation by itself but the simple data presentation of the “best” solution the GA algorithm managed to extract. Compared to existing system, the Black Box data representation directly provide a solution to a detected conflict, while the system currently used only displays the detected conflicting aircraft without further information to solve it.

Heat map: To better explain the reasoning behind the proposed solution was made, we decided to show on top of the proposed solution what was explored by the GA, and if whether it was good or bad. To do so, we created heatmaps of the explored trajectories showing how aircrafts trajectories can safely be modified.

In Figure1, the operator can see that: AFR3218 can only follow its trajectory or go to the left (most probably it is less efficient and not required). KLM1258 and EZY208 cannot follow their trajectories and need to turn left (only possibility). In addition, the user can see how much he can wait to turn each airplane, by seeing the end of the “safe zone” (green area) and the begin of the “dangerous zone” (red area). Such data representation is generated with the cumulative view of good and bad solutions. Each solution is convoluted with a gaussian kernel and then accumulated into a density map. Such technique helps do visually define areas also called contour maps (Scheepens et al. 2011).

Storytelling: To better explain the solution, the last visualization made, called Storyboard, shows a maximum of three things: 1) The timeline of the solution proposed by the algorithm, to see order after order where are each airplane (See Figure 2); 2) Possibly an alternate solution, showing that other solutions can be made, but are less efficient; 3) The Limit solution shows what needs to be done if the solution is not implemented right away to avoid any conflict. We use existing Data-Driven Storytelling techniques with step-based explanations and counterfactual explanations (Riche et al., 2018).

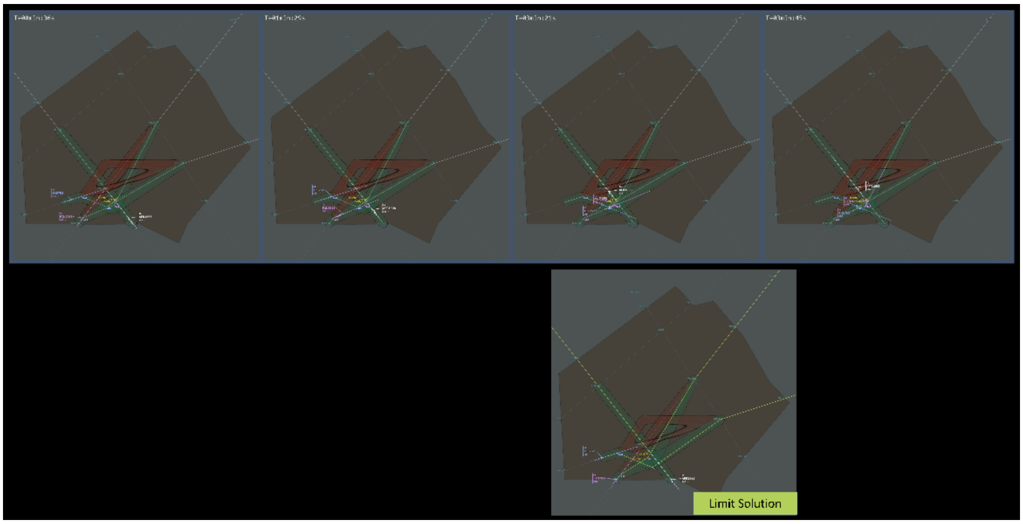

Figure 2: Storyboard presentation of the proposed solution. The sequence of images 1 to 4 shows the temporal steps to solve the conflict. The limit solution shows the good solution but with is close the minimum separation criteria between conflicting aircraft.

3. Method

This pilot study was conducted with 16 healthy French-speaking participants (8 men) aged 21-29 years (M = 24.56 ± 2.68), with 14-19 years of education. We only recruited participants who did not wear glasses, to avoid interference with the eye-tracker. None had a history of oculomotor, psychiatric, or neurological disorders. Before their inclusion in the study, participants signed an informed consent form, and an image rights consent form to allow video recordings.

During this simulation phase, we administered two different questionnaires at two different times. After each scenario, we administered a self-report ad-hoc questionnaire, assessing the understanding of the proposed solutions with two items measured on a Likert Scale from 1 to 5 ("The solution was easy to understand"; "I understand why the proposed solution has been generated") and the agreement with the proposed solution with a single item rated with a dichotomic answer "Yes/No" ("Do you agree with the proposed solution?"). To have a more detailed categorization, we separated each category (BB - Black Box; HM - Heat Map; SB - StoryBoard) into two different complexity levels depending on the scenario (E - Easy; H - Hard). Then, after each condition, we administered another questionnaire made up of Likert Scales from 1 to 5, to assess:

- The usability of the decision support system, divided into 3 items ("Learn to operate the tool would be easy for me"; "I find the tool clear and understandable"; "I find the tool easy to use"),
- The trust in the solution, in one item ("I felt confident when using the tool"),
- The situational awareness when using the tool ("The tool improved my Situation Awareness of the conflict presented"),
- The acceptability of the tool, with two items ("I would like to use this tool in the future"; "I like the new decision support interface"),
- The impact on work performance, with 4 items ("Using this tool in my job would allow me to solve conflicts faster"; "Using this tool in my job would increase my accuracy in solving conflicts"; "Using this tool would improve my work performance"; "Using this tool would make my work easier").

4. Quantitative data - Questionnaires

In the following section, we will present the preliminary results for the data gathered within the expert's group, composed of 9 participants with more than 10 years of experience in ATC/ATM, during the simulation phase of the Artimation project in Toulouse, July 2022.

4.1. Understanding of the proposed solution

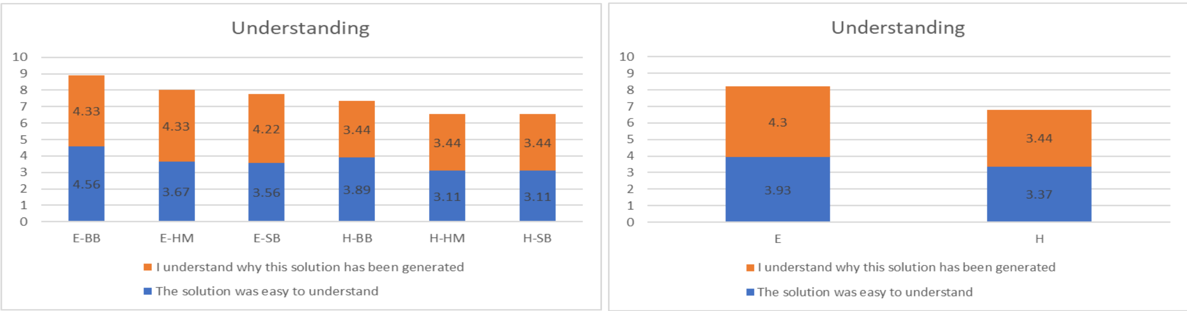

Figure 1: Descriptive analysis for Understanding items from post-scenario questionnaire, split by scenario complexity (right).

For these understanding items (Figure 1), it can be seen how for the item "The solution was easy to understand", the Easy scenario for the Black Box condition was, on average, rated better than the others (4.56). Then, on average, the second easier to understand was the H-BB scenario (3.89), followed by E-HM (3.67), E-SB (3.56), and H-HM with H-SB (both 3.11). For the item "I understand why the solution has been generated", the two best rated scenarios on average were E-BB and E-HM (4.33), followed by E-SB (4.22), and finally the three hard scenarios with 3.44. Moreover, it can be noticed that, for the first item, the scenario E-BB is the only one to be rated 5 out of 5 at the 25th percentile.

Splitting the answers by scenario complexity, it can be noticed that in both items the Easy scenario was rated as more understandable by the participants. Further analysis will be conducted in the next months of the project to understand if this factor is significant in the understanding of the AI outcome.

4.2. Usability of the proposed solution

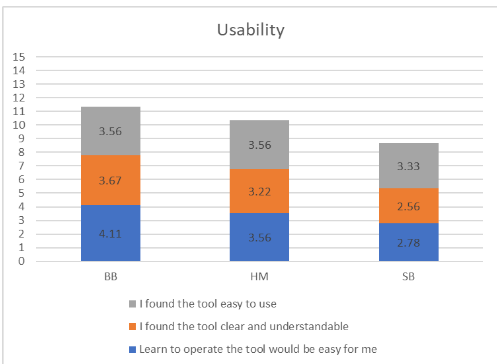

Figure 4: Descriptive analysis for Usability items from post-condition questionnaire.

As for the usability items in the post-condition questionnaire (see Figure 4), it can be noticed that the average value for the Black Box condition was higher than the values for the Heat Map condition and the StoryBoard condition, for the items "Learn to operate the tool would be easy for me" and "I found the tool clear and understandable". For the item "I found the tool easy to use", both the Black Box and the Heat Map conditions registered the same average value (3.56), higher than the StoryBoard average value (3.33). Moreover, the Black Box condition was the only one to have a value of 4 at the 25th percentile.

4.3. The situation awareness of the proposed solution

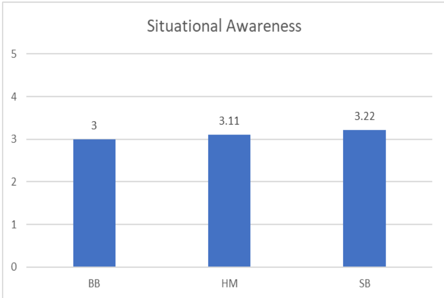

Figure 5: Descriptive analysis for Situation Awareness item from post-condition questionnaire.

The descriptive analysis of the Situation Awareness item (see Figure 5), separated by condition, shows that, on average, the condition that improved the most the Situational Awareness of the conflict was the StoryBoard (3.22), followed by the Heat Map (3.11) and, finally, the Black Box (3.00). It can be noticed that, at the 25th percentile, the higher value was the Heat Map one (3.00). No conditions reached the maximum (5) at the 75th percentile.

4.4. The trust and the acceptability of the proposed solution

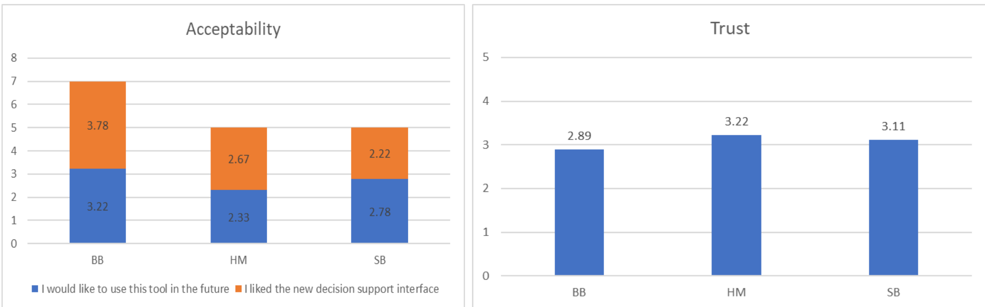

Figure 2: Descriptive analysis for Acceptability items from post-condition questionnaire (left). Descriptive analysis for Trust item from post-condition questionnaire (right).

The descriptive analysis for the Acceptability items (see Figure 6) shows that in both items considered the Black Box condition has a higher average rating. In particular, the average rating for the first item is 3.22, followed by the StoryBoard value (2.78) and the Heat Map (2.33). For the second item, the Black Box had an average score of 3.78, while the Heat Map was ranked second (2.67) and the StoryBoard third (2.22). Moreover, the Black Box condition was the only one to reach the maximum rating (5) and the highest minimum (2) for both items. Finally, the black box had the higher value at the 25th percentile for both the Acceptability items (3).

As for the "trust" item in the post-condition questionnaire, the more trusted condition was, on average, the Heat Map condition (3.22), followed by the StoryBoard (3.11) and, finally, the Black Box (2.89).

4.5. The efficiency of the proposed solution

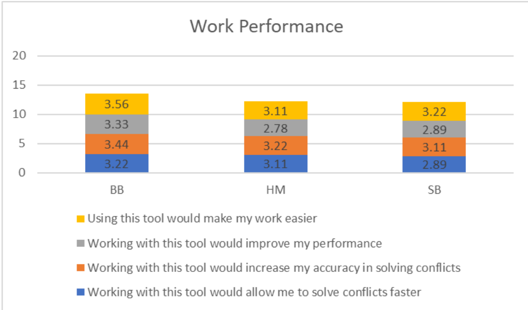

Figure 7: Descriptive analysis for Work Performance items from post-condition questionnaire.

The descriptive analysis for the 4 items assessing the work performance (see Figure 7) shows how, also, in this case, the Black Box was averagely rated higher than the other conditions in all 4 items. For the first 2 items, the Heat Map was ranked second, while for the last 2 items it was ranked third. Moreover, the Black Box condition is the only one to reach "2" as the minimum rating for all 4 items.

5. Qualitative data - Debriefings

The analysis of the debriefings conducted out at the end of the simulation allowed for better interpretation of the data collected from the post-scenario and post-condition questionnaires. 8 professional ATCOs out of 9 reported that they preferred the black box (BB) solution. They mentioned that it was easy and more understandable, mainly because it allowed them to make their decision in less time compared to the heat map (HM) or the storyboard (SB) solution.

AI support and types of conflicts: Four out of nine ATCOs felt that the AI solutions proposed were not useful for conflicts with two aircraft. They thought that the BB solution could be useful in conflicts involving three or more conflicts. In more complex scenarios, in which the ATCOs are experiencing more workload, they would be more willing to accept the solutions proposed by the tool.

Human Machine Interface: The HM and the SB solution were not appreciated by ATCOs because they were not straightforward to understand, ATCOs working in an *en-route* sector need to make quick decisions and implement them. 'ATCOs have one second to understand the proposal by a tool' remarked one of the experts. Having too much information and a cluttered screen surely does not help ATCOs make a quick choice and disturb the ones that like to work with the minimum necessary information. The HM solution was considered confusing because it is hard to distinguish the aircraft trajectories and conflicting pairs with the coloured envelopes superimposed. Having a better way to highlight the pairs in conflict would improve the solution. The red colour should be avoided because it means that there is a situation that calls for immediate ATCO action. In general, the SB solution was received with more reservations. ATCOs thought that the SB solution implementation would call for the presentation on a secondary screen or on the same screen with augmented reality. For the latter cases *en-route* would not be the ideal application, for the reasons previously mentioned.

Trust and XAI: The main outcome from the collected feedback is that trust in the solution or tool is a requirement in order to use it in operations. Also, that trust must be acquired before or after operational usage, either in training, with briefing or even during debriefings. Therefore, we can say that explainability is more important during those phases and not during the operational use of AI tools. Most ATCOs mentioned that if they would need more time to analyse and double check the proposals from the solution with explainable AI, that could ultimately translate in an increase of workload during operations and/or loss of situational awareness of other events in the sector.

Safety: One of the problems that ATCOs mentioned if these kinds of tools would be adopted in operations is related to the fact that if they trust the system enough ATCOs might implement suggestions without checking what has been proposed and loose skills overtime. Most of the ATCOs mentioned that they find the solutions proposed by the system were good but they if they are not matching their solution, it forces the ATCO to think twice or ultimately doubt his own solution. One ATCO complemented that he would be reluctant to accept a solution that is not his own simply because he might find himself in a situation that he does not feel that he can rapidly recover, because at that point he might be 'out of the loop'.

Training: Five ATCOs mentioned that it would be interesting to explore and understand better the advantages of the AI solutions for training. The focus could be on understanding how experts (maybe with different approaches or goals) would solve or work in certain scenarios. To make them visualize trajectories and different approaches based on different parameters could be very useful is to discuss and debrief. Not all ATCOs will choose the same solution but during training, it can be a good point of discussion. Two ATCOs alerted to the fact that using AI tools to learn in conflict solving scenarios too early in the training process could be dangerous, since ATCOs might end up mimicking the AI tools work strategy before developing their own.

6. Summary and conclusions

In our experimentation, we assessed the different level of explanation provided to air traffic controllers with a conflict resolution algorithm. As a general outcome, time pressure for conflict resolution plays the major role in the decision making which can explain why the black box is the preferable solution no matter the level of difficulty. Participant felt that on real situations, they would not have time to review any explanation. In real situations, ATCO experts felt they rather have the simplest design as they just need a solution, assuming that the system can be trusted. Nevertheless, more explanation increases the user situation awareness and the trust in the proposed solutions while not degrading the efficiency of the user decision. Adding explanations in simulation or on demand, on the other hand, could help enhance the trust in the tool, and better understand its behaviour, while keeping a more straightforward design such as the black box for time pressured situations. This conclusion could potentially be applied to other decision-support tools for time pressured task, where explanation could be provided while adapting to use the tool, and on demand in real situations.

Our experimentation has also many limitations where ATCOs mentioned that the low fidelity simulation experiment was not ideal to get a realistic feeling of the impact of the tools in their work and operations. Furthermore, our design for the explanation remains dense and complex in regards of the number of presented information and their density. A longer training period may be required to ensure that the data retrieval of our explanation do not add a too high cognitive load.

While we report preliminary results with 9 expert ATCo, we can still extract trends and directions for the design of more transparent and explainable systems. More explanation would be beneficial for the initial training period of air traffic controller and will increase thrust and convivence in automatic system.

References

Bach, B., Dragicevic, P., Archambault, D., Hurter, C. and Carpendale, S. (2017), A Descriptive Framework for Temporal Data Visualizations Based on Generalized Space-Time Cubes. Computer Graphics Forum, 36: 36-61

Bertin, J. (1983). Semiology of Graphics. University of Wisconsin Press.

Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman (Eds.). 1999. Readings in information visualization: using vision to think. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

Degas, A., Islam, M. R., Hurter, C., Barua, S., Rahman, H., Poudel, M., Ruscio, D., Ahmed, M. U., Begum, S., Rahman, M. A., Bonelli, S., Cartocci, G., di Flumeri, G., Borghini, G., Babiloni, F., & Aricó, P. (2022). A Survey on Artificial Intelligence (AI) and eXplainable AI in Air Traffic Management: Current Trends and Development with Future Research Trajectory. Applied Sciences, 12(3), 1295. https://doi.org/10.3390/app12031295

Durand, N., & Gotteland, J.-B. (2006). Genetic Algorithms Applied to Air Traffic Management. In Metaheuristics for Hard Optimization: Simulated Annealing, Tabu Search, Evolutionary and Genetic Algorithms, Ant Colonies, Methods and Case Studies (pp. 277–306). Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-30966-7_10

Hurter, C., Conversy, S., Gianazza, D., Telea, A.C. (2014). Interactive image-based information visualization for aircraft trajectory analysis, Transportation Research Part C: Emerging Technologies, Volume 47, Part 2, Pages 207-227.

Hurter, C., Tissoires, B., & Conversy, S. (2009). FromDaDy: Spreading Aircraft Trajectories Across Views to Support Iterative Queries. IEEE Transactions on Visualization and Computer Graphics, 15(6), 1017–1024. https://doi.org/10.1109/TVCG.2009.145

Riche, N. H., Hurter, C., Diakopoulos, N., & Carpendale, S. (Eds.). (2018). Data-Driven Storytelling. A K Peters/CRC Press. https://doi.org/10.1201/9781315281575

Scheepens, R. , Willems,N., van de Wetering, H. , Andrienko,G., Andrienko, N., van Wijk, J. J (2011). Composite Density Maps for Multivariate Trajectories in IEEE Transactions on Visualization and Computer Graphics, vol. 17, no. 12, pp. 2518-2527.