Enhanced Dynamic Airspace Configuration Algorithm

Simulated application in Milan ACC

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***Abstract* — The global air traffic is experiencing steady growth, driven by increasing demand for air travel for both business and leisure purposes. According to Eurocontrol [1] [2], the number of flights in Europe is projected to increase by 2.5% per year up to 2030, reaching approximately 12 million flights. This substantial growth has put significant pressure on Air Traffic Management (ATM) systems, highlighting the need for new solutions to address emerging challenges.**

The rise in air traffic might lead to congestion in specific airspace causing flight delays and increased traffic complexity, which is directly linked to the Air Traffic Controller’s (ATCOs) workload [3].

The current airspace structure, based on Elementary Sectors that can be collapsed according to traffic situations is not the best optimized solution to accommodate high values of traffic, considering the potential occurrence of external factors such as weather event (e.g. Convective areas) or Military area reservations, including Dynamic Mobile Areas (DMA). The SESAR3 Industrial Research Project HARMONIC Solution 382 faces this challenge by fostering the validation of Dynamic Airspace Configuration (DAC) concept. ENAV, the Italian ANSP, will make use of LTLMT (Local Traffic Load Management Tool) developed by IDS Airnav to support the Flight Manager Position (FMP) in the identification of the best ACC (Area Control Centre) configuration to be applied in specific timeframe; such software will be powered by Machine Learning (ML) algorithm to estimate the workload with brand new sectors’ shapes and to identify the best configuration to be applied to avoid any unbalanced situation. DAC Algorithm, developed by University “La Sapienza” of Rome, is enhanced respect to the previous experience in SESAR context (PJ.09-W2 Solution 44) because it will consider not only the traffic (in terms of counts), but also additional constraints such as DMA and convective phenomena.

In the context of HARMONIC Solution 382, a validation campaign through Real Time Simulation on Milan ACC operational environment will be run by ENAV in May 2025 to validate the enhanced DAC concept.

I. INTRODUCTION

Dynamic Airspace Configuration (DAC) concept consists of organizing, planning, and managing airspace configurations to respond optimally to any change in traffic demand and unexpected events, allowing a better distribution of Air Traffic Controller workload.

The objective of the DAC process is to identify optimized airspace configurations by exploiting not only the operational Sectors, but also considering different shapes taking into account traffic Flows, ATCO workload and ATCO availability as well as the traditional count methodologies (Hourly Entry Counts and Occupancy). The identified optimized airspace configuration should meet forecasted traffic demand and reach the defined performance targets both at local and network levels with minimal impact on business/mission trajectories.

One of the main applications of the DAC is to reorganize airspace sectors in response to real-time traffic conditions. To ensure that, different approaches have been analyzed in order to optimize airspace sectors. Initial research into DAC [4] laid the groundwork by conceptualizing dynamic adjustments to airspace, based on the flexible airspace boundaries.

The work presented in [5] explored how air traffic complexity metrics can be utilized to configure airspace more effectively, helping to alleviate bottlenecks and prevent congestion. These complexity metrics are central to developing configurations that respond not just to the number of flights but also to their spatial and temporal distribution.

Several solutions have been proposed in the last decades. An early approach was proposed in [6], where the authors used computational geometry to manage dynamic airspace configurations, allowing for more precise and flexible sector boundaries. More recently, the work presented in [7] employed a genetic algorithm to adjust airspace configurations dynamically, demonstrating how optimization algorithms can improve operational efficiency. In [8], the authors introduced an optimization model based on state-task networks (STN), which optimizes the allocation of tasks within the airspace, ensuring a more balanced distribution of traffic. Then, in [9] Graphic was introduced, a graph-analytic approach, which leverages data science to enhance airspace adaptability, highlighting the growing role of analytics and big data in air traffic management.

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Each of these studies presents several simplifications that do not consider some additional complexities like weather conditions and/or military restrictions. Moreover, the proposed solutions often introduce limitations in terms of shape and usability for human operators.

The scope of this paper is to present the approach methodologies for the development of the DAC which take into account, in addition to the traffic data, the possible presence of severe weather conditions, and military area restrictions.

II. BACKGROUND

A. *Previous Experience and related Projects*

The DAC Concept was formerly part of SESAR 1 and SESAR2020 Wave 1 and Wave 2 projects [10], reaching a V3 maturity level. In particular, SESAR2020 PJ09 Wave 2 Solution 44 was the natural continuation of SESAR 2020 Wave 1 validation activities carried out separately on DAC (PJ08.01) and in the solution PJ09.02.03 on DCB (Advanced Demand and Capacity Balance), combining the two concepts in a seamless process from the planning phase up to the execution phase, covering the gap between ATFCM and ATC activities. By refining the DAC operational concept and algorithm, the solution developed automated sector configuration proposal ensuring that Situational Awareness was ensured during operations. The tools also ensured a successful exploration of options using traffic and sector what-if functionalities. At the end of the validation process the following recommendations about the application of the DAC concept into operations were expressed:

- Sector shapes that are radically different from existing ones are not operationally efficient because there is no pre-existing operational experience.
- Sometimes, it is more effective to make smaller changes more frequently to sector shapes instead of radical changes.
- Combining ATCOs roster management into the design and application of DAC measures can increase efficiency.
- Enhancement of the DAC algorithm with the consideration of new constraints, such as weather events and airspace reservations.

Such recommendations were taken into consideration in the development of the DAC algorithm described in this paper.

B. *Context of the Application*

The Flow Manager Position (FMP) plays a crucial role within the European Air Traffic Flow Management (ATFM) framework. Located at Area Control Center (ACC), the FMP is responsible for monitoring and managing air traffic flow and capacity in each ATFM phase (strategic, pre-tactical and tactical) to ensure safe and efficient operations. The FMP collaborates closely with the Network Manager Operations Centre (NMOC) to implement ATFM measures, such as reroutes or ground delays, to balance demand and capacity. Basing on the traffic data (extrapolated by Flight plans or updated with current Position report), identify potential congestion, and communicate with airlines and adjacent FMPs to optimize traffic flows.

The Airspace subject to ATC service by ACC can be divided into one or more Control Areas (CTA). The CTA are essentially portions of the entire airspace and the union of every CTA must be equal to the entire airspace controlled by the ACC. The CTA can be divided, in turn, into one or more Sectors that are taken in charge by Air Traffic Controllers. Such Sectors are volumes defined with a horizontal shape and lower/upper limits. The shapes are defined in strategic phase within each ANSP considering several factors, e.g. traffic flows, air navigation infrastructures, airports, etc.

In each AIRAC cycle, such sectors' shapes might be changed according to specific operational needs, nevertheless few changes are typically applied within one year, deferring the accommodation of airspace configuration to pre-tactical and tactical phases. The Sectors are divided into Elementary Sector (ES) and Collapsed Sector (CS); the latter are the combination of more Elementary sectors. This approach allows to obtain several combinations of sectors that are tagged as Configuration. Each CTA can have tens of Configurations that consider different sets and number of sectors. An example of LIMM CTA-East Configuration with 3 sectors (each sector has a different color) is reported in Figure 1.

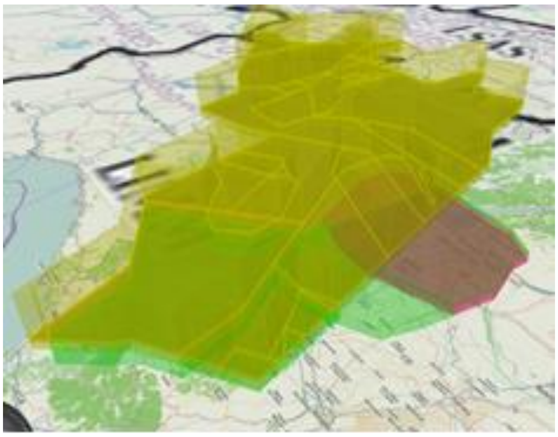

Figure 1. Example of sector configuration

Even if there are plenty of combinations of sectors that can be arranged as Configurations, this might not be sufficient to identify an optimal solution that should avoid the issue of a Regulation. The DAC allows increasing the number of possibilities with brand new sectors; moreover, the estimation of workload distribution (see Section IV.B) will support the operator in finding the optimal solution that aims at the best distribution of workload for each sector belonging to the Configuration.

III. OPERATIONAL ENVIRONMENT

A. Milan ACC airspace

The airspace under the responsibility of Milano ACC represents one of the busiest areas in Europe, with a high density of managed flights (including both overflights and arrivals and departure) due to the concentration of medium and high airports on a very complex orographic scenario that goes from the Alps to the Tuscan-Emilian Apennines (see Figure 2). The constantly growing demand for traffic requires studying and testing increasingly effective solutions to accommodate the continuous request in airspace that in a few years would risk reaching the limits of saturation, with the current operating methods.

Figure 2. LIMM ACC airspace with flight trajectories in a sample day

The aspects described above have identified the Milan operating scenario as the best candidate to experiment with a dynamic airspace organization. This approach aims to constantly balance the number of flights between various sectors. By doing so, it maximizes and optimizes the capacity of the entire airspace. Currently, some operating sectors have small residual capacities, while others are nearing maximum capacity. The dynamic airspace organization would utilize these residual capacities more efficiently, all while maintaining high safety standards. Additionally, it holds the potential to further reduce delays.

B. Supporting tools

Currently, the FMPs are supported in their decisions by European network tools provided by EUROCONTROL, such as Collaboration Human Machine Interface (CHMI). CHMI provides access and interaction with the European ATFM system, allowing FMPs to effectively manage air traffic flow and capacity. Through CHMI, FMPs can monitor real-time traffic data, visualize air traffic flows, and analyze sector loads and airport capacities. The tool facilitates coordination and allows the implementation of ATFM measures such as flight level capping, rerouting, and ground delays.

In addition to this, ENAV decided to be supported also by the Local Traffic Load Management Tool (LTLMT). The LTLMT performs traffic monitoring against available capacity and runs what-if analyses prompting users with the operational impact of these recommendations. This tool has the capability to access traffic information, by retrieving flight profiles through the B2B services of NM and updating them with ETO and OLDI messages directly retrieved by the local ATM system, in particular by the FDP (Flight Data Processing). This capability allows to process more updated trajectories which results in a more accurate estimation of counts in each Traffic Volume monitored.

Therefore, the main features of the LTLMT are:

- **Traffic monitoring**, for each Traffic Volume computes traffic demand (including the Intruders flights) – see Figure 3. FMP staff are warned in case of capacity unbalance. Such monitoring includes also the Traffic Complexity, computed considering the number of flight interactions (horizontal, vertical, speed) together with raw counts (entry, occupancy).

- **Sector Configuration what-if** support ACC roles to identify the best configuration to be applied considering expected traffic, constraints, number of available CWPs, and timeframe.

- **Traffic what-if** analyses are performed to suggest action on flights, eventually, combined with capacity measures.

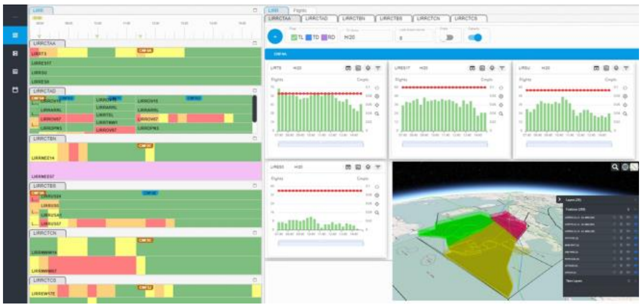

Figure 3. LTLMT monitoring dashboard

The Sector Configuration What-If page is crucial for the DAC application. Indeed, it supports the analysis of CTA airspace either via the direct selection of existing configurations or engaging the ICO algorithm [11] to identify the best ACC room configuration, including those that are based on DAC sectors.

The user can set different parameters to define the what-if analysis, such as the timeframe of simulation, the minimum and maximum number of sectors considering staffing information, and the Metric the user wants the analysis has to be based on, e.g. H/20 means that Hourly Entry Count are considered as the main metric for the output

The Configuration Combination is the section where the list of configurations is shown as output of the what-if analysis based on the parameters that have been set. Each configuration has a color that corresponds to the worst load value for the sectors in the configuration for each time range (see Figure 4.). The list of possible configurations is sorted in a ranking related to a specific score calculated by LTLMT. The best configuration is positioned in the first row.

Figure 4. Configuration combination list

Several factors contribute to imbalances between demand and capacity in the context of Air Traffic Flow Management (ATFM). These include:

- **Adverse Weather Conditions**: phenomena such as thunderstorms, fog, and strong winds, can significantly reduce airspace and airport capacity.
- **Airspace Restrictions**: Temporary airspace closures or restrictions due to military activities, special events, or emergencies can limit available capacity.
- **Other factors** such as ATCO Staffing, Technical failures, Runway Availability, Regulatory Constraints, Differences in aircraft performance (mix traffic), Emergencies, etc.:

These factors must be continuously monitored and managed to minimize imbalances and ensure the safe and efficient flow of air traffic.

C. Constraints

Regarding the impact of adverse weather on en-route operations, it is largely due to the presence of convective areas within the airspace [12]. In fact, the presence of convective clouds like Cumulonimbus (Cb) represents one of the most important aviation hazards, since they are often associated with severe phenomena like turbulence, icing, lightning and hail. For those reasons, when pilots encounter deep convective areas, it is recommended to avoid it laterally. This procedure largely impacts the ATFM in terms of the capacity of the airspace sectors [13] [14] [15], since:

- The sectors affected by the presence of convective areas will reduce their capacity by an amount that is directly proportional to the extension of the convective areas.
- The sectors adjacent to those affected by convection may experience unexpected congestion, due to the cross-border maneuvers caused by the avoidance flights.

For those concerning the ATC side, the ATCOs need to manage more complex traffic scenarios, including rerouting flights around weather and executing additional ATC tasks that concur to increase their Workload [13].

For these reasons, adverse weather conditions necessitate dynamic and flexible ATFM measures to ensure safety and minimize disruptions, which often lead to reduced sector capacities and increased delays.

As mentioned before, another aspect to be considered is the airspace restrictions. In the next future, the implementation of Advanced Flexible Use of Airspace (AFUA) is expected considering the applicability of the Dynamic Mobile Areas (DMA) concept. DMAs are currently being developed under other SESAR Projects and they are defined as temporary mobile airspace exclusion areas, whose aim is to minimize the impact on the network while satisfying the needs of military airspace users. Three types of DMAs are identified, which can be used both in a free route environment and in a fixed route environment. Nevertheless, in the framework of the HARMONIC Validation exercise, only DMA Type 1 is considered. The DMA of type 1 (see Figure 5) is a volume of airspace of defined dimensions, described either as an integral part of a MT, or independently at flexible geographic locations agreed upon in a CDM process, satisfying Airspace Users requirements in terms of a time and/or distance constraint parameters from a reference point as specified by AU (e.g. Aerodrome of Departure).

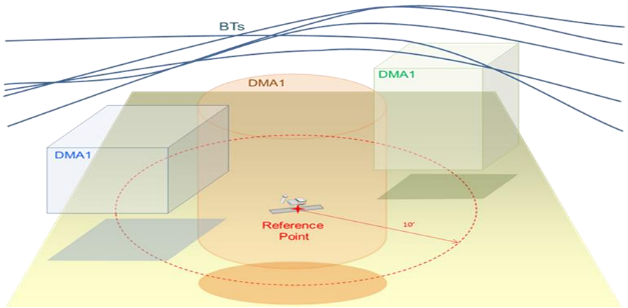

Figure 5. Graphical view of DMA Type 1

IV. DAC ALGORITHM

A. *Dynamic Airspace Configuration Problem*

The main decision variable in *Airspace Configuration Problem* (ACP) is the airspace configuration, which is a suitable division of the airspace $\mathcal{S}$ into sectors $\mathcal{S}_h$. Each sector is a prism respecting a set of business rules related to its geometry and its workability for human operators. In the following, we will call a $\mathcal{C}_H$ a generic airspace configuration composed of H sectors. The sectors in $\mathcal{C}_H$ do not overlap the one with each other, and their union covers the airspace.

As a main decision driver to our problem, we use the notion of workload function to measure the score of complexity of a sector. The main driver to discern solutions in our algorithm is the workload, as it depends dynamically on the traffic conditions. We will indicate the workload function as $F(\cdot)$. From a practical point of view, the workload function is parametrized over the set of expected trajectories expressing traffic information, weather information, and military restrictions.

A trajectory is a sequence of points in a 4-D space. The components of each element of a trajectory $\mathcal{Y}$ are chosen according to the convention $(longitude, latitude, altitude, time)$. For the purposes of this paper, each trajectory is associated uniquely with a flight, and the two terms must be considered as synonyms.

The weather information and the military restrictions are modeled as prisms, indicating areas that should be avoided by traffic or where certain operations must be applied.

The objective of the ACP is the minimization of a global workload function, denoted by $W(\cdot)$, giving a summarizing measure of the workload through the airspace. Therefore, the airspace configuration problem (ACP) is the problem of finding the best airspace configuration $\mathcal{C}_\mathrm{H} = \{\mathcal{S}_1, \dots, \mathcal{S}_\mathrm{H}\}$, over the airspace $\mathcal{S}$, minimizing the global workload function W:

$$\mathrm{ACP}: \begin{cases} \min\limits_{\mathcal{C}_\mathrm{H}} \mathrm{W}(\mathrm{F}(\mathcal{S}_1), \dots, \mathrm{F}(\mathcal{S}_\mathrm{H})) \\ \quad\quad \mathrm{s.t.}\ \ \mathcal{C}_\mathrm{H} \in \Gamma_\mathrm{H} \end{cases}$$

Where Γ_H is the set of all airspace configurations of H, i.e. $\Gamma_H = \{\mathcal{C}_H : \mathcal{C}_H$ *is an airspace configuration for the airspace* $\mathcal{S}$ *composed of* H *sectors*$\}$.

The global workload function may assume different forms, but for the purposes of this paper we will assume that $W(\cdot)$ is the combination of the absolute sum of all the workloads for each sector in the configuration, i.e. $F(\mathcal{S}_h)$, and a measure balancing the workload among different controllers.

The *Dynamic Airspace Configuration Problem* (DACP) is the dynamic version of ACP. During the day, the control authority wants to recompute the sectors to better fit the workload and capacity requirements for the current traffic situation. Operationally, the maximum number of time windows when it is possible to modify the sectors during a day is limited according to a minimum switching time (in our case, 1 hour). In the following, it is assumed that there are T time windows indexed by t.

On the other hand, in DACP the authority may be interested in maintaining a certain configuration decided in advance, for instance to facilitate control operations. Please note that the baseline does not necessarily represent an offline configuration, the most common choice is to resemble the previous sectorization. With this choice, the algorithm weighs the cost of changing the configuration for a new workload assignment.

These considerations modify the single problem for DACP for a time window, i.e. $DACP_t$, from the formulation proposed for ACP:

$$DACP_t : \begin{cases} \min\limits_{\mathcal{C}_\mathrm{H}} W(\mathcal{C}_H; \mathcal{T}_t, \mathcal{W}_t, \mathcal{M}_t) + d(\mathcal{C}_H, \mathcal{Y}_t) \\ \quad\quad\quad\quad s.t.\ \ \mathcal{C}_H \in \Gamma_H \end{cases}$$

As we indicated with $\mathcal{Y}_t$ the baseline and with d is a function measuring a certain distance from the baseline.

Finally, *the Dynamic Airspace Configuration Problem (DACP) is the problem of finding a new configuration for each time window through the day by repeatedly solving* $DACP_t$, *according to the baseline* $\mathcal{Y}_t$.

To solve $DACP_t$, we decided to simplify the space of possible solutions by dividing the airspace $\mathcal{S}$ into small sub-sectors s_i. Each sub-sector has the same properties as a sector. Moreover, to enhance the operability and the changes from the baseline, the sub-sectors are chosen as subregions of existing sectors, and some combinations of them will recreate the original sector.

Each sub-sector can be combined with other sub-sectors to create another sector. Since not all the combinations are allowed, we kept only the ones satisfying the business rules and subsequently approved by the operative team.

Instead of choosing among all possible configurations, i.e. $\mathcal{C}_H \in \Gamma_H$, we will decide only on the subset of configurations formed by sectors derived as a combination of sub-sectors.

Depending on the number of possible configurations, we opted for two algorithmic solutions:

1. Brute force
2. Switching and incremental heuristics.

The Brute force approach assumes there is a contained number of possible configurations, and the solver is called a limited number of times. In this case, there is enough time to explore all the feasible configurations and find out the global optimum.

The Switching and incremental heuristics operate by starting from the first feasible solution, namely the baseline $\mathcal{Y}_t$, and

then creating a new configuration by switching sub-sectors among the sectors in the configuration, maintaining feasibility. The incremental (or decremental) part refers to when, for operational reasons, the algorithm needs to change from a configuration of cardinality H to one of higher (or lower) cardinality.

B. *Workload Estimation*

When solving DACP for real-world instances, the major problem is to define the workload function. Several definitions of workload can be applied and organizations around the world tend to use different formulas. The workload is affected by the regulatory rules in use and most importantly by the software adopted. Other characteristics may arise only in certain control regions, depending on the topology of the control area. Finally, when dealing with dynamic configurations, a new workload is generated by passing from one configuration to the other.

Our goal is to learn an approximation function $\hat{F}(\mathcal{S}_h\ ;\theta)$ of the workload function $F(\mathcal{S}_h\ )$ by opportunely setting the parameters θ. For what that concerns the nature of the approximator, we have chosen to adopt deep neural network [16]. In particular, we used Long-short term memory networks (LSTM) [17] to deal with sequence information, present in the trajectories and in the prism of sectors, weather triggered areas and military restricted regions.

The architecture of the deep neural network used is articulated into the subnetworks:

1. LSTM1: an LSTM network returning an embedding related to the single trajectory,
2. LSTM2: a second LSTM connecting multiple trajectories,
3. LSTMS: an LSTM included to take into consideration the sector information,
4. LSTMW: an LSTM included to take into consideration the weather information,
5. LSTMM: an LSTM included to take into consideration the military information,
6. ENCT: a feedforward encoder for the traffic information,
7. ENCS: a feedforward encoder for the sector information,
8. ENCW: a feedforward encoder for the weather information,
9. ENCM: a feedforward encoder for the military information,
10. ENC: a feedforward encoder having the embeddings from LSTM2, ENCS, ENCW, and ENCM as inputs, and collapsing them to a single value.

The network is composed of four branches. The first takes as input the trajectories and by parameters sharing computes the embeddings for each trajectory using LSTM1. Then the embeddings are given to LSTM2, and its output is opportunely collapsed. The second branch takes as input the sector information and processes it through LSTMS, then the embeddings are collapsed and given to ENCS. The third branch takes as input the weather information and processes it through LSTMW, giving ENCW a collapsed version of its embeddings. Finally, the fourth branch takes as input the military restrictions and processes them analogously through LSTMM and ENCM.

The four branch embeddings are then merged and processed into a large encoder ENC, returning the expected workload as output. The structure of the network is reported in Figure 6.

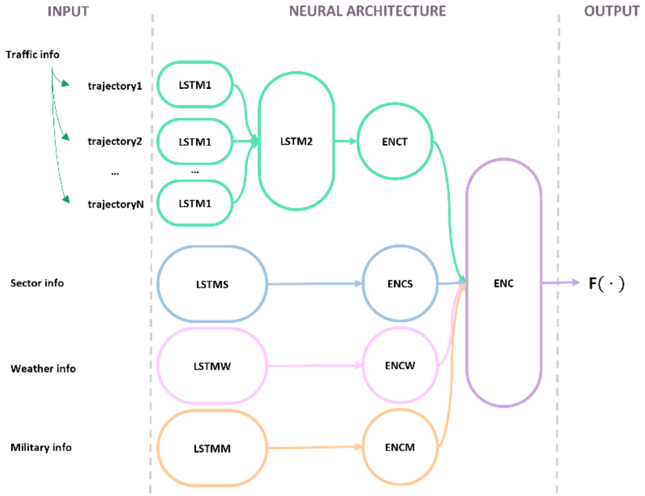

Figure 6. Structure of the network

The algorithm is composed of two main processes: learning and optimization, which are both reported in Figure 7.
The learning process aims to train the neural network used for workload estimation. It takes as input the dataset composed of trajectories, weather information, military restrictions, and sectors, all divided into several time windows of 1 hour. The labels are the workload measures computed using Fast Time Simulations.
The FTS (Fast-Time Simulation) model was employed to generate the training data for the algorithm. The simulation focused on the Milan Control Area airspace, modelling three types of scenarios each with several variants: n.1 Baseline scenario, n.9 weather scenarios incorporating different CB volumes and n.2 military scenarios considering two different DMAs (with the same shape but with different vertical extensions). All 12 simulation scenarios utilized scheduled traffic intersecting the Milan Control Area on August 18, 2023, and September 8, 2023.
An ATCO workload model was implemented to assess the ATCO's workload by assigning a weight in seconds to each task. Specific tasks were introduced to consider CB volume crossings, with the workload proportional to the intensity of the CB.
Original routing of the traffic sample was used for the baseline and weather scenarios. The military scenarios were simulated with rerouted traffic to avoid DMA volumes (modified routes were obtained from R-NEST, an EUROCONTROL platform).

Moreover, each scenario was simulated with incremented traffic loads, up to +150% more flights, with 10% steps.
FTS produced a rolling hourly workload of 10 minutes for the 58 traffic volumes analyzed. A detailed task list was extracted for each flight, specifying the time, TV, and execution coordinates for each task and the 4D trajectory.
All the data is given to the training routines, collecting the learning parameters and selecting the best-trained model according to performance indicators computed on a selected test set. The procedures are conducted using Pytorch [18].
In the optimization process, traffic, weather, military, and baseline information are given as input to the optimization algorithm (DACA) at each time window. As expressed in section V.I, to solve the single instance of the problem we use as an objective a global workload function, which is the one computed using neural networks in the learning process.
For each time window, the optimization algorithm returns the proposed airspace configuration.

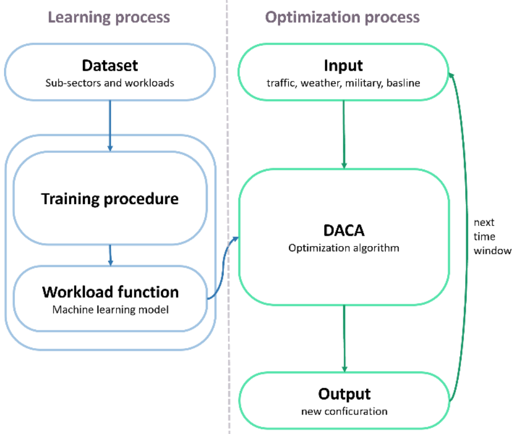

Figure 7. The algorithmic baseline.

V. EXPERIMENTAL SETTINGS

As reported in Section IV.A, Milan ACC is a high-complexity FRA environment with complex sectors arranged in three CTA: CTA West, CTA East and CTAA. This environment is a good example of an operational scenario to evaluate the benefits brought to FMPs by DAC and by the integration and data exchange of enhanced local tool with NM.

This operational scenario will represent the core of the Validation exercise that will be performed from 5th to 9th of May 2025 by ENAV and IDS AirNav in the context of Solution 382 of SESAR3 Harmonic Project.

The exercise (identified as TVAL.02-HARMONIC-2-TRL6) will make use of an enhanced version of LTLMT, in particular by implementing:

- acquisition and management of simulated traffic data and airspace constraints received from INNOVE (simulation platform by EUROCONTROL) for advice of the unavailability of a Military Area (AUP/UUP, DMA type 1), and from the Weather Provider for advice of the existence of connective areas (Meteo Service Provider).
- development with AI/ML techniques of an enhanced DAC algorithm receiving as input these airspace constraints and calculating dynamically sector configurations taking into account this further information.
- development of further ATFM measures as Level Capping and Horizontal Rerouting

The validation exercise will be executed using the Real Time Simulation technique through dedicated Use Cases considering different traffic samples (current and future) that will be run to assess improvements in safety and human performance due to a better DAC-DCB toolbox that aid the LTM.
The considered Use Cases have been grouped in the following three macro topics:

1. **Development of the enhanced DAC-DCB Toolbox:**
   - DAC algorithms: Enhance sector design and configuration to improve performance and optimization.
   - Configuration Pathway: Develop additional features to be included in DAC/DCB toolbox: configuration pathway optimizer.
   - Automated configurations: Automated tools and procedures resulting in more efficient and faster adjustment of airspace.
2. **Adaptation of CDM process:** Enhance coordination between NM, local actors, etc.
3. **Integration of Military requirements**, by means of DMA Integration. Reception of DMA type 1 from INNOVE to consider them in the identification of the best DAC configuration.

The traffic samples that will be injected into the validation platform during the validation exercise have been identified in order to evaluate the benefits brought by the proposed solution both for a typical current summer day of traffic in Milan Airspace (i.e. 11th August 2023) and a future 2030/2033 day considering the same day increased by approximately 20%-25% in accordance with what is expected from current traffic growth estimates for the next 10 years.

VI. CONCLUSIONS

In this paper, we have presented the Validation of Dynamic Airspace Configuration concept using the LTLMT to support the FMP in the identification of the best ACC configuration to be applied in a specific timeframe and powered by Machine Learning algorithm to estimate the workload with brand new sectors' shapes to avoid any unbalanced situation. DAC

Algorithm developed by University “La Sapienza” of Rome is enhanced with respect to the previous experience in the SESAR context because it will consider not only the traffic (in terms of counts), but also additional constraints that can limit the available capacity, like airspace restrictions due to military activities and convective phenomena. In particular the latter represents one of the most important aviation hazards since they are often associated with severe phenomena like turbulence, icing, lightning, and hail, forcing pilots to avoid them laterally, largely impacting the ATFM in terms of the capacity of the airspace sectors.

In the context of HARMONIC Solution 382, a simulation campaign through Real-Time Simulation on the Milan ACC operational environment will be run by ENAV in May 2025 to validate the enhanced DAC concept, expecting to meet the following objectives:

- Provide evidence of the benefits of using advanced DAC and DCB toolbox in the INAP phase.
- Evaluate the improvement of the airspace configuration process when included in the configuration pathway optimization.
- The integration of DMA in the DAC process and the CDM process that needs to be implemented.

It is worth noting that ENAV will evaluate the possibility to further investigate this topic, by considering also additional constraints, such as the cross-border aspects with the ACCs of surrounding ANSPs, the U-space airspace integration, the extension to the tactical phase and the improvement of the HMI to avoid information overload. We will also focus on the enhancement of the operational process to include continuous automated refinement for maintaining or increasing efficiency and effectiveness,

Finally, we will try to increase the number of optimization criteria by incorporating additional Key Performance Indicators (KPIs), such as occupancy and fuel consumption. This will help to improve the overall performance of the solution.

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