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Copyright Statement

ARTIMATION

TRANSPARENT ARTIFICIAL INTELLIGENCE AND AUTOMATION TO AIR TRAFFIC MANAGEMENT SYSTEMS'

This D3.2 REPORT ON THE DEVELOPMENT PLAN BASED ON ATM TASKS WITH SUPPORTING AI is part of a project that has received funding from the SESAR Joint Undertaking under grant agreement No [894238] under European Union's Horizon 2020 research and innovation programme.

Abstract

This document identifies potential ATM tasks to be supported by AI and XAI algorithms within the ARTIMATION project and presents a detailed roadmap for the development.

To generate those results, two workshops were conducted: one to identify the specific ATM segments where to apply the AI algorithms and the other to matches the chosen task with the most appropriate artificial intelligence system. In both, Project members, ATM experts, and students from ENAC were involved and interviewed singularly.

The results of the first workshops identified the two chosen tasks, each belonging to specific categories: Task A – AI issues instructions (conflict resolution) and Task B – AI optimizes utilization of available capacity (delay propagation).

The results of the second workshop, identified, instead, the best artificial intelligence, explainability and visualisation solutions to apply to each task and the related development roadmap.

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List of Acronyms

Term	Definition
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AR	Augmented Reality
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATM	Air Traffic Management
EA	Evolutionary Algorithms
GBH	Gradient Boosting Machine
KPI	Key Performance Indicator
LIME	Local Interpretable Model Agnostic Explanations
MAS	Multi Agent System
ML	Machine Learning
RF	Random Forest
SCM	Structural Causal Model
SHAP	Shapley Additive Explanations
SVM	Support Vector Machine
UAV	Unmanned Aerials Vehicles
VR	Virtual Reality
WP	Work package
XAI	Explainable Artificial Intelligence

1 Introduction

1.1 Purpose and scope of this document

This document reports the results of **T3.2 ATM tasks & AI support identification and T3.3 development plan – the roadmap.** It follows the work reported in the ARTIMATION project-*D3.1 Report on State of Art AI support in ATM* [1], in which the state of the art for AI techniques, methods and algorithms, transparency and explainability in AI algorithms, techniques and approaches for data visualisation and challenges in ATM with respect to AI has been provided.

First, it identifies **Potential ATM tasks to be supported by AI algorithms** developed within ARTIMATION project, with the support of ATM experts and students from ENAC, interviewed singularly and during a dedicated workshop.

Secondly, matching the user needs identified in the previous tasks and the available AI solutions, presents **a detailed development roadmap for the proof of concept** of an XAI system supporting the identified tasks. In particular, the development roadmap is focused on two main steps: the first one is about novel techniques to support a better understanding of AI model, through the multivariate data analytics based on heterogeneous data sources using multimodal machine learning algorithms. The second step regards lifelong machine learning issue, by putting the "human into the loop". To do that, an internal workshop has been organised, to put together all the expertise from the different partners.

The results documented in this document will steer the work in WP4 and WP5 and will be used to design the validation scenarios (in WP6).

1.2 Structure of the document

In total, this document consists of 5 chapters, which are further subdivided into subsections. The chapters and their main topics are the following:

Chapter 1 describes the **purpose** and **scope** of this document. Furthermore, it details the document's **structure**.

Chapter 2 firstly introduces the motivations that led to the implementation of new AI techniques in the ATMs domain together with a brief categorization of these techniques. Secondly, this chapter describes the **Artificial Intelligence Techniques** and **Lifelong Machine Learning Models**; the **Explainability Techniques** and the **Visualisation Techniques** that have been identified as more relevant for the ARTIMATION project. To determine the pros and cons of each algorithm and technique, the advantages, disadvantages, risks and KPIs were listed. This information has been used as the starting point for the second Workshop.

Chapter 3 describes the methodology used to identify the ATC's tasks that could be supported by AI and the specific AI tool to be implemented. To identify the specific ATM segments were to apply AI algorithms and to match the user needs identified in the previous tasks and the available AI solutions, two workshop were held. For both, the aims, the organisation, and the management are described.

Chapter 4 describes the results and the outcomes of the workshops. Based on the results obtained, the tasks and the related supporting tools to be implemented are described.

Chapter 5 contains the roadmap on the development plans that will be used to steer the work in WP4 and WP5 and to design the validation scenarios (in WP6).

2 Selected AI algorithms, explainability techniques and visualisation techniques

The final objective of WP3 is to choose specific AI solution able to support selected tasks. This chapter describes the AI algorithms, the lifelong machine learning solutions, the explainability and visualisation techniques that have been selected and considered during the second workshop.

2.1 Current AI presence in ATM

Research papers from different conferences and journals, mainly from the ICRAT conference, ATM seminar event, and the Transportation part C journal, have been used to review the AI/ML algorithms used in the ATM domain. As presented in *Deliverable 3.1, AI application* in ATM is divided into four sub-groups based on general applications.

Prediction, (e.g., prediction of the traffic, prediction of the runway occupancy time). Multi-Agent Systems (MAS), Artificial Neural Network (ANN), Random Forest (RF), Gradient Boosting Machine (GBM), Support Vector Machine (SVM), and Linear Regression are mostly used in predicting tasks in ATM. MAS can be used to predict the future state of the simulated objects in air traffic with real data like traffic prediction, delay prediction, and meteorological indicators. It can also be used to solve complex problems in a decentralized way in ATMs. For example, to optimize en-route air traffic, the capacity/demand balance, or the route network. The advantage of MAS is the natural decomposition of the problem that is associated with its usage. NN, RF, GBM, SVM, and linear regression are primarily used to predict indicators of the trajectory of an aircraft and state indicators of an airport. These models have also been used for other types of predictions such as route choice, sector configuration, controller action prediction, or short-term 4D trajectory prediction. Multi-Agent Systems predict complex tasks.

Optimization/Automation, e.g., sequencing arrival airplane, avoiding conflict, optimizing a trajectory. Multi-Agent Systems (MAS), Evolutionary Algorithm (EA), mostly genetic algorithms, and Simulated Annealing (SA) are used for AI optimization and automation. They focus on optimizing the traffic and avoiding collisions. Optimizing the general traffic and avoiding collision is the most important thing to enhance the general traffic safety. Optimization results must be accepted by human operators such as ATCO.

Analysis, e.g., assessing the workload of an ATC in a sector, evaluating the essential factor influencing the arrival of an airplane. Analysis of ATM activities using AI model is mainly composed of techniques that cluster (i.e., DBSCAN, BIRCH, or auto-encoder ANN) trajectories to analyse route choice, arrival, or delays, and more precise analysis. The precise analysis contains trajectory analysis to detect ATCOs actions, speech recognition, and analysis or utterance of ATCO. Explainability is less required in this category.

Modelling/ Simulation, e.g., simulating the air traffic of airspace, modelling the arrival of an airplane. Multi-Agent Systems are mostly used in AI modelling. Nonetheless. It is broad, stretching from modelling aircraft arrival to assess risks in ATM, simulate network delay, simulation of air traffic, or simulate all ATM environments. Other AI models focused on more simple tasks, such as modelling a go-around pilot decision with a neural network. Explainability is less required in this category and is already provided to a certain extend.

Nowadays, computer science in ATM plays a major role in data management and decisions making processes. Even if the human remains the main actor, computer science is important. The expectation is, in fact, for the latter, to have a more relevant part in the future with the increasing air traffic (notwithstanding actual COVID-19 situation) [2] and its complexity (notably with the insertion of new aerial vehicles such as drones, e-VTOL into the airspace) [3]. Being one of the most researched topics in computer science, AI should be part of the picture.
Unfortunately, although several research works have already been carried in AI for the ATM domain, it has not been 'fully operational’, nor has it brought any benefits to the end-users.
Slow progress in the use of AI in the ATM domain is explainable because the ATM domain is a binding domain with life at stake, and safety is the top priority.
Historically, safety has been achieved in ATM with human-in-the-loop—in particular, but not restricted to, ATCO—, and will most likely—as contend by the authors—evolve by designing tightly human-centred systems, requiring those systems to be understandable by the end-user, and to adapt to its characteristics—mental and physical—and to its psychological state. For example, if the operator's workload exceeds his/her cognitive capacity, or if incapacitation is occurring, the system could automatically detect his/her cognitive state and use this assessment to execute actions autonomously along an escalating scale of automation (i.e., adaptive automation).
In other domains such as healthcare, criminal justice—among others—, the increasing interest in AI to support high-consequence human decisions has spurred the field of XAI and User-Centric XAI (UCXAI) [4]. This primordial aspect is yet to be fully assessed in ATM, but the interest is growing [5].

Adding the XAI techniques to existing AI algorithms in ATM will make a step forward for more integrations of such techniques into the operators' usual or new task.

2.2 Artificial Intelligence techniques

In the ARTIMATION project, some ground tasks in the ATM domain, such as Take-off Time Prediction and Delay Propagation and Conflict Resolution, must be addressed. Among the vast range of AI/ML algorithms, the two most used algorithms, Artificial Neural Networks (ANN) and Random Forest (RF), are considered for the ATM tasks in this project based on the works completed in Deliverable 3.1 [1]. ANN is considered as a black box that lacks transparency. It is opaque by nature. Whereas RF is transparent, but the explanation is absent. An explanation will be added for both algorithms. EuroControl provided the dataset as the External Advisory Board (EAB) and suggested addressing the issue of explanation for delay propagation.

Furthermore, we will address the lifelong ML approach to achieve continual learning of new tasks. Another issue that is considered while selecting the task is the availability of data. ATM task such as optimize capacity is suggested as a higher priority during the workshop on T3.2 which is further stated in Chapter 3 of this document. Yet, due to the lack of data and time constraint of the ARTIMATION, the task could not be considered. Instead, conflict resolution, the second most prioritized task that came out as the workshop's outcome, is regarded based on the data availability.

2.2.1 Algorithms for classification and prediction Tasks

Artificial Neural network (ANN): An ANN is an AI algorithm designed to act like a human brain. It is a simple but vital part of artificial intelligence operations and is prevalent in our day-to-day lives. A complex definition would be that an ANN is a computational model with a network architecture made up of artificial neurons. This structure has specific parameters through which one can modify it for performing certain tasks. They have extensive approximation properties. This means they can approximate a function to any level of accuracy irrespective of its dimension. ANN finds extensive applications in areas where traditional computers do not fare too well.

Considering the ATM domain, ANN has been deployed in many tasks such as prediction, optimization, analysis, and simulation. Several ATM tasks related to prediction such as runway configuration [6], aircraft climb [7], aircraft descent length [8], aircraft phase of flight [9], take-off time [10] [11], sector configuration transitions [12], airport capacity [13], modelling for decision making [13], and prediction of the propagation of trajectory uncertainty [15] have been conducted using ANN.

Again, other ATM tasks such as optimization tasks for aircraft landing [16] and free air-space [17], analysis tasks such as pilot decision making [14], controller action [18], trajectory clustering [19], context-aware speech recognition, and understanding system for air traffic control [20] and simulation tasks [17] have been performed with ANN. Deep learning ANN such as Deep Deterministic Policy Gradient (DDPG) model [21] for conflict detection and Deep Q-Network (DQN) [22] for aircraft sequencing and separation have been developed.

Advantages in using an ANN:

1) Neural networks are flexible and can be used for both regression and classification problems. Any numeric data can be used in the model because a neural network is a mathematical model with approximation functions
2) Neural networks are suitable to model with non-linear data and many inputs. It is reliable in an approach of tasks involving many features. It works by splitting the problem of classification into a layered network of simpler elements
3) Once trained, the predictions are fast
4) Neural networks can be trained with any number of inputs and layers
5) Neural networks work best with more data points

Disadvantages in using an ANN:

1) Neural networks are black boxes, meaning we cannot know how much each independent variable is influencing the dependent variables
2) It is computationally costly and time-consuming to train with traditional CPUs
3) Neural networks depend a lot on training data. This leads to the problem of over-fitting and generalization. The mode relies more on the training data and may be tuned to the data

Risks associated with the ANN:

1) The data sets are only for two years. It could be good to have datasets for several years
2) Neural networks are “slow” for many reasons, including load/store latency, shuffling data in and out of the GPU pipeline, the limited width of the pipeline in the GPU, the unnecessary extra precision in most neural network calculations, the sparsity of input data and many other factors

Random Forest (RF)*:* It is another most popular ML model used in various tasks related to ATM. RF is a flexible, easy-to-use ML algorithm that produces a great result most of the time. It is also one of the most used algorithms because of its simplicity and diversity.

RF is one of the ensemble methods for supervised learning, developed with several binary decision trees; thus, it is called "forest." Here, the target value is predicted based on the results from several different trees. During the classification or regression, the decision is made at each level of the trees depending on the values of different features. For the two different tasks, i.e., classification and prediction, the model's outcome are determined by voting or averaging the individual outcome of the trees, respectively.

Considering ATM tasks, RF has deployed mainly in prediction tasks such as taxi-speed prediction [23], aircraft landing time prediction [24], aircraft trajectory predictions [25], pre-tactical route prediction [26], and so on.

Advantages in using the RF:

1) RF minimizes the effect of overfitting in decision trees and increases accuracy
2) It can be deployed for both regression and classification tasks
3) Categorical and numerical values can be processed in the training of RF
4) Missing values in the training set are well handled in RF
5) As RF is a rule-based methodology, the training dataset is not required to be normalized

Disadvantages in using the RF:

1) Training RF requires increased computation power and memory because of its nature of developing many decision trees and combining their outcomes
2) The execution time for training a RF is also high due to the reason described in (1)
3) RF is an Ensemble Technique that makes it less interpretable to point out the significant features for prediction or classification

Risks associated with the RF:

1) Increased time and space complexity
2) Less interpretable model because of ensemble nature

RF Key Performance Indicators (KPI)

1) At least two ML algorithms will be considered with a focus on transparency and accuracy
2) At least two years (2019 and 2020) datasets will be considered and with total samples 7M
3) One synthetic dataset will be considered
4) The Module should reduce 30% of the take-off time prediction errors

The expected deadline for the Artificial Neural Network and the Random Forest has been set for October 2021. For more details, see Figure 21. The roadmap.

2.2.2 Lifelong machine learning

In machine learning, a ML model is built by training it on a given dataset. Subsequently the model is made to run on tasks like prediction, classification, or clustering on a new dataset. Commonly, a classifier built in one domain works poorly in another domain. Hence, a classifier built with some training dataset often fails to perform well when the same learning algorithm is trained with a new training dataset. Furthermore, it needs to go through the ML training process again to update the model with a new dataset. Append all the previous training datasets, it is computationally expensive, and there may be other issues such as redundant information that can increase false-positive rates. Thus, the idea of lifelong ML is to use the previously learned knowledge during the training with a new dataset and keep continuously learning.

Continual Neural Networks (CNN): In recent years, a lifelong ML approach called continual learning is popularized for neural networks and deep learning in the machine learning research community. Neural networks built using multi-layer perceptron (MLP) architecture suffer from catastrophic forgetting, (i.e., an existing model forgets all the trained information when training is done with a new training dataset). This fact can degrade the performance of the models learned for the earlier tasks. *Continual learning* is an incremental learning approach that solves the catastrophic forgetting problem. In the ARTIMATION project, algorithms such as "Learning without Forgetting", and "Progressive Neural Network" [35] (also, see details in D3.1 [1]) will be implemented. The goal is to identify the best algorithm that is well suitable for the ATM domain.

Advantages in using CNN

1) Continual neural networks can solve the catastrophic forgetting problem (i.e., the model can retain knowledge from previous learning)
2) Has the flexibility of considering various task relationships
3) There exist some frameworks of "Learning without Forgetting" and "Progressive Neural Network" that can be used in the project

4) Evaluation framework also exists for "Learning without Forgetting" and "Progressive Neural Network"

Disadvantages in using CNN

1) Parameters can explode with an increasing number of tasks
2) Methods are trained using a benchmark dataset. Hence, performance may not vary with the real dataset from the ATM domain
3) Metaknowledge extraction may not be possible
4) Requires previous task data

***Evolutionary RF learning*:** Minimal works in lifelong ML have been done for algorithms other than neural networks. In this project, the objective is to develop a lifelong ML algorithm for RF. Here, Evolutionary algorithms will be incorporated with RF such that RF will continually learn from one generation to the next generation.

Advantages in using Evolutionary RF learning

1) It is possible to extract meta knowledge through feature selection by both feature importance and features' evaluation
2) New representation for lifelong ML
3) Meta-learning and learning new tasks with small training samples
4) Data perturbation and multi-modal learning is possible

Disadvantages in using Evolutionary RF learning

1) Need to define a suitable objective function for learning
2) Slow for joint training
3) There is no existing framework

Risks associated with Evolutionary RF learning

1) Several iterations may require getting a satisfactory performance
2) Time constraint may be an issue since it is a young search area in ML

Evolutionary RF learning KPI

1) A lifelong machine learning approach will be developed for at least 2 AI algorithms.
2) The approach will be tested on at least two years' datasets.

The expected deadline for the Continual Neural Network has been set for February 2022 and the one for the Evolutionary RF learning for April 2022. For more details, see Figure 21. The roadmap.

2.3 Explainability techniques

The techniques of adding explanations to intelligent systems developed with Artificial Intelligence (AI) is comparatively contemporary to the algorithms/methods of AI and mostly addressed with the concept of Explainable Artificial Intelligence (XAI). The term Explainability affiliates the interface between humans and decision-makers, which is concurrently comprehensible to humans and accurate representation of the decision-maker [27]. In XAI, explainability is the interface between the models and the end-users through which an end-user gets clarification on the decisions he/she gets from an AI/ML model. The AI/ML models learn the underlying characteristics of the available data and subsequently try to classify, predict, or cluster new data. The stage of explainability refers to the period in the decision-making process when a model generates the explanation for the decision it provides. The stages are found to be either along the inference mechanism or after the inference mechanism, precisely, ante-hoc and post-hoc [28]. Depending on the stages of explainability and selected AI/ML algorithms, (i.e., ANN and RF), three different methods of adding explanation are considered. The methods are: Adaptive Neuro-Fuzzy Inference System (ANFIS); Local Interpretable Model-Agnostic Explanations (LIME); Shapley Additive Explanations (SHAP). Comparative aspects based on the advantages and disadvantages of the methods are presented in Table 1.

Table 1. Advantages and disadvantages of different XAI methods.

XAI Methods	Advantages	Disadvantages
ANFIS	• ANFIS is considered as one of the best trade-offs between fuzzy systems and neural networks. • It is a combination of ANN and Fuzzy inference system to find out correlating input and output through mathematical algorithm and modelling.	• ANFIS utilizes higher memory and computation power while translating prior knowledge into the network topology.
LIME	• LIME learns the working mechanism of any black-box model for each of the samples. • Simple implementation with Python library for model explainability. • It is comparatively faster than the other available methods for explainability.	• It can only produce at local level, i.e., for some specific decisions only. • Unable to generate explanation on the inference mechanism of the whole model.
SHAP	• SHAP exploits all possible predictions for an instance using all possible combination of inputs. • Due to the exhaustive nature, it provides guaranteed consistency and local accuracy in addition to explaining the whole model. • Implementation is simple with Python library.	• SHAP is still not optimized for all types of ML models. • It takes longer time to calculate the Shapley values for each of the features.

The prime reason of adding explanation to prediction, optimization/automation, analysis, modelling/simulation tasks in the domain of ATM is to increase trust of humans on the decision-making process of the AI/ML models and improve human decisions or predictions based on the models [29]. Moreover, people are not rational, and their decisions are often driven by the biases and heuristics [30]. However, abundant relevant information also does not necessarily assist people to making proper decisions. In human decision-making for the stated dimensions the heuristics and biases are mostly controlled by statistical constraints [31]. Regardless of the domain expertise, people generally cannot produce fully optimal decisions [32]. On the contrary, XAI can be beneficial to human decision-making by increasing the trust on the automated systems. This can be investigated through human experiments testing AI systems with explanations compared with traditional AI systems alone for different dimensions of the design space.

Risk associated with different XAI methods

1) The level of understanding varies from user to user. Some explanations might be misinterpreted by the users depending on their level of expertise.
2) As the metrics for evaluating the explanations and the methods of generating them are not properly established, irrelevant explanations might be produced for models and their decisions.

Different XAI methods KPI

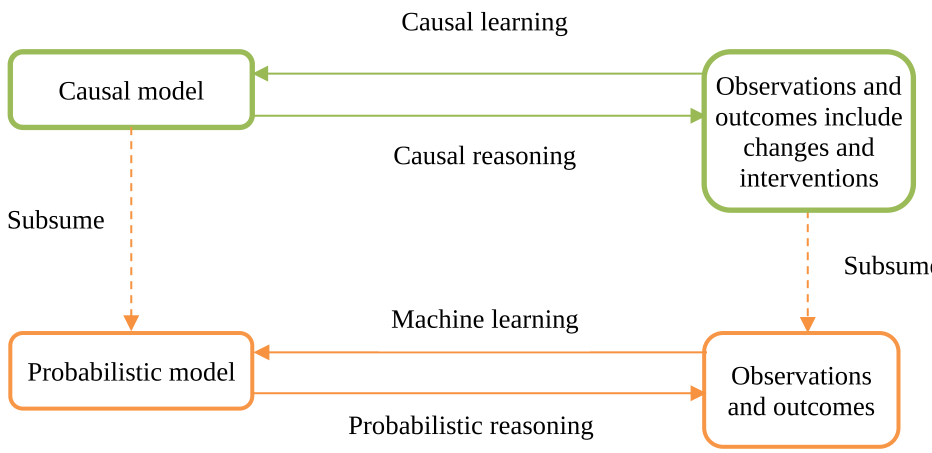
1) At least 3 XAI algorithms will be considered one with innovation and two existing to compare.
2) Increase Transparency and explainability by 5-10%.

The expected deadline for LIME has been set for December 2021. Instead, the expected deadline for the SHAD and the ANFIS has been set for February 2022. For more details, Figure 21: The Roadmap.

2.3.1 Causality within explainability

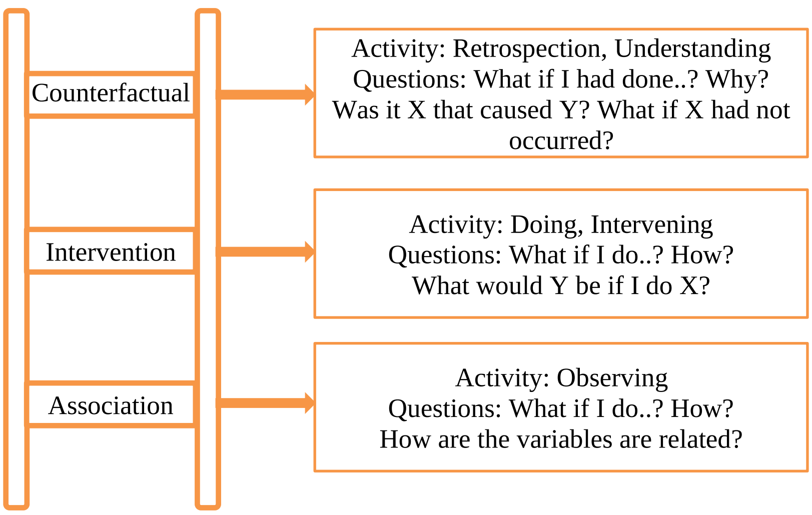
In this project, **Structural Causal Model (SCM**) is considered to infer and integrate causality within the ML models. The SCM involves a probability model with additional information not contained in traditional machine learning models. Like the probability theory, causal reasoning is the process of obtaining conclusions from a causal model about the outcomes of random experiments. The additional information of SCM allows analysing the effect of the intervention, i.e., changes in the data distribution. ML has purely empirical implications on observational data; on the other hand, SCM provides the necessary condition for including data under interventions. Figure 1 shows the structural difference between traditional machine learning and causal inference problems.

Figure 1. Structural difference between machine learning and Causal learning adapted from [33]



In general, SCMs are usually transparent. The SCM consists of three components, which Judea Pearl in his book [34] referred to as "The Ladder of Causation", (Figure 2). These three components are *association*, *intervention*, and *counterfactuals*. Machine learning models capture the first rung of the ladder (i.e., association) from the data or observations. Given observation $(x_1, y_1), \dots \dots, (x_n, y_n)$ where $x_i \in X$ are inputs variables and $y_i \in Y$ are outputs and each $(x_i, y_i) = 1, \dots \dots, n$ has been generated independently by the same unknown random experiment. The goal in ML is to find a function $f\colon X \to Y$ that can approximate the solution of f with minimum errors.

Figure 2. The ladder of causation adapted from [34]



The second rung of the ladder of causal is the intervention that involves the association between input and output variables and can help identify how the decision can vary under perturbation. The top rung of the ladder of causation is the counterfactuals. Counterfactuals allow making possible modifications of an SCM by changing all its noise distributions. Thus, we can hypothesize what would have happened if variable X had been treated differently.

Counterfactual questions provide the answer to the questions, for instance, “was its X that caused Y?” and “What if X had not occurred.”

Advantages in using SCM

1) SCM is transparent and can increase the transparency of an ML model and its decision
2) Easy to develop for a linear model
3) SCM can provide quantitative measures for causal inference
4) Exiting framework can be used to construct the SCM for the ATM domain
5) SCM can help in lifelong ML development
6) SCM can help to determine the types of data enhancement that would improve ML models

Disadvantages in using SCM

1) It Does not work if too many hidden variables do not exist or cannot be extracted from the dataset
2) Non-linear model is hard to construct
3) It requires good domain knowledge to construct counterfactual questions

Risk associated with SCM

1) Dataset may be inadequate for SCM
2) Defining appropriate counterfactual questions

SCM KPI

1) At least one approach will be used for causality
2) Increase the transparency of the AI model by 5-10% using causality

The expected deadline for the SCM has been set for May 2022. For more details, see Figure 13: Roadmap.

2.4 Visualisation techniques

Different visualisation techniques are envisaged to open algorithm black boxes and leverage user ability to better understand how algorithms operate and fine-tune them for better performances.

The problem will be tackled from different angles, i.e., using different visualisation techniques, each presenting advantages that may overcome the disadvantages of the others. Those techniques can be regrouped into the two following categories:

- ‘Static’ Visual Analytics: techniques allow a global view of the whole system or behaviour.
- Interactive Visual Analytics: techniques that allow the end-user to interact with the data and adequately understand it.

The techniques envisaged are presented in the following through the lens of these categories.

2.4.1 'Static' Visual Analytic

Visualisation techniques highly depend on the data being visualised, as the visualisation technique tries to emphasize traits inherent to the data nature, or on the contrary, to overcome the lack in it. The envisaged data is of two types: multivariate data; time and/or geographical dependent data.

Geographical and/or time-dependent data

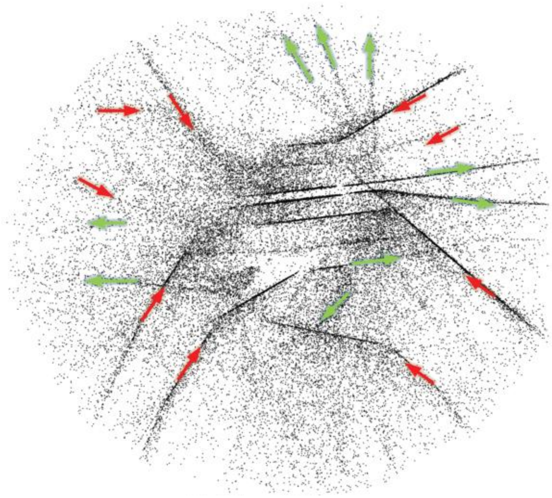
Geographical and/or time-dependent data will come from two different sources into the scope of the ARTIMATION project:

- Most of the input data of the AI algorithm the consortium focuses on during this project is highly time-dependent (e.g., regulations, departure time), geographical dependent (e.g., LFBO airport), and most of the time, time and geographical dependent (e.g., trajectories).
- Many AI algorithms process data by steps (e.g., generations of Genetic Algorithms), which can be seen as time-dependent data.

Particle visualisation

Particle visualisation is the representation of time-dependent data as animated moving particles (Figure 3).

Figure 3. Particle visualisation of trajectory data.



Advantages in using particle visualisation

1) Helps to show flows directions
2) Helps to have a better understanding of the dynamic of the data
3) Help to decrease the cluttering of showing every edge

Disadvantages in using particle visualisation

1) Creates visual interferences when too dense information
2) Is applicable only to flow data, i.e., geographical and/or time dependent data.

Risk associated with particle visualisation

1) Scalability issue.

Particle visualisation KPI

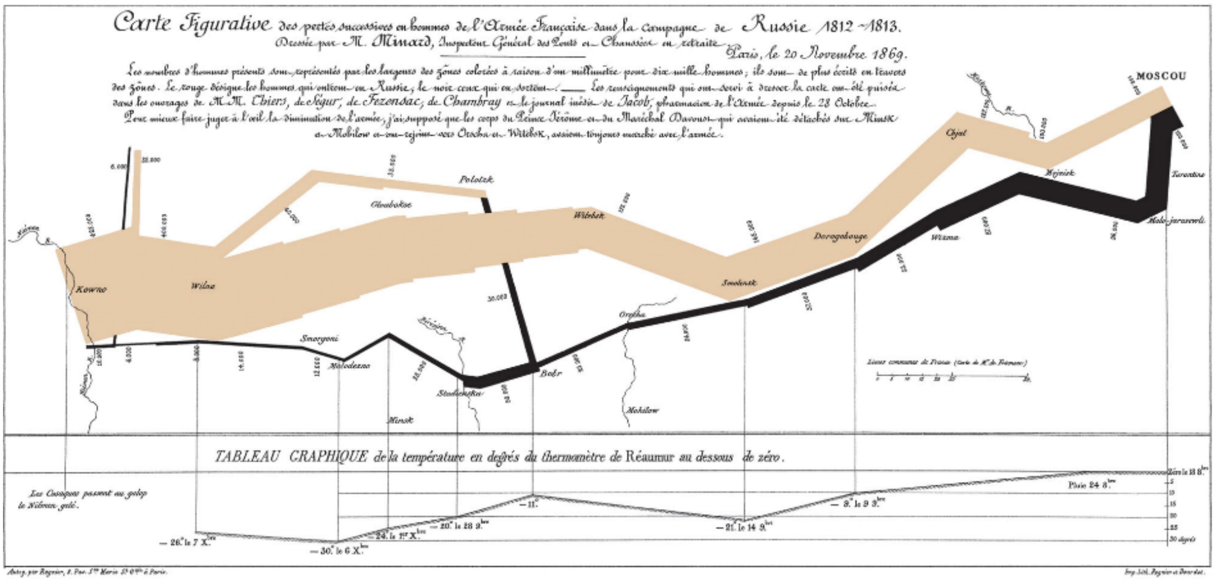
1) This visualisation technique will be applied to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories.

The expected deadline for the Particle Visualisation has been set for April 2022. For more details, see Figure 21. The roadmap.

Sankey Diagram/ Alluvial Diagram

Sankey Diagram/ Alluvial Diagram is a type of flow diagram in which the width of the arrows is proportional to the flow represented (Figure 4).

Figure 4. Sankey Diagram of time and geographical dependent data. The diagram represents the successive losses in men of the French army in the Russian campaign 1812-1813 established in 1869 by Minar.



Advantages in using Sankey Diagram/ Alluvial Diagram

1) It simplifies too dense information
2) It helps to show flows directions, taking advantages of the visual representation
3) It is possible to make significant flows/ factors stand out with it

Disadvantages in using Sankey Diagram/ Alluvial Diagram

1) It can make it difficult to differentiate when flows have similar widths
2) Applicable only to flow data, i.e., geographical and time dependent data

Sankey Diagram/ Alluvial Diagram KPI

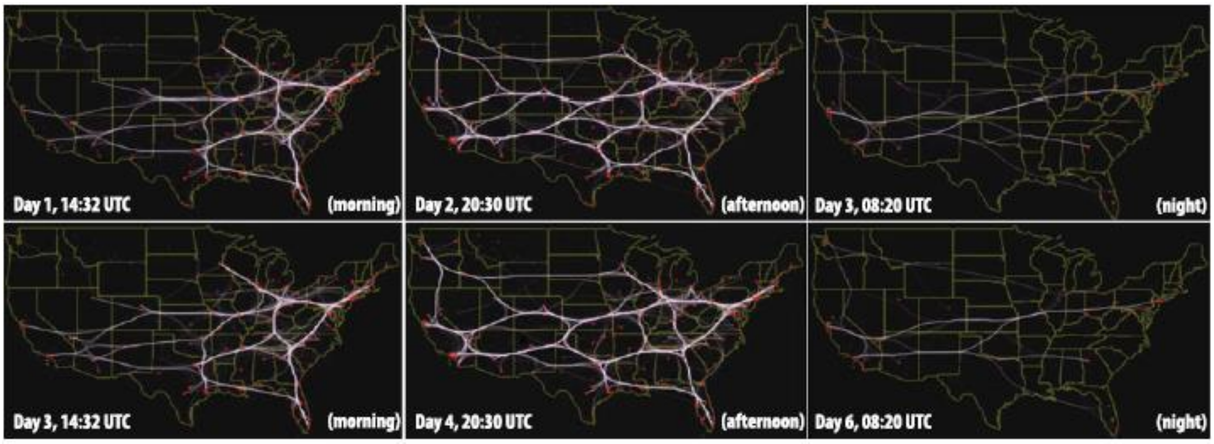
1) This visualisation technique will be applied to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories

The expected deadline for the Sankey Diagram/ Alluvial Diagram has been set for October 2021. For more details, see Figure 21. The roadmap.

Edge Bundling

Edge Bundling is a visualisation technique that bundle the adjacency edges together to decrease the clutter usually observed in complex networks (Figure 5).

Figure 5. Multiple Edge Bundling of trajectories over the USA airspace.



Advantages in using Edge bundling

1) It removes visual complexity of several edges crossing and interfering with one another
2) Help to show trends in data.

Disadvantages in using Edge bundling

1) That it can infer strong distortion with the data

Risk associated with Edge bundling

1) Long implementation time

Edge bundling KPI

1) This visualisation technique will be applied to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories.

The expected deadline for the Edge bundling has been set for January 2022. For more details, see Figure 21. The roadmap.

Multivariate data

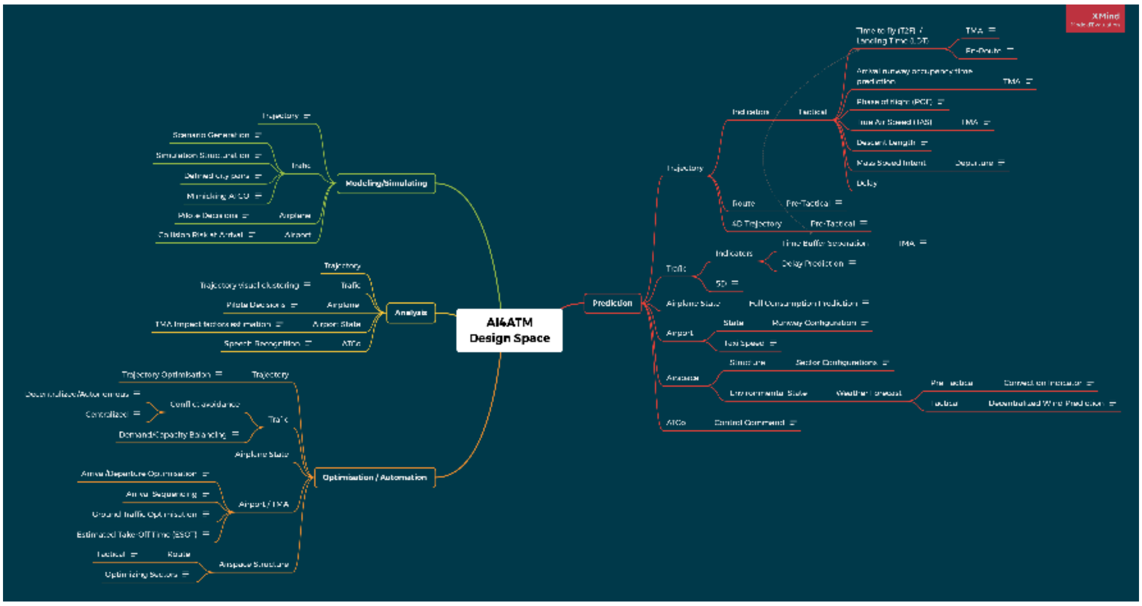
Multivariate data will come from two different sources into the scope of the ARTIMATION project:

- Some of the input data of the AI algorithm the consortium focuses on during this project will be processed multivariate data, mostly numerous features for prediction algorithm.
- Many AI algorithm internal processed data is multivariate, must it be the different optimisation criteria, or the multivariate data from the different layers of an ANN.

Visual Mapping

Visual Mapping allows to visually represent and follow the associative path of thought, or concepts (Figure 6).

Figure 6. Visual mapping of AI in ATM design space



Advantages in using visual mapping

1) It helps understand complex information with a visual representation
2) It allows to identify relationships among the different data and information
3) It allows to categorize and organize the data

Disadvantages in using visual mapping

1) Requires high user expertise to be fully useful

Risk associated with visual mapping

1) Requires meaning full information to show

Visual mapping KPI

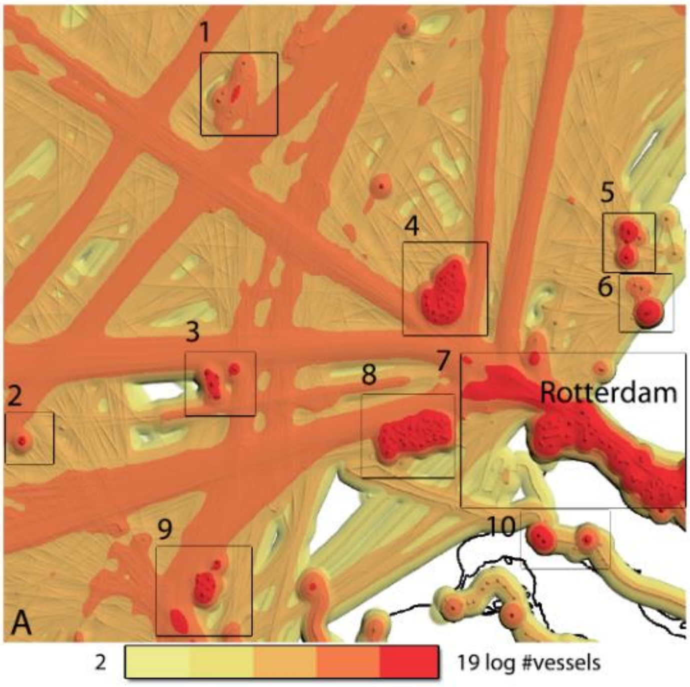
1) This visualisation technique will be applied to explain the internal process of an AI algorithm

The expected deadline for the Visual Mapping has been set for May 2022. For more details, see Figure 21. The roadmap.

Density map visualisation

Density map is a graphical representation of statistical data that maps the intensity of a variable quantity to a range of tones or a colour chart on a two-dimensional matrix (Figure 7)

Figure 7. Density map of vessels in Rotterdam port [36]



Advantages in using density map visualisation

1) The technique is showing ecological data density perception

Disadvantages in using density map visualisation

1) The technique is giving limited XAI
2) The technique is losing any information on the flow direction to only show the density

Risk associated with density map visualisation

1) This technique has an important computation time

Density map visualisation KPI

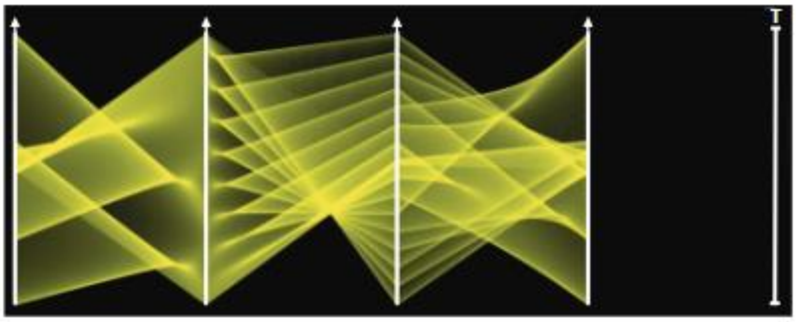
2) This visualisation technique will be applied to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories.

The expected deadline for the Density map visualisation has been set for April 2022. For more details, see Figure 21. The roadmap.

Parallel coordinate / Parallel Set

Visual representation of n-dimensional data as a polyline with vertices on parallel axes representing the dimensions (Figure 8).

Figure 8. Parallel coordinates [37]



Advantages in using Parallel coordinate / Parallel Set

1) It allows to represent high dimensional data as a 2-dimensional visualisation
2) It allows to perceive the trend shown by data entries from the visualisation

Disadvantages in using Parallel coordinate / Parallel Set

1) Can become over-cluttered and therefore, illegible when they're very data-dense
2) Does not work with high dimensional data.

Parallel coordinate / Parallel Set KPI

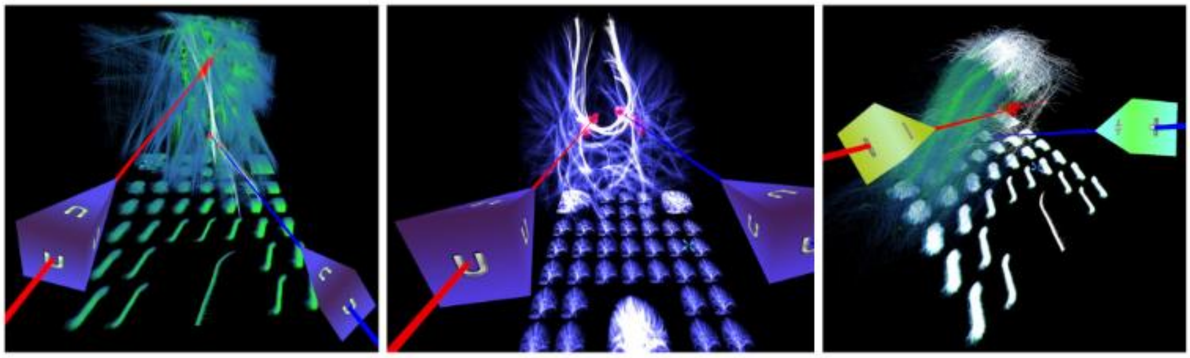
1) One application to visualise the process of an AI algorithm to optimise trajectories to avoid conflicts

The expected deadline for the Parallel coordinate / Parallel Set has been set for January 2022. For more details, see Figure 21. The roadmap.

Virtual Reality

Virtual reality (VR) simulates the physical presence of a user in an artificially generated environment by software [38].

Figure 9. Immersive multidimensional visualization system (FiberClay)



Advantages in using VR

1) This technique increases user knowledge and information, notably using the depth
2) VR can trigger human's instinct to think about and process data in multiple dimensions.

Disadvantages in using VR

1) Requires a specific device, and
2) The user to switch of device.

Risk associated with VR

1) The major risk of using this technique is its complex implementation.

VR KPI

1) This technique will be used with the Sankey diagram visualisation in VR to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories.

The expected deadline for the Virtual Reality has been set for February 2022. For more details, see Figure 21. The roadmap.

Augmented reality

Augmented reality (AR) is the superimposition of reality and elements (sounds, 2D or 3D images, videos, etc.) calculated by a computer system in real time. (Figure 10)

Figure 10. (STREAM) Immersive data analytic with Augmented Reality [39]

Advantages in using VR

1) This technique presents the following advantages of using original world devices with augmented information (contrary to VR)

Disadvantages in using VR

1) It presents the disadvantage of needing a specific device.

Risk associated with VR

1) The major risk of using this technique is its complex implementation

AR KPI

1) This technique will be used with the particle visualisation in VR to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories

The expected deadline for the Augmented Reality has been set for March 2022. For more details, see Figure 21. The roadmap.

Animated transition

Animated transition allows to visualise the transition between two (or more) distinct data representation.

Advantages in using animated transition

1) Help a user to link visualisations by a smooth transition between each other’s

Disadvantages in using animated transition

1) user can get lost with too many animated items

Risk associated animated transition

1) The risk when creating animated transition is the complex implementation

Animated transition KPI

1) Animated transition will be implemented between at least to two representations

The expected deadline for the Animated transition has been set for May 2022. For more details, see Figure 21. The roadmap.

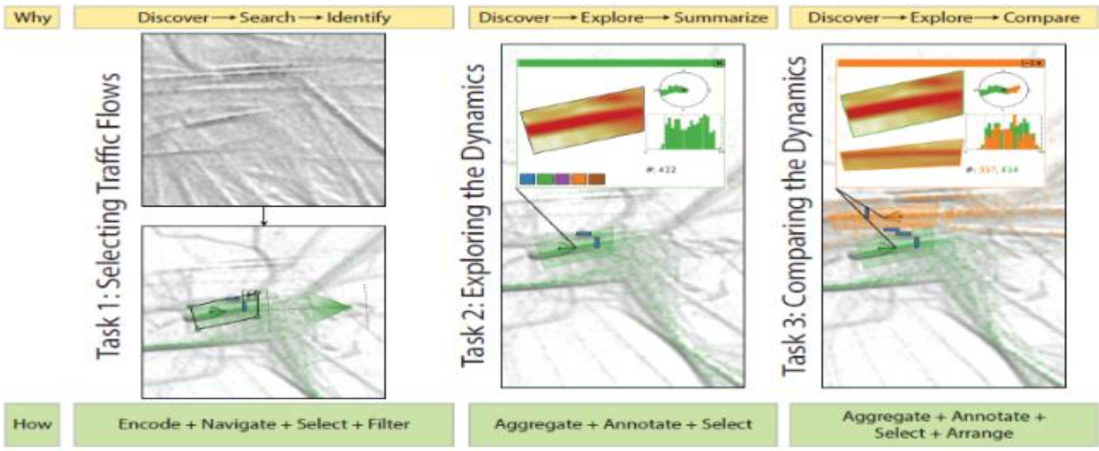
2.4.2 Interactive Visual Analytics

Interactive visual analytic is a good way to enhance knowledge of the user and will be used in addition to 'Static' visualisations.

Focus plus context technique

Focus plus context technique allows to see the object of primary interest presented in full detail while at the same time getting an overview available (**Error! Reference source not found.**) [40].

Figure 11. Focus plus context on vessels trajectory in Rotterdam port. A user can select vessels based on the angle of their movement and selection zone (left), see in detail some metrics (middle) and compare it with another selection (right).



Advantages in using focus plus context

1) This technique has the advantage of showing multiple information with different perspective

Disadvantages in using focus plus context

1) But it has the disadvantages of potentially create a lot a visual interference

Risk associated with focus plus context

1) The risk of this technique is the implementation time of various representations

Focus plus context KPI

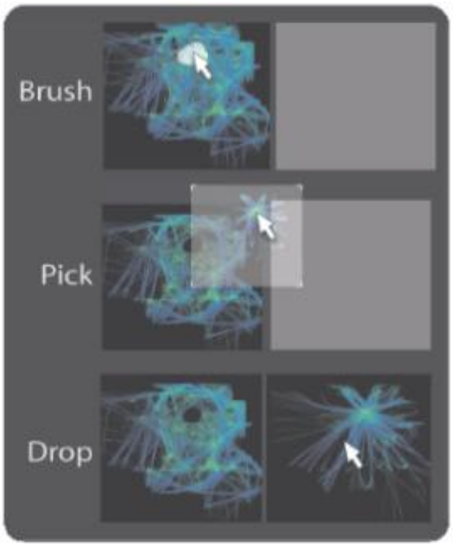
1) This technique will be used to interact with at least one visualisation techniques explaining the internal behaviour of one AI system, or its solution

The expected deadline for the Focus plus context has been set for December 2021.For more details, see Figure 21. The roadmap.

Brushing and Linking

This technique allows a user to select data from the dataset and isolate it into another view or by creating a separate dataset in the same view (**Error! Reference source not found.**). This selection can be recursive, refining more and more the dataset into a tree of sub views/sub dataset [41].

Figure 12. Brushing and Linking: Selection and isolation of aircraft trajectories into sub views to better understand a subset of the data.



Advantages in using Brushing and Linking

1) This technique has the advantage of allowing the end user to explore multidimensional data by navigating from a general level down to the next, and
2) To search through the representations, he wants

Disadvantages in using Brushing and Linking

1) But it also has the disadvantage of potentially multiplying the computation time by the number of visualisations

Risk associated with Brushing and Linking

1) The risk of this technique is the implementation time of various representations

Brushing and Linking KPI

1) This visualisation technique will be applied to explain the optimisation process of trajectories to avoid conflict of an AI algorithm on different set of trajectories, by linking different visualisations

The expected deadline for the Brushing and Linking has been set for November 2021. For more details, see Figure 21. The roadmap.

3 Methodology for tasks identification and roadmap definition

Two workshops have been carried out to identify the tasks that could be supported by the AI, XAI and visualisation solution:

- In workshop T3.2 the tasks to be supported by AI solutions have been prioritised with the involvement of external participants
- In workshop T3.3 the tasks and specific AI, XAI and visualisation solutions have been selected with the involvement of internal participants. Subsequently the Project Roadmap has been developed

3.1 Workshop on T3.2

The T3.2 workshop has been planned to identify potential ATM tasks supported by AI algorithms developed within the ARTIMATION project. For this purpose, ATM experts, students from ENAC, representatives from EUROCONTROL, ENAC, MDH, University of Rome "La Sapienza", together with members of the Advisory board of other relevant SESAR projects (i.e., MAHALO, AISA, SAFELAND) have been involved and interviewed singularly and together during this workshop. This workshop has also identified the specific ATM segments were to apply such AI algorithms (e.g., airport operations, approach, en-route, tower). This activity took place on 6th July 2021.

3.1.1 Scope of the Workshop

The main objective of the T3.2 workshop was to identify potential ATM tasks to be supported by AI algorithms, resulting in a prioritized list of tasks to be supported by AI for different sectors and operations. Quantification of the expected enablers and barriers for XAI have also been among the outcomes of the workshop, together with a collection of use-case (stories) and scenarios to be considered for the validation activities of the ARTIMATION algorithms.

3.1.2 Organization of the Workshop T3.2

To achieve the T3.2 goals, the workshop was developed using the collaborative platform miro.com.

Due to the number of participants, four different virtual tables were structured to allow every participant to contribute differently to the same steps.

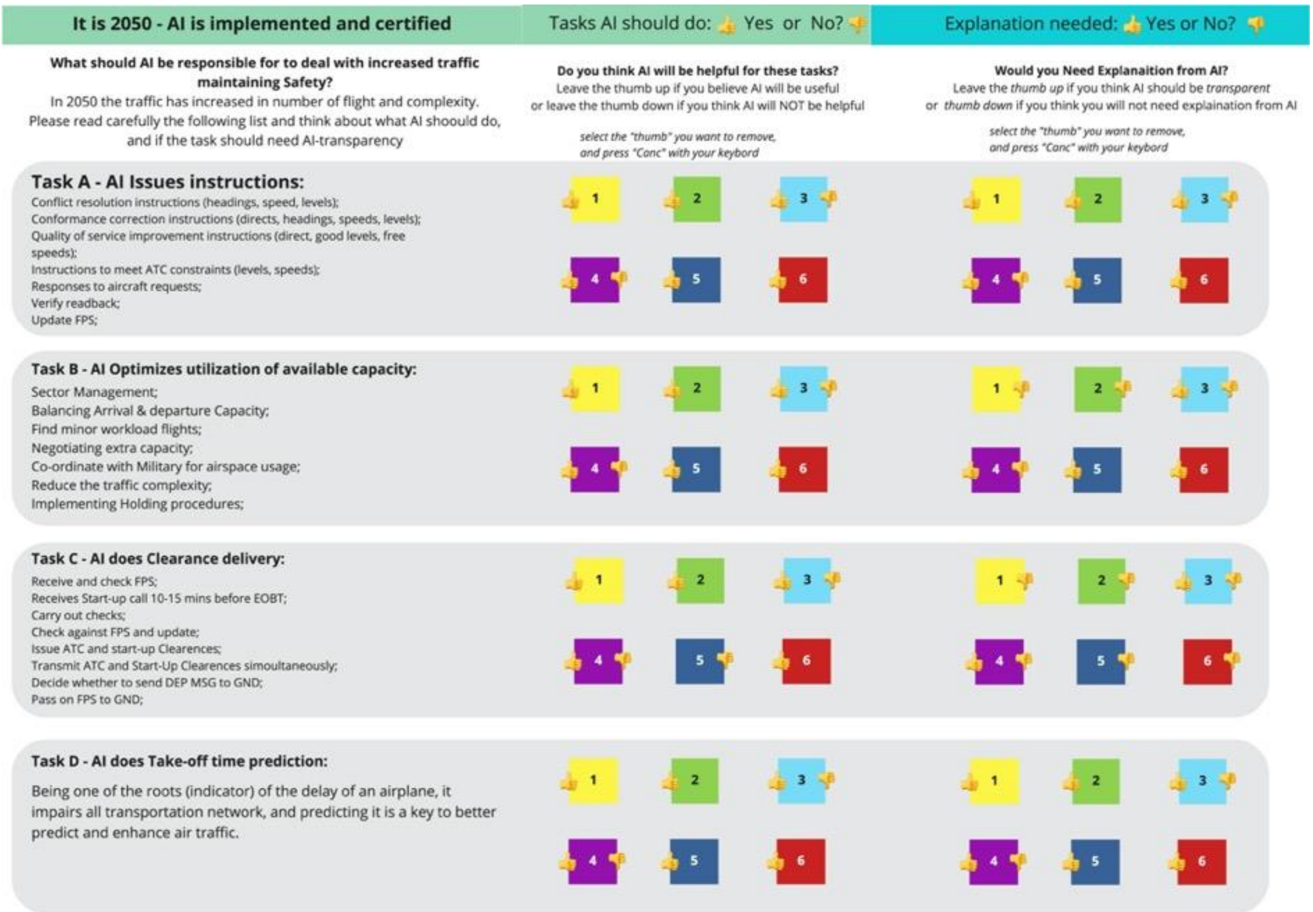
The participants were recruited by direct invitation through emails to ARTIMATION Advisory Board members and a Google Form published on officials ARTIMATION's Twitter and LinkedIn accounts and on the official ARTIMATION website.

The Miro Board was structured to answer simple questions with complex implications: which ATM tasks should be supported by AI? How transparent should the AI be to humans?

After a first brief familiarization with MIRO, in which participants had to write their full name, country, job titles, company, and years of experience, participants started the workshop divided into five steps.

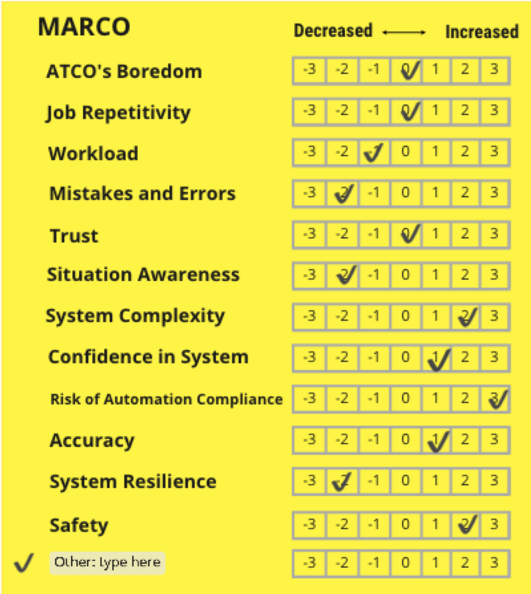
During the first step, four different ATM Tasks were presented (Issue instructions, Optimize utilization of available capacity, Clearance delivery, Take-off time prediction).
Participants were asked to leave a thumb up if they thought that the task would need AI and explainability, or a thumb down if not (Figure 13).

Figure 13. Step 1: Tasks



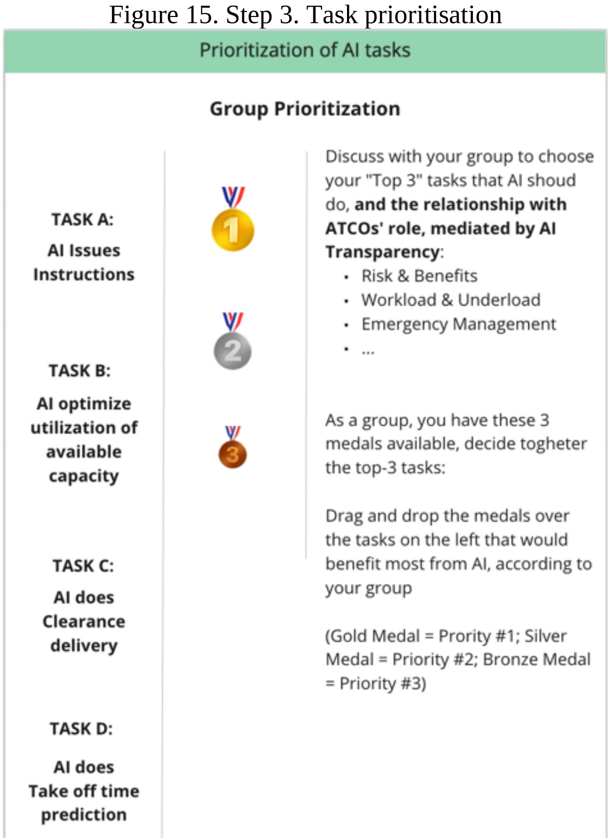
The second step involved expressing a rationale for the decisions taken in step 1. Participants were asked to imagine if AI were implemented in the previous tasks, and express what, in their opinion, would be the impact on ATCO's boredom, job repetitively, workload, mistakes, and errors, trust, situation awareness, system complexity, confidence in the system, risk of automation compliance, accuracy, system resilience, and safety. To express the rationale, participants had to drag and drop a tick along a continuum from -3 (decreased) to +3 (increased) (Figure 14).

Figure 14. Step 2: Impact of AI on ATCO



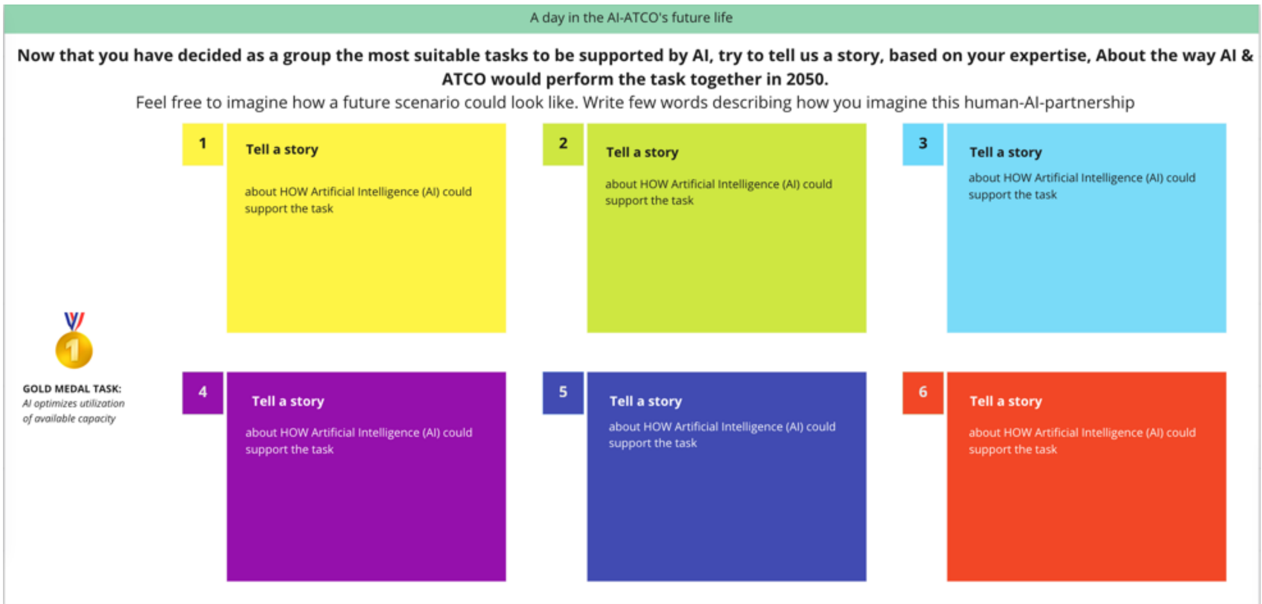
Step 3 involved a small-group discussion in prioritizing the four presented ATM tasks to be helped by AI/XAI, assigning a gold, silver, and bronze medal to the top-3 tasks to be helped (Figure 15).

Figure 15. Step 3. Task prioritisation



The fourth step had the goal to generate some use-cases and scenarios, in the form of stories, about how AI and ATCOs would perform the "winner" task together in 2050.

Figure 16. Step 4. Use cases and scenarios



Finally, the fifth step involved an open plenary discussion in talking about the most suitable task to be supported by AI to see if every table produced the same outcome and if every participant agreed or not. The discussion has been oriented to discuss enablers, barriers, limitations, and positive and negative aspects.

3.1.3 Conduction of the Workshop T3.2

A total of eighteen participants took part in the workshop. The participants and their background will be presented in the following table

Table 2. Participant's workshop T3.2

N	Organization	Job Title	Years of experience	Nation
1	**ENAV**	**ATCO**	**15**	**Italy**
2	**ENAC**	**ATCO (Student)**	**//**	**France**
3	Mälardalen University	Researcher	4	Sweden

4	ENAC	Post Doctorand	4	France
5	Deep Blue	Human Factors Consultant	1.5	Italy
6	**Skyguide**	**Head of Human Factors**	**20**	**Switzerland**
7	**Deutsche Flugsicherung**	**ATM and AI expert**	**20**	**Germany**
8	**EUROCONTROL**	**ATM Expert**	**30**	**France**
9	Deep Blue	Video Editor	1	Italy
10	Mälardalen University	Doctoral Student	3	Sweden
11	Mälardalen University	Senior Lecturer	7	Sweden
12	Sapienza University	Cognitive Neuroscience researcher	11	Italy
13	Sapienza University	Bioengineering researcher	11	Italy
14	Mälardalen University	Research Assistant	1	Sweden
15	**CRIDA A.I.E.**	**ATM R&D Engineer**	**2**	**Spain**
16	ENAC	Professor	20	France
17	ENAC	Researcher	//	France
18	Mälardalen University	Associate Professor	10	Sweden

In bold, the external participants.

The workshop, held on the 6th of July 2021, followed the times planned in the following agenda:

Table 3. Timetable workshop T3.2

N.	Schedule	Topic
0	*9:00*	*Welcome*
1	9:15	Familiarization with ARTIMATION and XAI solutions
2	9:30	Familiarization with Miro
3	9:30	*Workshop kick-off*
4	10:15	Individual exercise: assessing the potential AI help in different ATM tasks
5	*11:00*	Individual exercise: assessing the potential AI impact on different ATM tasks' characteristics
6	11.30	Small group exercise: tasks' guided prioritization
7	12.15	Interactive activity: describing a potential future scenario support on the top priority identified by the group
8	*11.30*	*End of the workshop*

3.2 Workshop on T3.3

This T3.3 workshop aimed at matching the user needs identified in the previous tasks and the available AI solutions. A detailed development roadmap has been defined for the proof of concept of a XAI system supporting ATM functions in predicting air transportation traffic and optimizing traffic flows. In particular, the development roadmap has been focused on two main steps: The first one has investigated novel techniques to support a better understanding of AI model, through the multivariate data analytics based on heterogeneous data sources using multimodal machine learning algorithms. The second step has investigated the lifelong machine learning issue, by putting the "human into the loop". In this regard, passive Brain-Computer Interface technology will be employed, to investigate the implication of different levels of algorithms transparency modalities on the operator's mental and emotional state. The workshop took place on 5th August 2021.

3.2.1 Scope of the Workshop T3.3

This Workshop is part of ARTIMATION's Task 3.3 and is the completion of the Workshop on Task 3.2, aimed at identifying which specific tool/s to develop, which XAI visualisation/s to adopt, and which development pipeline to adopt in the project (covering WP4 and WP5).

3.2.2 Organization of the Workshop T3.3

The T3.3 workshop, as the previous T3.2 workshop, was carried out on the collaborative platform MIRO (miro.com) and was conceived for Consortium members' participation, specifically MDH, ENAC, UNISAP, and DBL. It was set up as follows:

- *Introduction and expected outcomes:* the workshop started with the introduction from UNISAP and DBL of the activities and the display of the expected outcome to align all partners.

- *Presentations:* each partner gave a presentation bringing knowledge and information on each specific subject of competence, in particular:

  - **<u>DBL:</u>**
  - Which task to support in relation to the workshop T3.2 outcomes
  - Which tool to develop to support the identified task/s

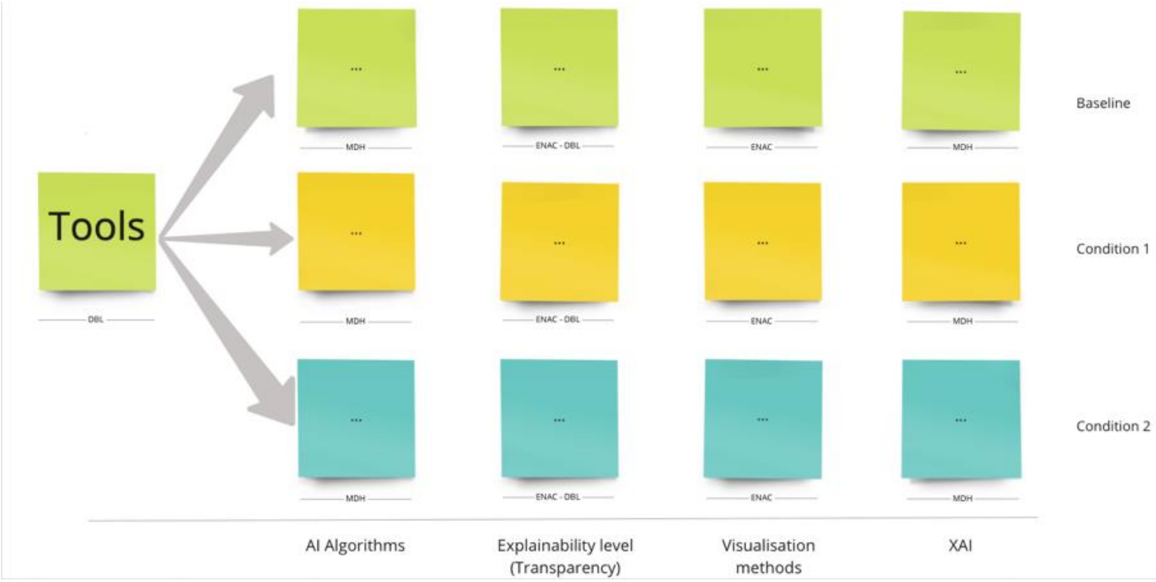
  - **<u>MDH</u>**
  - List of AI algorithms to support the identified tool/s
  - List of explainability methods for the AI algorithms

  - **<u>ENAC</u>**
  - Methods of explainability visualisation for the tool/s
  - List of explainability methods (at different levels)

- *Discussion:* given the presentation from each partner, the next activity, performed in a plenary discussion, was to elect the task to be supported by the AI algorithms, the XAI methods, and the Visualisation techniques, and the consequent tool to be developed. The identification of the tool allowed achieving the next and last step of the workshop (Figure 9).

- *Chains:* it was necessary to establish the level of confidence the tool had to develop. For this reason, chains were created, unifying the different knowledge from the partner. The chains were created as follows:

Figure 17. Chains



3.2.3 Conduction of the Workshop T3.3

The participants and their background will be presented in the following table

Table 4. Participant’s workshop T3.3

N.	Organization	Job Title	Years of experience	Nation
1	UNISAP	Bioengineering researcher	11	Italy
2	DBL	Human factors intern	1	Italy
3	DBL	Human factors intern	1	Italy
4	MDH	Associate Professor	10	Sweden
5	MDH	Senior Lecturer	7	Sweden
6	ENAC	Professor	20	France

The workshop followed the times planned in the following agenda:

Table 5. Timetable workshop T3.3

N.	Schedule	Topic
0	*10:00*	*Welcome*
1	10:15	Introduction and Expected Outcomes
2	10:30	Presentations
3	11:00	Plenary Discussion – Tool decision
4	11:20	Chains – levels of confidence
5	*12:00*	*End of the workshop*

4 Results and Outcomes

4.1 ATM tasks & AI support identification (Task 3.2)

This chapter will summarize the results and outcomes of workshop T3.2. From the results of the workshop the 2 tables elected as “winner task” are **AI issues instruction**, and **AI optimizes available capacity**. Because of the results of step 1 (AI/XAI need), AI optimizes available capacity has been elected as the best task to be supported by AI.

4.1.1 AI Need for ATM Tasks

The workshop's first step involved evaluating AI helpfulness for four different ATM tasks: Task A - Issue instructions (e.g.: Conflict Resolution Instructions, Conformance Correction Instructions...); Task B - Optimize utilization of available capacity (e.g.: Sector Management, Find Minor Workload Flights, Reduce Traffic Complexity...); Task C - clearance delivery (e.g.: Receive and Check FPS, Issue ATC and Start-Up Clearances...); and Task D - take-off time prediction (e.g.: Being one of the roots (indicator) of the delay of an airplane, it impairs all transportation network). 84.4% of the participants answered the yes/no question.

Two tasks obtained 100% yes, namely Task A - Issue instructions and Task D - take-off time prediction.
Task B - Optimize utilization of available capacity, and Task C - Clearance delivery obtained the 86.67% of yes for finding AI helpful to support the ATCOs.

Table 6: Need for AI

ATCOs’ Tasks	Need for AI (Frequency)	Need for AI (Percentage)
Task A - Issue Instructions	15	100%
Task D - Take-Off Time Prediction	15	100%
Task C - Clearance Delivery	13	93%
Task B - Optimise available capacity	13	87%

4.1.2 Level of XAI for ATM Tasks

The workshop's second step involved evaluating XAI's need for four different ATM tasks: Task A - Issue instructions; Task B - Optimize utilization of available capacity; Task C - Clearance delivery; and Task D - take-off time prediction. 83.3% of the participants answered the yes/no question. One task obtained 100% yes, namely Task A - Issue instructions, followed by Task D - take-off time prediction. Task B - optimize utilisation of available capacity obtained 66.67%, yes, and Task C - Clearance delivery obtained 46.67% yes for needing XAI to support the ATCOs. Hereafter the detailed results of the descriptive statistics of the second part of the first step are shown in the following tables.

Table 7: Need for XAI

ATCOs' Tasks	Need for XAI (Frequency)	Need for XAI (Percentage)
Task A - Issue Instructions	15	100%
Task D - Take-Off Time Prediction	11	73%
Task B - Optimise Available Capacity	10	67%
Task C - Clearance Delivery	7	50%

4.1.3 Rationale for XAI

Participants were asked to imagine if AI were implemented in the previous tasks and express what in their opinion would be the impact on ATCO's boredom, job repetitively, workload, mistakes, and errors, trust, situation awareness, system complexity, confidence in the system, risk of automation compliance, accuracy, system resilience, and safety. To express the rationale, participants had to drag and drop a tick along a continuum from -3 (decreased) to +3 (increased).

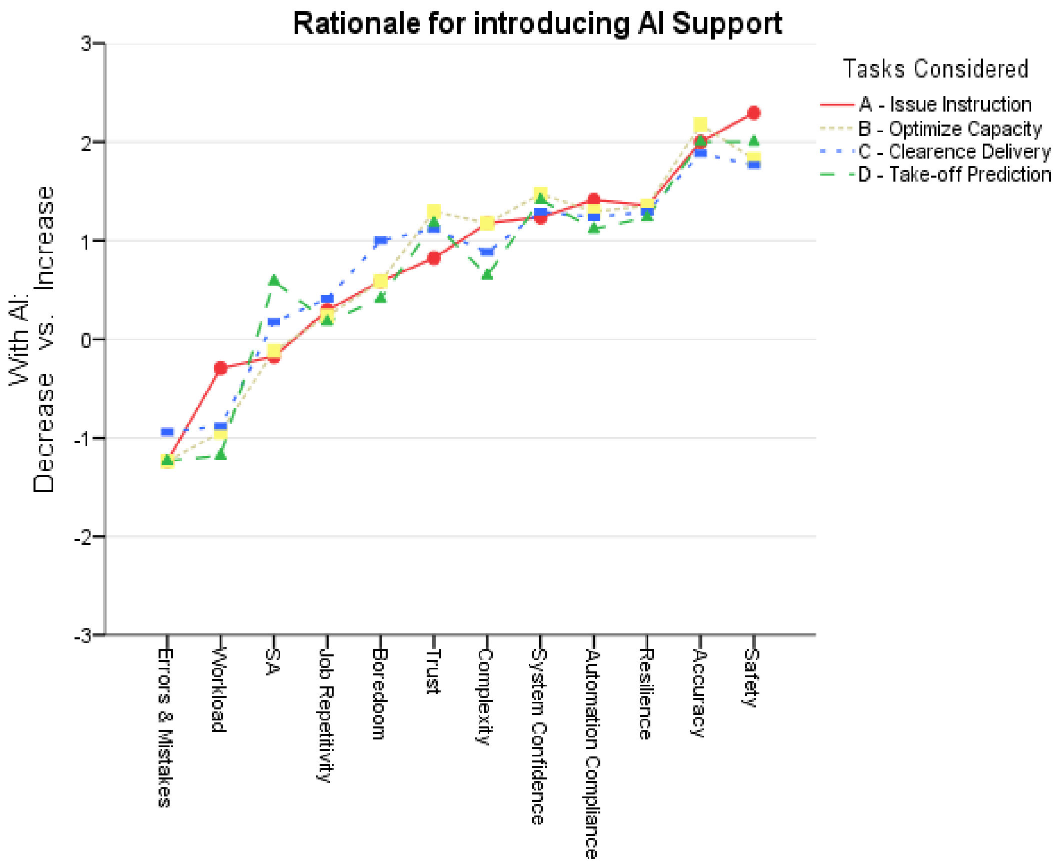
From the results (Figure 10), it emerged that for every ATCOs task, there were pros and cons. As far as Task A - Issue instructions are concerned, the main pros were increased accuracy and safety, while the most rated con was the situation awareness.

For Task B - Optimize available capacity, the rationale showed us that the primary pro was about an increased accuracy, while the main con was related to an increased risk of automation compliance.

The rationale of Task C: Clearance delivery highlighted how the main pro concerned an increased safety, while the main cons were increased ATCOs boredom and risk of automation compliance.

Finally, Task D - Take-off time prediction showed that the main pros were about safety and accuracy, while the main con was about an increased risk of automation compliance.

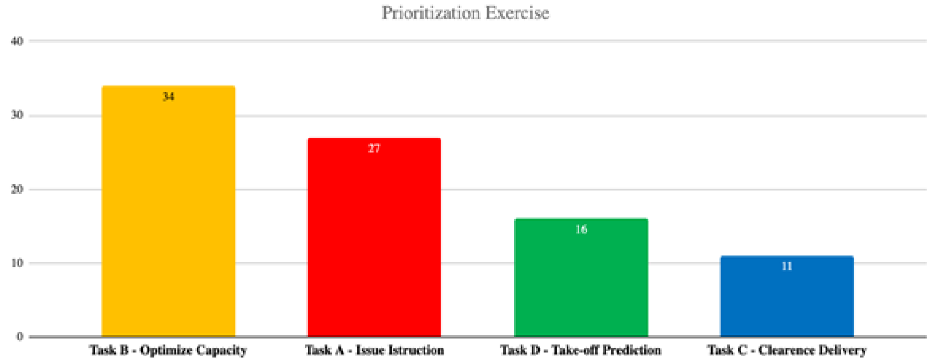
Figure 18. Rationale for introducing AI support



4.1.4 Prioritisation of XAI support to ATM tasks

The workshop's third step consisted of a small group discussion to rank the tasks for helpfulness and relationship to ATCOs role. The small group could assign medals to the task: the gold medal was associated with an equivalent of 10 points; the silver medal was 7 points; and the bronze medal just 4 points. As shown in the table below, two out of the four small groups identified Task B as the best task to be helped by AI transparency, scoring 34 points. The remaining two tables elected Task A as the best task to be supported, scoring 27 points, but differently from Task B, which ranked 2nd in the other two tables, it ranked 2nd in one table and was not ranked in the other. Task D in all the tables ranked as the 3rd task to be supported, while Task C ranked second in one table, third in another, and not ranked in the remaining two tables. The ranking result is shown in the table and graphic below (Figure 11), and it allowed participants to focus and imagine use-case and scenarios (stories) to describe how AI and ATCO would perform the task together in 2050.

Figure 19. Prioritisation of XAI support to ATM tasks



After this prioritisation discussion, the two “winner tasks” elected during the workshop were Task B – AI Optimises Available Capacity, and Task A – AI Issues Instructions, including their respective sub-tasks.

4.1.5 Potential Use-case Scenarios (Stories)

Once the two main tasks were identified, the workshop's last activity consisted of hypothesizing the human-AI-partnership. Participants were asked to contextualize how AI and ATCO would perform the task together in 2050. The table below shows some story examples of the two winning tasks identified by the participants in this workshop.

Table 8. Participant’s story examples

	Story 1	Story 2
Task B	The system automatically **recognizes that the operator is overloaded** (e.g., too high traffic condition). In that case, some AI solutions can support the controller, mainly in the sector where the ATCO is not operating. In this case, the system leaves some messages (like post-it) on the video screen of the ATCO, informing him/her about the decisions it took on behalf of the controller. (Automation Level 3: Conditional Automation)	In 2050, traffic complexity has changed entirely, with an increased number of aircraft, and a high level of heterogeneity of the flying object-from UAV, to personal aircraft and new commercial flights--. In the first week of July, many people are moving from North Europe to South Europe, but some peaks from West to East from delivery are present. AI would support this task by **automatically modifying route networks and sectors to fit the flows better and ease conflict detection and avoidance.** (Automation Level 3: Conditional Automation)
	Story 3	Story 4
Task A	It is about automation paradoxes. In 2050, I cannot imagine human-ATCO working in collaboration with AI/full automation. Humans will not be able to build proper situational awareness and recover from critical situations. **The new role/task should be high-level management deciding about**	**AI is supporting ATCO operational tasks**, from Conflict Detection and Resolution (CD&R) to conformance monitoring and coordination with collateral sectors. The AI will provide alerts to the ATCO when any problem arises, together with a set of possible solutions to it (including the KPIs of each solution), the human oversees the system, the considered optimal solution by the system is automatically implemented (full automation). The trust is gained during

	the strategy applying business needs. (Automation Level 5: Full Automation)	training, but the user can have access to specific explanations on demand, and the system will provide them with an overview clear and in a timely manner of what problems and resolutions are being implemented (Automation Level 5: Full Automation)

4.2 TASK 3.3: Chain Task – AI – XAI - Interface

This specific activity performed during the Workshop on T3.3 had the purpose of identifying possible tools to be implemented during the timeframe of the ARTIMATION project, linking each tool with specific AI and explainability methodologies, assigning, in conclusion, a reasonable level of confidence (how much the consortium is sure that the solution can be developed).

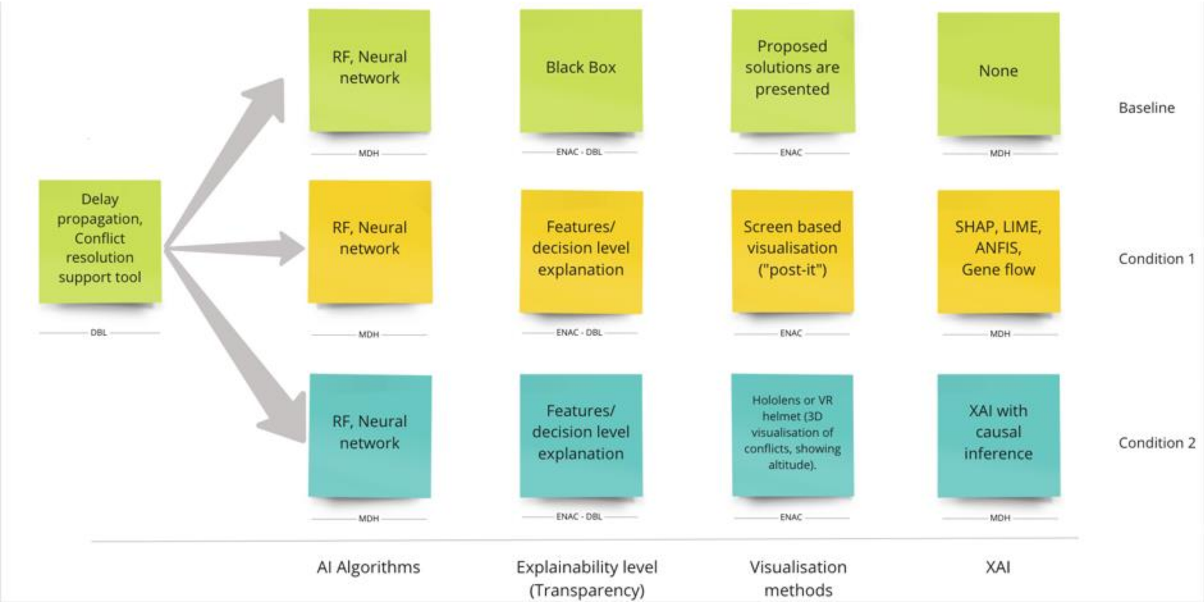
This activity has been performed through the MIRO platform, and the objective of the task was to try to build possible developing "CHAINS," starting from the desired tool and putting for each "LINK" all the methodologies needed to realize such a tool (Figure 12).

The main work done during the workshop was to find, among the tasks selected in workshop 1, which sub-tasks were implementable by the project, making a trade-off among available algorithms, technical feasibility, data availability... In particular, the driving factor for the choice was dataset availability.

At the end of the discussion two tasks have been selected

- **Delay Propagation**: sub-tasks for Task B – AI Optimises Utilization Capacity
- **Conflict Resolution**: a hybrid between Task A - AI Issues Instructions and Task B – AI Optimises Utilisation Capacity

Figure 20. Overview of the selected tools, algorithms, visualisation methods and XAI



Currently, the ATCO tries to avoid very complex situations (e.g., more than three aircraft at the same time) by forecasting the upcoming traffic before a critical situation could happen. Anyhow, soon (e.g., 2030), the traffic is supposed to increase drastically, for instance, by the presence of many drones. Therefore, it could be challenging to avoid such complex situations. In this regard, the ARTIMATION project will develop three tools that might be implemented to support the ATCO.

1: Basic AI (with no XAI). The basic AI tool consists of an AI system that aids and supports the ATCO's work by suggesting possible solutions. The validation process aims to observe how the ATCO responds to the AI under different workload conditions (Automation Level 2: Task Execution Support).

2: XAI "post-it" on desktop visualisation. The XAI "post-it" tool aims to support the ATCO's work by suggesting possible solutions to everyday situations. In addition to the previous system (1), the AI will also explain to the ATCO why it provides that solution. The validation process aims to observe how the ATCO responds to the AI under different workload conditions and different AI levels of explainability. In detail, there are three explainability levels: in level 1, the AI gives no or simple explanation; in level 2, a full explanation of the proposed solution; in level 3, a full explanation of the proposed solution with the possibility of modifications by the user.
Different levels of transparencies and explanation will be provided, eventually triggered by a passive-BCI system. This system would be able to recognize the actual level of cognitive load or stress experienced by the operator, and switch among different levels of transparency depending on it. Of course, the operator can select by himself the preferred level of transparency (Automation Level 3: Conditional Automation).

3: XAI with 3D Visualisation of conflict. The XAI with the 3D visualisation is always an AI system intended to support the work of the ATCO by providing possible solutions, as in the

previous system (2). In addition, to better understand the decisions taken by the AI, the ACTO will have a 3D instrument at his/her disposal that will allow him/her to visualize the information better. From an HF perspective, using a 3D tool could provide a better explainability of the system than a 2D one. For instance, the 3D immersive technologies (e.g., VR or HoloLens) can visually provide aircraft's altitude information, making it easier to identify the corresponding aircraft's position and resolve a possible conflict.
In the validation process, it could be investigated if/or when:

- the 3D visualisation tool contributes to creating a higher user's trust and acceptance in case of a level 1 explanation.
- the 3D visualisation tool better support the full explanations of the ATCO with the one of the AI (level 2)
- the 3D visualisation tool better supports the ATCO interactions with the AI (level 3).

To be noted that this will be only possible in case the XAI contains 3D data (Automation Level 3: Conditional Automation).

The AI needed to realize the tools can be obtained by the algorithms described above (i.e., paragraph 2), Artificial Neural Networks (ANN) and Random Forest (RF), and the explainability techniques ANFIS, LIME, SHAP can be as well as applied and tested, to identify the best configuration to obtain the needed levels of transparency. Visualisation techniques will be optimized for their employment in desktop or VR/AR-related applications.
The level of confidence of the tools is HIGH. The passive BCI systems have already been implemented and tested by the consortium in previous projects (i.e., NINA and STRESS projects) while regarding the proper AI methodologies to be used for the implementation of this tool, different choices have been identified, and among them, it will be selected the most effective configuration able to reach a reasonable accuracy. Regarding the visualisation techniques, a possible bottleneck could be VR/AR, which must be effective and comprehensive of all the information needed by the operator, and of course, ATCOs should become confident to use such technology during their operational activity.

Below are listed some items (Scenarios and variables) that will be further detailed in the Validation Plan:

- Independent Variables 1: Condition of Overload vs no Overload vs Underload
- Independent Variables 2: Levels of Explainability: Level 1 vs Level 2 vs Level 3 (taking also into account 2D vs 3D)
- Dependent Variable 1: Series of subjective batteries on
    - Human performance, and acceptance.
- Dependent Variable 2: Objective measures indexed by neuro-physiological measures.

5 Conclusions

Based on users' feedback and constrains emerged from T3.2 Workshop, ARTIMATION's Project decided to develop two different tools, to be tested at three different levels of explainability and visualisation solutions.

The two tools involve two different visualisation techniques, the "Screen-Based visualisation" and the "3D visualisation", whereas the three levels of explainability involve one baseline with no XAI, XAI presented with Screen-Based Visualisation and XAI presented with 3D Visualisation.

The two tools have been selected making a trade-off between users' needs and dataset availability for the two "winner tasks" (I.e., Task A – AI Issues Instructions; Task B – AI Optimises Utilisation Capacity). The Project will test the impact of explainability and different visualisation techniques on ATCOs' Acceptability and Human Performance.

The tasks involved (i.e., Delay Propagation; Conflict Resolution) are sub-tasks for Task B – AI Optimises Utilization Capacity (Delay Propagation) and a hybrid between Task A - AI Issues Instructions and Task B – AI Optimises Utilisation Capacity (Conflict Resolution).

It is important to note that the main objective of the project is understanding the impact of explainability and visualisation on acceptability and performance. So, the selected tools should be considered as representative use cases to test the impact of the different levels of explainability and visualisation.

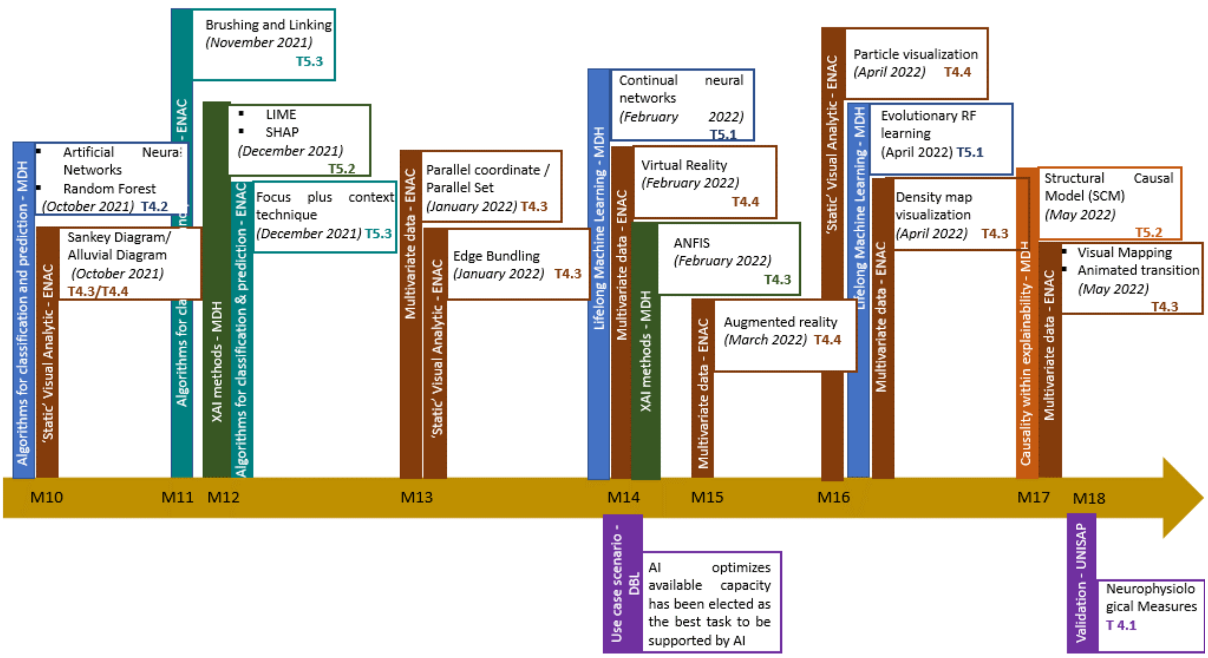
It has also to be highlighted that, during the discussion taken to select which tasks to support and so which tools to develop within the project, it resulted clear that the main limitation in research when dealing with AI tools in ATM is nowadays the lack of dataset to be included in AI training.

5.1 Roadmap-development plan

Through the present document there were identified tools for the proof of concept of a XAI system supporting ATM functions in predicting air transportation traffic and optimizing traffic flows.

Therefore, as graphical representation of the methods, techniques and applications defined in the present D3.2, below is reported a figure presenting all the activities described in the D3.2, with a connection to the GANTT development and to the Tasks described in the Grant Agreement.

Figure 21. The roadmap



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