EXPLORATORY RESEARCH

Concept Report

Deliverable ID:	**D2.2**
Dissemination Level:	**Public**
Project Acronym:	**MAHALO**
Grant:	**892970**
Call:	**H2020-SESAR-2019-2**
Topic:	**SESAR-ER4-01-2019**
Consortium Coordinator:	**DBL**
Edition Date:	**28 May 2021**
Edition:	**00.03.00**
Template Edition:	**02.00.02**

Founding Members

EUROPEAN UNION EUROCONTROL

SESAR JOINT UNDERTAKING

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Document History

Edition	Date	Status	Author	Justification
00.00.01	15/10/20	Draft	Tiago Monteiro Nunes	Proposed table of content
00.00.02	10/12/20	Draft	Brian Hilburn, Carl Westin	Sections drafted
00.00.03	15/12/20	Draft	Clark Borst	Section drafted
00.00.04	22/12/20	Internal review	Carl Westin	Reviewed report. Document harmonized
00.00.05	29/12/20	Internal review	Matteo Cocchioni	Reviewed report. Document harmonized
00.01.00	29/12/20	Final release	Stefano Bonelli	Deliverable approved for submission to the SJU
00.01.01	24.02.21	Revision	Carl Westin	Reviewer's comments
00.01.02	25.02.21	Revision	Clark Borst	Reviewer's comments
00.02.00	01.03.21	Final release	Stefano Bonelli	Deliverable approved for resubmission to the SJU
00.02.01	20.05.21	Internal review for update version	Brian Hilburn	Section drafted, Reviewed report
00.03.00	28.05.21	Final release	Stefano Bonelli	Deliverable approved for resubmission to the SJU

MAHALO

MODERN ATM VIA HUMAN / AUTOMATION LEARNING OPTIMISATION

This project has received funding from the SESAR Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement No 892970.

Abstract

This document is the updated *Concept Report*, deliverable D2.2 of the MAHALO project. This update supersedes the original D2.2, which was submitted 1 Mar 2021. D2.2 reflects the output of MAHALO Task 2.3, and builds on the earlier D2.1 *Integrated State of the Art Report*, which reviewed human performance- and Machine Learning (ML) issues relevant to the MAHALO project. This update reflects additional inputs from WP3 (ML model) and WP4 (E-UI development and validation) since the original D2.2 submission.

This report presents the MAHALO ATM concept of operations, including anticipated human roles, information requirements, and candidate test protocols. Test protocols include operational scenarios, test procedures, experimental design, data collection procedures, and data analysis approaches. This report also identifies candidate ML architectures to be used in MAHALO.

This D2.2 is intended to be a living document. Given the ambitious aims of the MAHALO project, and the fast-moving nature of developments within the field of machine learning, iterative architecture redesign of the machine learning methods will be necessary. In parallel, test scenarios and procedures for human-in-the-loop testing will be refined over the course of the following work packages. The research team intends to maintain updates to this D2.2 document throughout this process, and to maintain a running log of provisional methodological decisions, as well as a list of open issues still to be addressed (the next submission date will be in September 2021).

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1. Introduction

This document is the updated *Concept Report*, deliverable D2.2 of the MAHALO project. This update supersedes the original D2.2, which was submitted 1 Mar 2021. D2.2 reflects the output of MAHALO Task 2.3, and builds on the earlier D2.1 *Integrated State of the Art Report*, which reviewed human performance- and Machine Learning (ML) issues relevant to the MAHALO project. This update reflects additional inputs from WP3 (ML model) and WP4 (E-UI development and validation) since the original D2.2 submission.

The MAHALO project has two high-level goals. The first is to develop a hybrid machine learning capability for detecting and resolving air traffic control conflicts. The second goal is to assess the impact of such a capability in terms of human performance, focusing on such constructs as mental workload, acceptance, trust, reliance, and human – machine system performance. To achieve these two ambitious goals, the MAHALO project must start from a clear specification of its concept of operations, simulation scenarios, and protocols for testing and data analysis.

This report has two main goals. The first is to present a refined MAHALO ATM concept of operations (ConOps). This MAHALO ConOps specifies the broad ATM context, information requirements, and human and machine roles, as they are envisioned for the MAHALO concept. This will drive all subsequent work in the MAHALO project, by helping define and refine scenario descriptions, test simulation scenarios, and test procedures.

The second broad goal of this D2.2 report is to present the provisional experimental design. Experimental design will cover all aspects of our human-in-the-loop test procedures, including construction of test scenarios, data collection instruments and protocols, specification of independent variables and dependent measures, and intended procedures for descriptive and inferential statistical analysis of real-time simulation data.

This D2.2 is intended to be a living document. Given the ambitious aims of the MAHALO project, and the fast-moving nature of developments within the field of machine learning, iterative architecture redesign of the machine learning methods will be necessary. In parallel, test scenarios and procedures for human-in-the-loop testing will be refined over the course of the following work packages. The research team intends to maintain updates to this D2.2 document throughout this process. D2.2 will maintain a running log of provisional methodological decisions, as well as a list of open design and testing issues still to be addressed (the next submission date will be in September 2021).

1.1 Report structure

The report consists of three chapters. Chapter 1 contains a brief introduction to the report and its goals. Chapter 2 overviews the MAHALO ConOps and presents the four key elements: the ATM context, the human agent, the machine learning agent, and the user interface. Chapter 3 details the first iteration of the experimental design approach. This includes detailed information on the research question, simulator setup, scenarios, independent and dependent variables, participants, experimental procedures, and plan for data analysis.

Major technical or workplan changes, new to this edition 2.00, are indicated in ***bold italic text***.

2. The MAHALO Concept of Operations

A Concept of Operations (ConOps) is a high-level description of the target environment and context. Information requirements, command structures, the roles of various agents, and other contextual factors flow out of a ConOps. This chapter presents the MAHALO ATM ConOps, and places it within the MAHALO framework for joint human – machine control. Figure 2.1 presents a high-level schematic of the MAHALO framework. The main components of this framework include:

- a **human operator** (i.e., Air Traffic Controller, ATCO) interacting with the system;
- a **Machine Learning (ML) agent** that can both learn from, and teach, the operator to either solve traffic conflicts more optimally or mimic the operator's individual or group-based problem-solving style; and
- a **User Interface (UI)** based on Ecological Interface Design (EID), which provides the operator an insight into the deeper structure of the work domain as well as the inner workings of the ML agent.

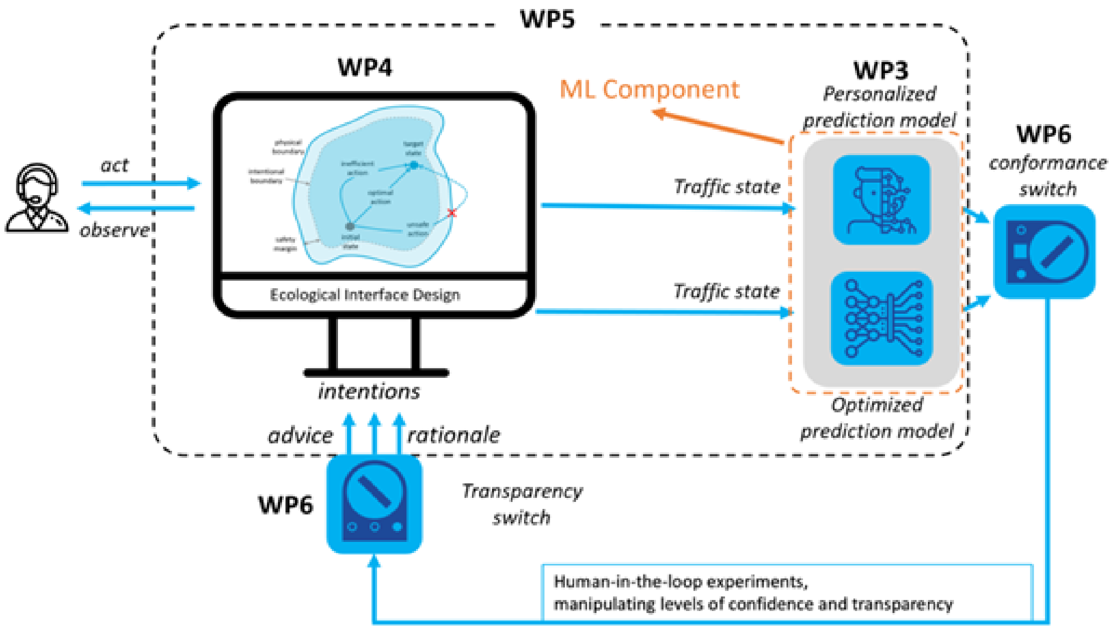

Fig. 2.1 MAHALO ConOps Schematic. Note that the "Personalized prediction model" includes both the group and the individual conformal model. Additionally, the *conformance* and *transparency* switches are static and serve as independent variables in the human-in-the-loop experiments.

2.1 The ATM Context

MAHALO targets a future ATM environment consistent with the digital European sky vision 2040 in the European ATM Master plan [SESAR, 2019] and with SESAR and CORUS ConOps for RPAS integration. Central to this vision are the concepts of dynamic airspace organization, flight-centric ATC, and human-centred operations, albeit with increased levels of automation. As noted in MAHALO D2.1, the project targets high capability (level 4) automation support in all four information processing levels (perception, analysis, decision-making, and action implementation).

As discussed in D2.1, some of the MAHALO project's high-level assumptions regarding the air traffic control task include the following:

- Sectorised airspace, with Tower-, Approach, and ACC regions;
- Data link air-ground communications;
- Sector size and traffic levels to be considerably larger and higher than current (pre-COVID) levels;
- Full ADS-B and SSR Mode S data sharing air-ground (aircraft state, meteo data, etc);
- A future environment consisting of 4DTM, where the majority of separation conflicts have been solved strategically in early planning phases;
- A future environment in which RPAS aircraft share airspace with manned vehicles, as they perform similar/complementary tasks;
- Human-centred (i.e., human-in-the-loop) conflict detection and resolution responsibilities;
- Significant task sharing between human and machine for monitoring and CD&R activities.

Specifying how this task sharing would function, requires examining the role of both the human operator (i.e., the controller) and the machine learning agent.

Since RPAS vehicles are by definition piloted by a human agent who is in contact with the control center in the same manner as a pilot of a manned airplane, the term *aircraft* refers to all types of vehicles flying in that specific air sector for which the ATCO is responsible.

2.2 The Human Operator

The job of an Air Traffic Controller (ATCO) in the ATC conflict detection and resolution (CD&R) task is to ensure proper separation between all aircraft within the sector for which the ATCO is responsible. ATCOs accomplish this by constantly monitoring the traffic situation on a plan view display (e.g. radar or situation display) and by giving commands to aircraft when a potential separation loss is predicted to occur in the future. In addition, ATCOs also strive for efficiency in traffic throughput.

In MAHALO, the human operator (i.e., ATCO) receives assistance from a ML agent to ensure safe separation and increased efficiency in the CD&R task. Because final authority of the CD&R task resides with the human operator, it is essential for successful collaboration between the human and machine agent that the human operator understands the ML system's advisories and possibly overrides such advisories when deemed necessary.

In this, the human operator and the ML agent will share the same safety goals (i.e., keep aircraft separated at least 5 nm horizontally and 1,000 ft vertically), but may adopt different, and sometimes perhaps conflicting, criteria in achieving those goals. For example, ATCOs adopt human workload management strategies in modulating their control actions, something which is generally irrelevant to computerized agents. There have been many studies conducted on ATCO strategies, which have been reviewed and described in the deliverable D2.1.

2.3 The Machine Learning agent

The **ML agent** is a main contribution of MAHALO. The reasons for using a ML agent as a traffic advisory algorithm have been explored in deliverable D2.1

The ML agent is envisioned as a teammate to the ATCO. The objective in the design of the ML agent is to increase controller acceptance and cooperation with the ML agent. MAHALO focuses on two factors that may foster acceptance: **conformance** and **transparency**. These are illustrated in Figure 2.1 as two "switches".

Conformance refers to the ML agent's ability to solve the CD&R task in ways that align with the individual ATCO's preferred problem-solving style. To achieve this ability, the automation can "learn" from the operator by being shown data on how the operator solves a given conflict. This approach is useful for two reasons. First, it can be beneficial for the ML agent to learn from individual ATCOs through expert demonstrations (Learning from Demonstration, **LfD**). Second, the system can be taught to use strategies close to what the human operator would usually use. This is **conformal behaviour** and is thought to help foster an operator's acceptance of automation, in that it is easier for a human controller to understand and accept a solution that is close to what he/she would do himself/herself. **Conformal AI** is, thus, extremely important to the MAHALO project in that it is one of the main ways the consortium hopes to increase acceptance.

Conformal AI is hypothesised to be most useful with novices (as opposed to experts), as a way to foster initial trust and acceptance. Once acceptance and trust is established the system can propose more optimal solutions that may be less conformal. If the system only proposes the ATCO conformal solutions then it is not really helping the ATCO improve his/her performance and may instead only add to a confirmation bias. Additionally, **Conformal AI** is an important tool but it, in itself, does not provide any further information to the operator about the inner workings of the system. Therefore, it is feasible to consider that the operator might interact with the system for a while and believe he/she knows why it gave a certain suggestion and, yet, no information will be given to verify if the reasoning is correct.

When the ML agents suggest a (more optimal) solution that differs from the individual ATCO's solution, the ATCO may find it difficult to understand how or why the system suggests this solution. The result may be that the ATCO rejects the advisory and chooses to disuse the ML agent. To mitigate this problem, **transparency** of the ML agent will be important. The goal of transparency is twofold: contribute to both understandability and acceptance of the system. Transparency would contribute to understandability by providing the user with more information about the reasoning for a given traffic advisory. Additionally, it may also contribute to acceptance since it gives the user a better understanding of the system itself.

Overall, both transparency and conformance will be used to achieve MAHALO's goals. The reason why these two factors are displayed in Figure 2.1 as "switches" is simply because within MAHALO these will be used to varying degrees, hence the system has to be able to vary the degree to which they are "considered" by the ML agent.

If the conformal part of the ML agent is helpful to foster early cooperation between the automation and the human, but is deemed unnecessary after a given time then it can be "switched off" to allow the system to suggest more optimal solutions.

Likewise, transparency usually comes at a cost as it increases the amount of information that is provided to the ATCO. If an ATCO has a transparent AI system to observe in addition to his/her regular tasks then this might lead to an increase in workload. Additionally, the ATCO might need only a small amount of information to understand a given traffic advisory but might require more information to understand another when a more complex traffic situation appears. This means that there is interest in making sure this transparency can be "turned down" in some situations or "turned up" in others.

MAHALO is considering three separate ML models for varying conformance:

- A **Personalized prediction model**, that learns and replicates the operator's *subjective* strategies to be used for **conformal behaviour.**
- A **Group prediction model** based on the most dominant (i.e., average) conflict resolution strategies derived from analysing all Personalized prediction models in a given sample.
- An **Optimized reward prediction model**, that is concerned only with achieving optimality according to the *objective* metrics given to it.

Current thinking calls for the first two models (personalized- and group prediction models) to be based on Supervised Learning (SL), whereas the third model will be based on Reinforcement Learning (RL). For details, see D3.1 Machine Learning Report, as well as the following text of section2.3.

The **conformal switch** will determine how conformal or optimal the system is at any given time. The **transparency switch** determines what type of information relating to the rationale and intentions of the ML system that will be provided to the ATCO together with the conflict resolution advisory. This allows the system to be versatile and empower the ATCO's with as much information as they might require at any given time. It also allows for experiments to be conducted on exactly how relatively important each of the two features is for performance and acceptance.

Again, in MAHALO the indicated transparency and conformance switches are experimentally manipulated independent variables, not real-time dynamic shifts.

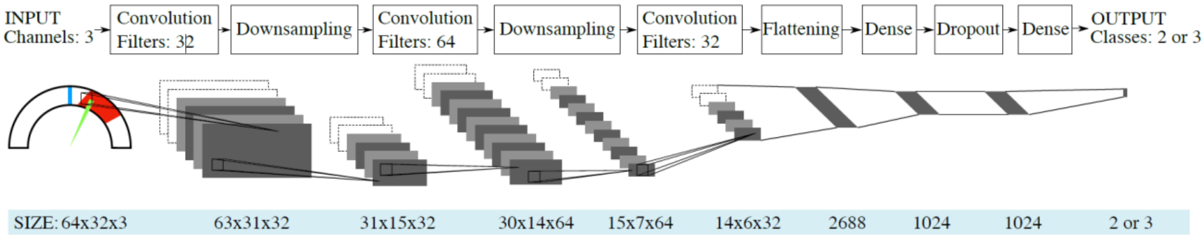

Fig. 2.2 Supervised Learning concept with Convolutional Neural Networks [Rooijen, S. van, Kampen, E.J. van, Borst, C. & Ellerbroek, J., 2019]

Figure 2.2 shows the ML concept for the **Personalized prediction model**. Convolutional neural networks are used to convert an input, in the form of an SSD or radar display, to a given resolution action by the agent, such as change in heading or speed. This supervised learning based ML model will be trained with real ATC operator data.

Updated details of the SL approach to be used for the personalized- and group prediction models can be found in D3.1, Machine Learning Report.

For the **Optimized prediction model,** the team considered several ML approaches, including

- DQN (Deep Q-Network) -- a variant of the traditional Q-learning algorithm in which a neural network estimates the value of a given state-action pair (Q value) while learning and in later decision making;
- DDPG (Deep Deterministic Policy Gradient)-- combines rule- and reinforcement based models, in such a way that RL selects solutions from the rule base;
- DQfD (Deep Q-learning from Demonstrations)—similar to DQN, DQfD learns a Q function, but it does so using a more efficient *prioritized replay mechanism*. DQfD can learn from human expert demonstrations and achieve better results.

For the Optimised Prediction Model, the research team has selected to develop a Deep Learning agent in such a way that two different approaches can be used: the first approach is DQfD as a proof of concept and the second is DDPG for the main project's experiments. Technical details and justification of this selection are found in the D3.1 Model report

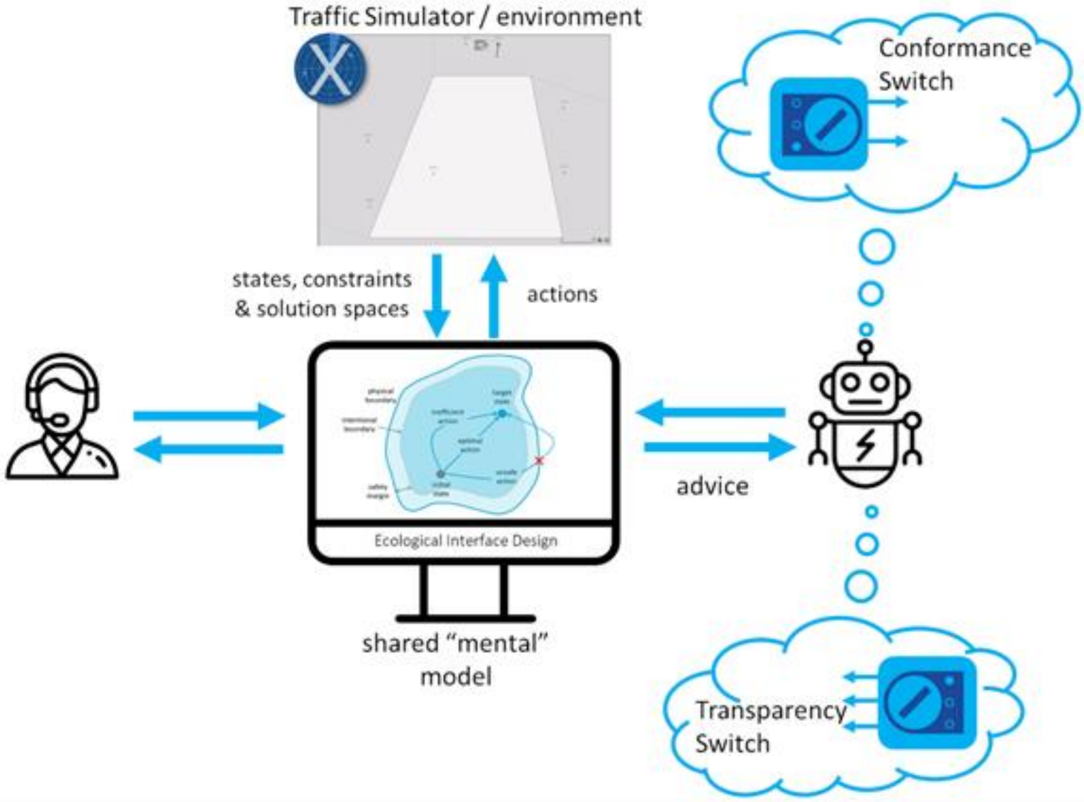

Fig. 2.3 Human Machine Interaction

Figure 2.3 shows a high-level abstraction of the MAHALO system and ML agent from an ATCO perspective. The ATCO will not know how the ML agent's algorithm is implemented or how it learns. The ATCOs only interaction with the ML agent will be through the advice given and the additional explanations that might be given. This means that the ATCO does not require expert training in AI or ML in order to be able to use the system. Ideally, the **transparency** aspect of the algorithm will allow the ATCO to understand why the system gives a certain traffic advisory solution without knowing the exact features (neural networks, learning algorithm, optimization criteria, etc) of the system.

2.4 The Ecological User Interface (E-UI)

The purpose of the Ecological User Interface (E-UI) is to provide both domain transparency and ML agent transparency in a visual way. By following the principles underlying the Ecological Interface Design (EID) framework, the E-UI will first and foremost portray the constraints and their relationships within the ATC work domain. A work domain that is governed by physical processes, such as ATC, physical/natural boundaries encompass a system's safe action state-space, or, the space of possibilities. That is, aircraft cannot fly, climb or descent slower or faster than what is physically possible for that specific aircraft. An ecological interface aims to make such boundaries directly visible in a way that supports a human operator in performing *any possible* action as long as it remains within the safe boundaries and brings the system to the desired target state. This means that inefficient actions are supported too, as long as they are safe.

Although the laws of physics form the common ground (or **shared mental model**) between human and automated agents, automated agents (such as the ML agent) may only strive to consider optimal actions, meaning that within the space of possibilities, the automated agent may further constrain what it considers as "good" solutions to problems. In other words, humans and computers may "navigate" differently through the space of possibilities in reaching desired target states.

In MAHALO, a display that portrays the ML agent strategy (e.g., in the form of a re-routing advisory) within the portrayed system boundaries, enables one to evaluate that strategy in terms of safety, but not necessarily efficiency. In certain situations, this may already provide sufficient information to human operators for accepting such advice. However, there is also evidence that human operators reject such advice, because they either cannot fully understand its rationality (i.e., low transparency) or the advice does not conform to what controllers would do (i.e., low conformance). For that reason, the E-UI also aims to add visual elements that will disclose more of the ML agent's inner workings. For example, a visualisation of the optimisation criteria the ML agent has considered in generating the advice, integrated within the visualised space of possibilities. This has not been done before, so MAHALO will be pioneering in this field.

The research team has decided to base the MAHALO Ecological User Interface (E-UI) on SectorX, a Java-based medium fidelity ATC research simulator developed by the TU Delft. SectorX has been adapted to realistically mimic the Maastricht Upper Area Control (MUAC) controller working position (CWP), including STCA, MTCA, and VERA capabilities. Details of the SectorX simulator and E-UI, including control functionality and design considerations, can be found in D4.1 E-UI Design.

3. Experimental design

MAHALO is planning to conduct three human-in-the-loop (HITL) experiments. The goal is to empirically explore how variations of a ML CD&R system that varies in conformance and transparency affects controllers' performance in solving conflicts and attitudes towards the system. While the three experiments build on the same experimental design approach, the sequential experiments are additive, and the timing and purpose within the MAHALO project varies. The three HITL simulations are:

- Simulation 1: The first simulation (currently planned for August 2021) will make use of novices (e.g., university students). This is a developmental simulation where the fully integrated ML CD&R system and its capabilities to provide conformal and transparency advisories will be tested. This is also the first experiment for testing the scenarios, data collection protocols, experiment procedures, questionnaire and debriefing material, and data analysis. The purpose of the experiment is to test the experimental design, not to collect data for answering the research question. Based on the outcome of Simulation 1, it is likely that we will revise the experimental design in preparation for Simulation 2A and 2B.

- Simulation 2A: The second simulation (currently planned for end of 2021), hosted by DBL Italy, will involve ATCOs as participants.

- Simulation 2B: The third simulation (currently planned for early 2022), hosted by LFV Sweden, will involve ATCOs as participants.

As previously anticipated, it seems that the ongoing COVID 19 pandemic will force some of the simulation activities (Simulation 1, at a minimum) into remote data collection protocols. The research team is therefore currently building its simulation development activities on the assumption that Simulation 1 data collection will make use of a mobile platform such as TeamViewer or Zoom, which can allow for remote SectorX simulation, and distance interaction between experimenter and participant. Running simulations remotely complicates the application of eye tracking equipment for gathering eye movement data as input to the ML models. Therefore, eye tracking is not planned to be used for Simulation 1.

If necessary, this distance simulation protocol would still permit conformance pre-test data collection, as well as the main experiment, to go forward. As highlighted in the previous edition of this D2.2, there would be potential confounds in this distance simulation approach (environmental control, hardware differences, etc), and the team is continuing to consider contingency plans (including, for example, combining a single data collection site with remote experimenter/s for distanced experimenter-participant interaction).

Again, the experimental design section is considered a living document that will be updated as the project progresses.

3.1 Research question

MAHALO asks a simple but profound question: in the emerging age of machine learning, should we be developing automation that matches the performance and strategies of the human, or should we be developing automation that is understandable to the human? Do we need both? Are there trade-offs and interactions between the two, in terms of air traffic controller trust, acceptance, or system performance?

For experiments, the research question is:

How does the strategic conformance and transparency of a machine learning decision support system for conflict detection and resolution affect air traffic controllers' understanding, trust, acceptance, and workload of its advice and performance in solving conflicts?

3.2 Experimental design

An identical experimental design is intended to be used in all three simulations (1, 2A and 2B). The experimental design comprises a two-step data collection procedure: 1) the **Conformance pre-test**, and 2) the **Main experiment.** Data from the Conformance pre-test is used to train the conformal and group conformal ML systems (see section 3.4.1 for a more detailed explanation).

Simulation 1 is intended to be a first test of the entire MAHALO system. The purpose is, however, not to answer the MAHALO research question but to validate that the experimental design and simulation procedures are working satisfactory. Depending on the outcome of Simulation 1, changes may be applied to the experimental design before running Simulation 2A and Simulation 2B. Between Sim 2A and Sim 2B there should, ideally, not be any major changes to the system. Sim 2A and Sim 2B comprise a two-step simulation: the "conformance pre-test" and the "main experiment".

For the Conformance pre-test, participants will be asked to play many short scenario vignettes. The purpose of this test is to collect individual-specific solutions to different conflicts and use this as a training dataset for the personalised ML system. As such, conformance and transparency effects are not explored as there is no decision support (i.e. ML system) provided in the Conformance pre-test.

For the main experiment, a 3 (conformance) x 3 (transparency) within-participant design is planned, resulting in nine experimental conditions per participant. Conditions will be randomized using a Latin square design. Experiments will combine a qualitative and quantitative approach to derive a whole picture of the relationship between ML conformance and transparency.

3.3 Simulator setup

Experiments will make use of the SectorX simulation environment, which can be run on a portable computer. Training of ML models will be performed offline, i.e. in between the **Conformance Pre-test** and the **Main experiment** and will be done on a cluster of machines at project partner locations in The Netherlands and/or Sweden.

An eye tracker from Tobii is likely to be used for gathering gaze data. The wearable Tobii Pro Glasses 2 was used in the Validation simulation (D4.2). The system worked well and collected data with an acceptable accuracy. A drawback of using a wearable eye tracker is the time and resource demanding mapping of gaze data with a static image representing the scene view. Because a static image must be used to map gaze data, dynamic elements in the interface and simulation are difficult to capture. Data that is not captured well includes aircraft movement, SSD interactions, and dropdown menus from the labels etc. A promising alternative is the use of a screen-based eye tracker, such as the Tobii Pro Fusion or Tobii Pro X3-120. This eye tracker is mounted underneath the display. This is a suitable alternative given that participants in the MAHALO simulations will work with only one display. These eye trackers also capture gaze data at higher speeds than the wearable eye tracker, allowing for richer data. For example, Tobii Pro Glasses 2 captures data at 50Hz while the Tobii Pro Fusion captures data at 250Hz.

3.4 Independent variables

For the main experiment, there are two independent variables:

1. Conformance with 3 levels
    a. C: Conformal (Supervised learning ML, Personalized prediction model)
    b. GC: Group average (Supervised learning ML, Group prediction model)
    c. NC: Non-conformal (Reinforcement learning DQfD ML, Optimized reward prediction model)

2. Transparency with 3 levels:
    a. T0: No transparency
    b. T1: Domain transparency (achieved by ecological elements in SectorX)
    c. T2: Agent transparency/Conformance rationale (compare ML system advisory to conformal advisory)

3.4.1 Strategic Conformance

The conformance of resolution advisories will be varied in three different ways: conformal to the individual (personalized prediction mode); conformal to the group (group prediction model), and nonconformal (optimized prediction model). The ability to provide conformal resolution advisories requires a three-step design process as illustrated in Fig. 3.1.

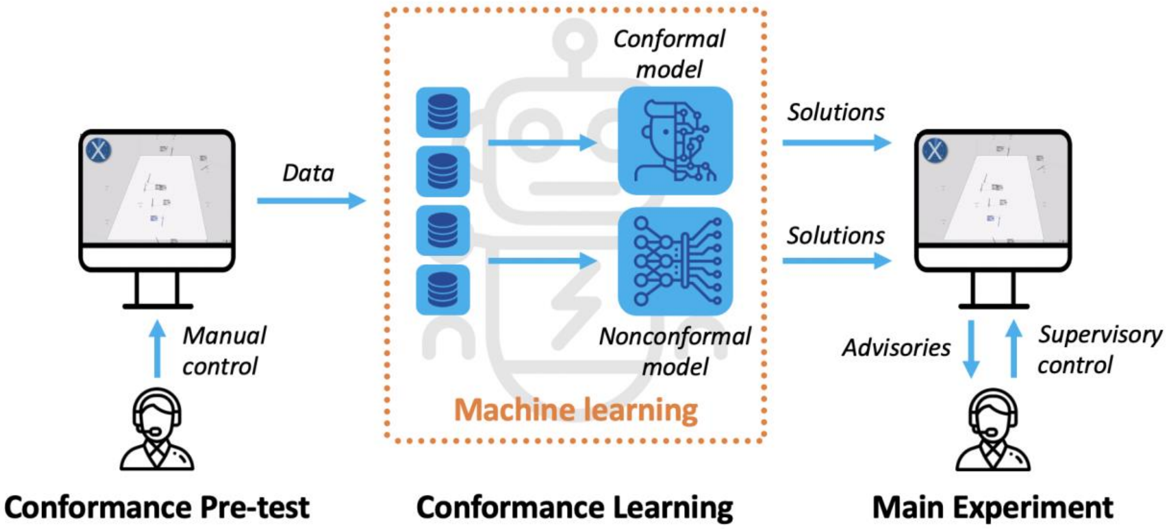

Fig. 3.1. Advisory conformance design process

The first simulation, the **Conformance Pre-test**, is conducted to collect data on how different individuals solve different conflicts. At this stage, individuals solve conflicts 'manually' (i.e., no decision support is provided). Fig 3.2 overviews the data collected for each solution generated by participants.

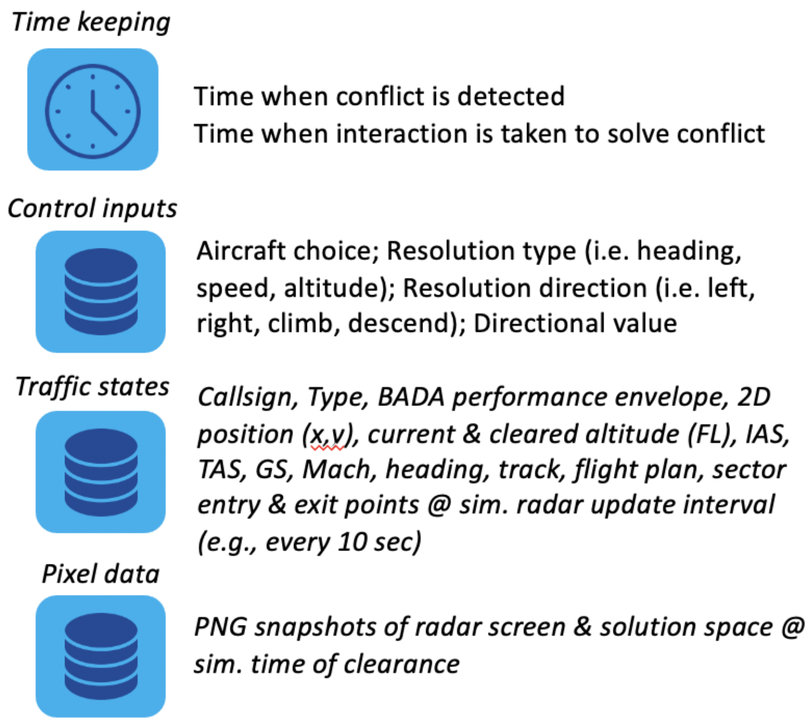

Fig. 3.2. Data collected in Conformance Pre-test

Time when conflict is detected can be measured in different ways, including eye-tracking, system interaction, and “speak-aloud” protocols where the participant is asked to indicate when a conflict is detected by, for example, verbalising or pressing a keyboard button. By using eye-tracking we could extract instances when the participant has focused on one of the aircraft in a conflict pair. Eye-tracking data does, however, not provide information on why a certain region or object if focused on, or how the information, if retained, is being used by the participant. Yet, with eye-tracking data we will know when the participant first direct visual attention to the one of the aircraft in conflict. System interaction can be used as a measurement for detection, e.g. by recording the time that the participant interacts with the aircraft label, or support tools such as the VERA tool in SectorX that is used to probe conflicts by measuring the closest point of approach between aircraft pairs. There are, however, uncertainties with using this method for identifying the time of conflict detection. Some time is likely to pass between the moment that a potential conflict is identified, and the first interactions with one of the aircraft involved in the conflict. It could also be that the participant interacts (or looks) at one of the aircraft without the perspective that it is in conflict. A third method is to ask participants to indicate when a conflict is detected, e.g. by means of pressing a key or verbalising it. A drawback of this method is that participants may forget to indicate the detected conflict or do so with some delay. However, the use of these methods in combination will provide us with a good understanding of approximately when in time the conflict was detected. Note that the required accuracy in identifying the time when a conflict was detected is rather low (uncertainty is expected to be in range of several seconds). The main purpose of identifying the time for conflict detection in the Conformance pre-test is for all the ML models to provide conflict resolution advisories before the participant detects the conflict in the Main experiment runs. Ideally, the resolution advisory is provided before the participant has come up with a solution for the conflict and implemented it.

In defining conformal and non-conformal resolution advisories, a participant’s solutions have to be decoded and classified to create an individual conformal model. Strategic conformance is not a dichotomous construct. Fig. 3.3. shows a conflict resolution decoding structure proposed by Westin (2017) based on the results in the MUFASA project. The figure classifies conflict solutions in a hierarchy where each step considers the solution in more detail. For example, the first stage considers the governing solution strategy (solution parameter hierarchy, control problem, or solution geometry). In the control preference strategy, the conflict is viewed as a control problem, focusing on the control action required to solve the conflict (e.g., vector aircraft ahead or behind). This preference considers that conflicts only can be solved by one aircraft going behind, in front, above, or below the other. (Westin 2017). In the geometry preference strategy, solutions are based on the desired spatial relationship between the involved aircraft. It acknowledges that a solution is based on the spatial orientation between two or more aircraft and their constraints as they evolve over time, rather than on discrete information about aircraft state and position. (Westin 2017). A more detailed consideration of solutions could include consideration of aircraft choice (e.g. aircraft A or B) and Resolution type (e.g. heading or altitude). The conformance levels of solutions that participants implement can then be classified according to different conformance levels as shown in Table 3.1.

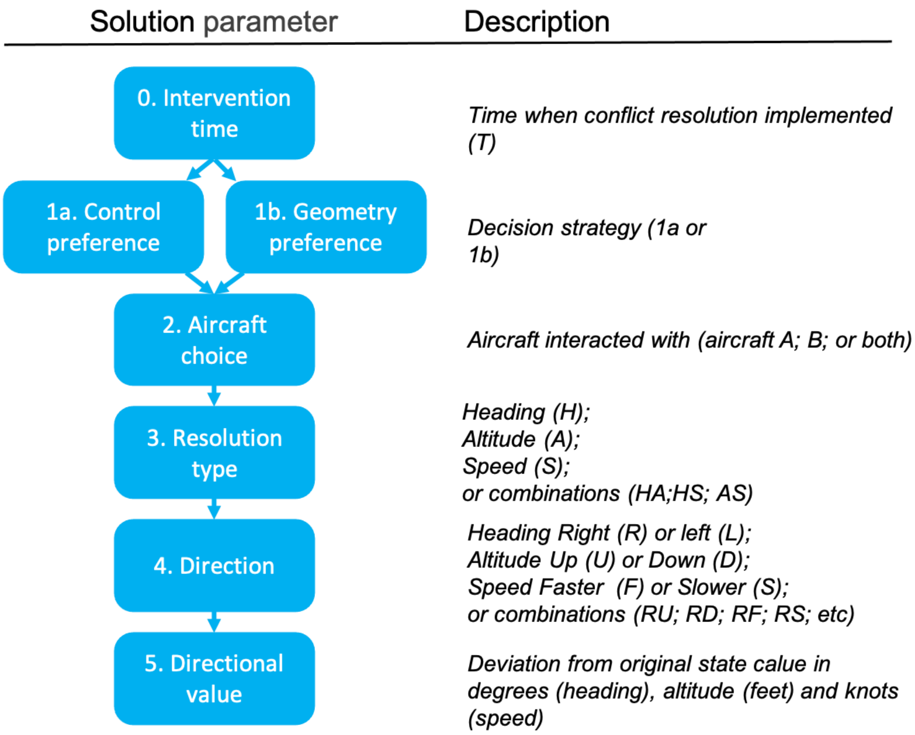

Fig. 3.3 Decoding of conflict resolutions (adapted from Westin, 2017)

It is not guaranteed that the conformance ML models used as a conformance variable will provide solutions according to the highest level of conformance (level 5). The conformance level that a conformal ML model can support depend on how consistent the participant is in solving similar conflicts over time. The objective is to support the highest level of conformance possible that participants in our sample support. In general, the conformance level of the conformance variable will depend on the participant that is least consistent. If all participants perform consistently according to level 5 conformance, we will be able to provide conformance at that level. Based on previous experience, however, we expect participants' performance in solving conflicts to vary - some are more consistent than others. We will control the variable by establishing a conformance level that applies to all participants, for which the least consistent participant will be limiting. We can also elect to discard a participant, if that participant shows to be an outlier (i.e. to have performed inconsistently compared to the others). Alternatively, we could also to divide participants in groups depending on how consistent they are (and that the sample size allows for doing).

Table 3.1. Conformance levels (adapted from Westin 2017)

Level	Conformance	Description
5	Exact replay	Solution strategy match, aircraft match, resolution type match, direction match, and directional value match.

4	Mismatched directional value	Solution strategy match, aircraft match, resolution type match, direction match. directional value mismatch (i.e., Heading differed by 20 degrees or more, and/or Speed differed by 20 kts or more).
3	Mismatched direction	Solution strategy match, aircraft match, resolution type match. Direction mismatch (e.g., Heading left instead of right; Speed decrease instead of increase).
2	Mismatched resolution type	Solution strategy match and aircraft match. Resolution type mismatch.
1	Aircraft mismatch	Solution strategy match but aircraft choice mismatch.
0	Solution strategy mismatch	

The solution data collected in the Conformance Pre-test is used as input to the ML agent. In the **Conformance Learning stage**, different ML models are trained according to the three conformance levels (personalized, group, and optimized prediction models). All models must learn from the conflict resolution data what characterises a conformal solution for each individual participant. This means that the ML agent has to build a conformal model for each participant (who took part in the Conformance Pre-test). As such, a model will be created for each individual. Note that, in contrast, there will only be one group conformance model for each group of participants (e.g. Italian controllers and Swedish controllers. Furthermore, there will only be one optimized ML model. Importantly, the optimized ML model will suggest conflict resolutions that are non-conformal to the individual's conformal model. An example of a conformal and nonconformal solution is shown in Fig. 3.4. Here, conformance is defined as level 1 conformance. In this example, the conformal solution is similar to the preferred solution: aircraft a is vectored to the right behind aircraft b. he nonconformal solution aircraft B is deviated to the left, behind aircraft A. The nonconformal solution consists of vectoring aircraft b to the left behind aircraft a: another aircraft is chosen for resolving the conflict.

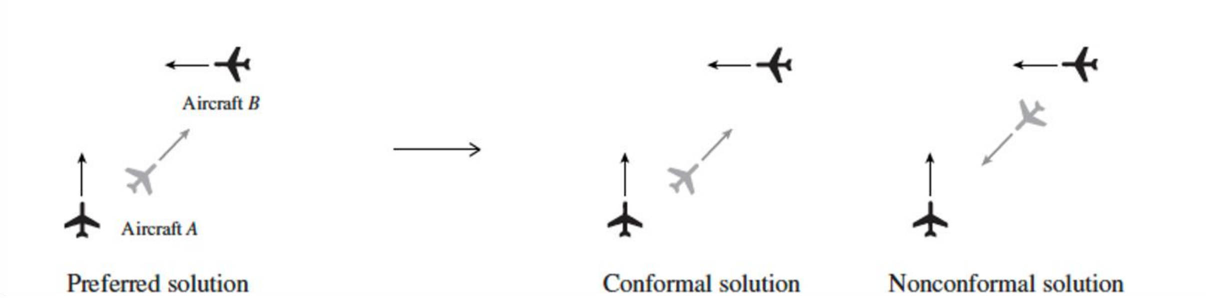

Fig. 3.4. Example of conformal and non-conformal solutions

In the final **Main experiment**, the same participants who took part in the Conformance Pre-test play the identical simulator and scenarios. Only this time, they will receive CD&R advisories from the ML agent. Only solutions provided by the ML agent with a personalized prediction model will be conformal. Solutions provided by the ML agents with a group prediction model and optimized prediction model will be non-conformal.

3.4.2 Automation Transparency

Automation transparency is achieved by providing additional layers on the ecological user interface with information about the underlying rationale for the solution recommended by the ML agent. Transparency will be varied in three levels:

T0: **No transparency.** Baseline condition where the ML agent recommends a solution to a conflict (e.g. in terms of a vector) without providing any underlying rationale.

T1: **Domain transparency.** How the ML agent has derived a particular solution. The visualized solution spaces can be used to present their recommended solutions. And highlight what information was taken into account that led to the advice.

T2: **Agent transparency/Conformance rationale.** The ML agent can present why it considers a solution conformal or nonconformal by explaining why a particular solution matches or deviates from the individual's preferred solution (i.e., why it is/is it not strategic conformal). For T2 we will explore ML interpretability methods (see D2.1 for examples) for identifying the relationship between input data and output solution.

3.5 Dependent measures

Subjective:

- Understanding (questionnaire)
- Acceptances (yes or no)
- Agreement with advisory (scale 1-100)
- Trust (scale)
- Workload/difficulty (scale 1-100)

Objective (performance):

- Track deviation (nm)
- Response time (seconds to answer advisory

Examples of trust scales are:

- Jian, Bizantz & Drury's Checklist for Trust Between People and Automation
- Merritt's Trust in Automation scale
- Madsen & Gregor's Human Computer Trust (HCT) scale
- Lee & Moray's Trust scales

The team is reconsidering the use of eye tracking measures as a dependent variable. However, eye tracking will still be used as an input data stream for training ML (e.g., regional attentional focus can help drive the monitoring scan and conflict detection process).

3.6 Scenario design

Several scenarios will be used in MAHALO simulations. For creating scenarios and running the experiment we will use the medium-fidelity ATC simulator SectorX. Figure 3.5 depicts SectorX and examples of the supported functionalities. SectorX has a customisable HMI and can be run standalone on a laptop or desktop computer. The design of specific scenarios can be divided in two separate parts: the **Conformance pre-tests** and the **Main experiment**. The scenarios in the Conformance pre-test and Main experiment will be similar and reuse the identical conflict situations. Each scenario will contain one conflict situation that we focus on. We will only consider conflict situations involving two aircraft. That is, unless the ATCO intervenes, the aircraft will lose separation. For Simulation 1, a variety of short scenarios including a variety of conflict geometries will be used. These scenarios will be used for testing scenarios that later are to be included in Simulation 2A and 2B.

We intend to use scenarios based on both current and future sector sizes and traffic densities. Sector sizes and traffic density values for scenarios will be developed together with input from domains experts available in the MAHALO network (LFV in Sweden and ANACNA in Italy). Scenarios will focus on high-level enroute in RVSM airspace (roughly FL290-370). A variety of traffic flying level and climbing/descending will be used.

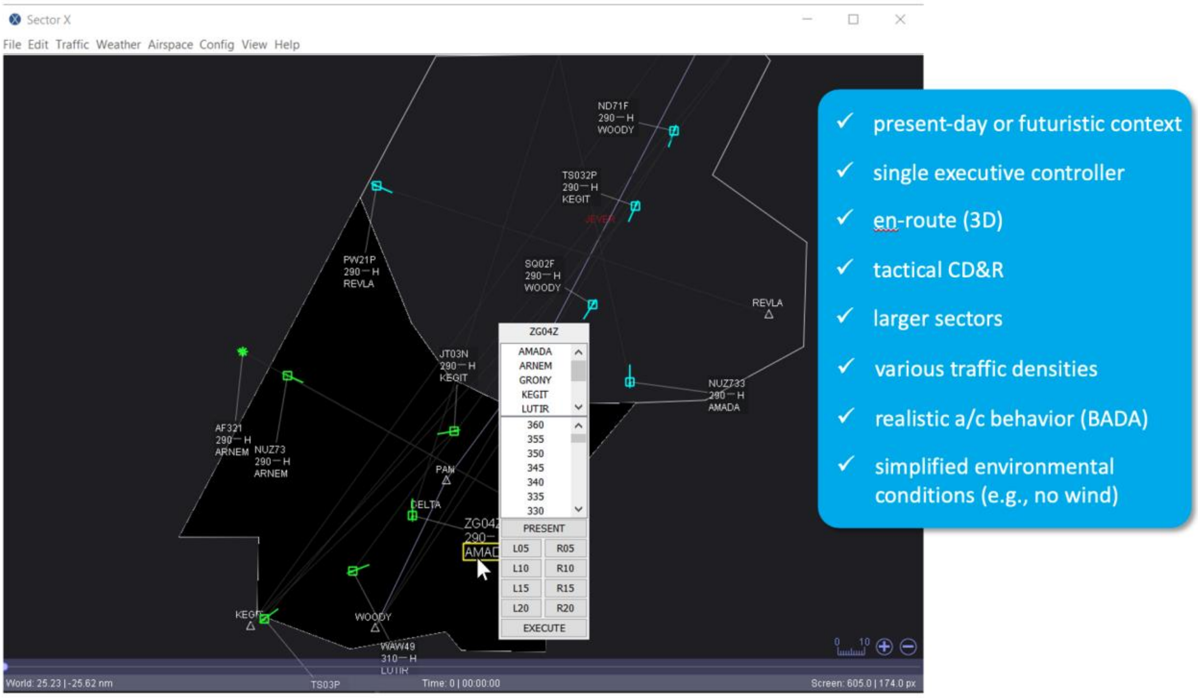

Fig. 3.5. SectorX showing MUAC combined Delta & Jever sectors

3.6.1 Scenarios in Conformance pre-test

The conformance variable requires multiple replications of the same scenario (and conflict) for determining controller consistency in conflict resolution performance. Each scenario will contain a **designed conflict** against which conformance measures are referred. As a reference, the MUFASA project repeated each scenario four times and then determined (manually by a researcher) how consistent each participant had been in solving the conflict. Four scenarios is a very small sample size to work with, and not suitable as a database for a machine learning system to learn participants' conformal solution strategies. For this a large amount of data on how an individual solves not only one type of conflict, but a large variety of conflicts.

3.6.2 Scenarios in Main experiment

A minimum of nine scenarios are required to cover the research conditions in the main experiment where conformance and transparency is varied. Short traffic scenarios, i.e., vignettes will be used. If scenario duration is five to ten minutes, it will take 45 - 90 minutes per participant. In addition, time will be needed for consent procedures, simulation briefing, demographics questionnaire, training time, measurement questionnaires, and debriefing. Each scenario will contain a **designed conflict**, identical to the conflict used in the Conformance pre-test, against which dependent measures are recorded. This is the conflict for which an advisory will be provided.

3.7 Test participants

Number of participants (ATCOs) remains to be defined. Given the large data input requirements for training the ML model, participants have to participate in both the Conformance pre-test and Main experiment. This is an essential requirement in the experimental design and manipulation of the conformance variable.

Given ATCO time and cost limitations, and possible COVID restrictions, a large number of participants in MAHALO is not feasible. However, a large enough sample of ATCOs is necessary in order to find problem solving (i.e., CD&R) variability. Notice that with no variability in CD&R strategies across controllers, there is no difference between personal- and group conformal models. MAHALO is forced to work with a smaller sample size of participants for simulations. The number of participants remains to be defined. We aim for at least 10 participants in Simulations 2A and 2B, respectively.

3.8 Simulation procedures

For the experiments we will use either a real time Hybrid ML or a Wizard of Oz approach for providing conformal and transparent advisories. The real time Hybrid ML system would be able to determine and provide conformal and transparent advisories during real time interaction with the system. Developing a well-functioning Hybrid ML system in the MAHALO project is ambitious. The possibility for using a Hybrid ML system in the experiments depends on the maturity of the ML system by the time for experiments, and the feasibility for travelling with this system (to simulations conducted in The Netherlands, Italy, and Sweden). The fall-back option is to apply a Wizard of Oz approach where conformance and transparency are manipulated by the researchers behind the scenes.

Training of ML models will be performed offline, i.e. in between the Conformance Pre-test and the Main experiment. Training ML models is data and time consuming. It is expected that the training of the ML models will take in the order of several hours. Therefore, it is important to allow for adequate time between the Conformance Pre-test and the Main experiment (i.e., several weeks).

Three types of ML models will be trained, which require different sets of training data:

- Personal prediction models for individual,
- Prediction models for the group, and
- Optimized prediction models

The personalised models use supervised learning approaches to train on the data generated by the ATCOs in the Conformance pre-test. The amount of data is therefore limited by practical considerations of available manpower and testing time per person. The training data for the personalised prediction models can be augmented with some artificial data, for example by mirroring measured data or by adding noise., but this will have an impact on the conformance level that can be obtained, so care should be taken in doing this.

The optimized prediction models will be trained on artificial data, i.e., artificially generated scenarios, which means there is no real limit on the amount of training data that can be generated.

3.9 Experimental protocols

Several protocols will be developed in preparation of the experiments. The following list specifies documents to be produced:

For participants:

- Informed consent
- Experiment briefing document
- Training syllabus/guidelines
- Questionnaires
- Demographic
- De-briefing

For experimenter:

- Experiment design document
- Latin square design
- Detailed procedures
- Eye-tracking setup and calibration checklist
- Training scenarios
- Measurement scenarios
- ML system configuration, setup and calibration
- Statistical analysis procedures (e.g. which analyses to use; who should do analyses etc)

3.10 Data analysis

Dependent measures will be analysed statistically using tools such as SPSS, Python, Excel, and Matlab. To verify results, at least two researchers will statistically analyse results independently. Example analyses of quantitative data include:

- Repeated measures ANOVA - for interval and ratio data, if normally distributed

- Friedman test – for data not normally distributed
- Cochran's Q-test – for binary data (e.g. acceptance)

In addition, we will conduct qualitative analyses of observation notes and verbal communication during simulations, and post-simulation debriefings. Conclusions will be derived from considering results from both the quantitative and qualitative analysis of data.

Eye-tracking data can be analysed to determine how conformance and transparency affects participants' visual attention (fixations, saccades, dwell time) and scan patterns (fixation sequences over time) in CD&R. Moreover, eye-tracking data can be used together with subjective measures (e.g. questionnaires) to assess trust (e.g. fixation duration and fixation count) and workload (e.g. blink rate and pupil diameter).

3.11 Ethical considerations

Ethical considerations are handled separately in Deliverable 8.1 (PODP-Requirement No 4). There will be further reference to ethical considerations in Deliverable 8.2, to be delivered concurrently with the final experimental design.

REFERENCE LIST

Haselt,, H. van, Guez, A. & Silver, D. (2015). Deep reinforcement learning with double Q-learning. https://arxiv.org/abs/1509.06461

Hester, T. et al (2017). Deep Q-learning from demonstrations. https://www.google.com/url?q=https://arxiv.org/pdf/1704.03732.pdf&sa=D&ust=1608297505453000&usg=AOvVaw1S2cjA7wz8Ra3fl2qsxrSA

Jian, J.Y., Bisantz, A.M., & Drury, C.G. (2000). Foundations for an empirically determined scale of trust in automated systems," *Int. J. Cog. Erg.,* 4(1),53-71.

Klomp, R. E., Riegman, R., Borst, C., Mulder, M., & Paassen, M. M. Van. (2019). Solution Space Concept : Human-Machine Interface for 4D Trajectory Management. Thirteenth USA/Europe Air Traffic Management Research and Development Seminar, 1–9.

Lee, J. D. & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation. *International Journal of Human–Computer Studies*, 40, 153–184.

MAHALO (2021). Machine Learning (ML) Report, D3.1.

MAHALO (2021). E-UI Design Document and Demonstrator Report, D4.1.

MAHALO (2021). E-UI Validation Report, D4.2.

Madsen, M. & Gregor, S. (2000). Measuring human-computer trust. *In Proceedings of the 11th Australasian Conference on Information Systems*, pp 6-8, 2000.

Merritt, S.M. (2011). Affective processes in human-automation interactions," *Human Factors*, 53(4), 356-370.

Rooijen, S. van, Kampen, E.J. van, Borst, C. & Ellerbroek, J. (2019). Personalized Automation for Air Traffic Control using Convolutional Neural Networks. MA thesis, Technical University of Delft.

Rooijen, S.J. van, Ellerbroek, J., Borst, C. & van Kampen, E.J. (2019). Conformal Automation for Air Traffic Control using Convolutional Neural Networks. In Proceedings of the ATM Seminar, Vienna. June, 2019.

SESAR [2019]. Concept of Operations for European UTM Systems - CORUS. SESAR Joint Undertaking, Luxembourg: Publications Office of the EU, Oct. 25.

SESAR [2019]. European ATM Master Plan. Digitising Europe's Aviation Infrastructure. Executive View. 2020 Edition. SESAR Joint Undertaking, Luxembourg: Publications Office of the EU, Dec. 17.

Wen, H. Li, H., Wang,Z., Hou, X. & He, K. (2019). Application of DDPG-based Collision Avoidance Algorithm in Air Traffic Control. 12th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 2019, pp. 130-133, doi: 10.1109/ISCID.2019.00036.

Westin, C. (2017). Strategic Conformance: Exploring Acceptance of Individual-Sensitive Automation for Air Traffic Control. PhD thesis. Control and Simulation Section, Aerospace Engineering Faculty, Delft University of Technology, The Netherlands. ISBN 978-94-6299-659-5

ACRONYMS

4DTM	Four Dimensional Trajectory Management
ADS-B	Automatic Dependent Surveillance - Broadcast
AI	Artificial Intelligence
ANOVA	Analysis of Variance
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATM	Air Traffic Management
BADA	Base of Aircraft Data
CD&R	Conflict Detection and Resolution
DDPG	Deep Deterministic Policy Gradient
DQfD	Deep Q-learning from Demonstrations
DQN	Deep Q-Network
E-UI	Ecological User Interface
EID	Ecological Interface Design
FL	Flight Level
GS	Groundspeed
IAS	Indicated Airspeed
LfD	Learning from Demonstration
MAHALO	Modernising ATM via Human-Automation Learning Optimisation
ML	Machine Learning
MTCA	Medium Term Conflict Alert
MUAC	Maastricht Upper Airspace Centre

MUFASA	Multidimensional Framework for Advanced SESAR Automation
RL	Reinforcement Learning
SL	Supervised Learning
SSD	Solution Space Diagram
SSR	Secondary Surveillance Radar
STCA	Short Term Conflict Alert
UI	User Interface
VERA	Verification of Separation and Resolution Advisory