



STAM-based methodology to prevent concurrence events in a Multi-Airport System (MAS)

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ABSTRACT

Pre-tactically managing the imbalances of the network and organizing the resources of the airspace is one of the main objectives of Dynamic Demand & Capacity Balancing (dDCB). Introducing Short-term Air Traffic Flow and Capacity Management (STAM) measures such as minor ground delays or slight speed adjustments applied to a selected number of flights on the day of operations, supports the dDCB process by reducing the traffic complexity and the probability of Air Traffic Controllers interventions. This paper introduces a rolling horizon methodology for detecting concurrence events, analysing their trajectory interdependencies and applying a strategic mitigation measure that shifts the Estimated Take-Off Time (ETOT) within the assigned Calculated Take-Off Time (CTOT) window. The methodology proposes a collaborative decision-making process for a better coordination of departures from airports feeding airspace volumes with high air traffic demand. The experimental part of this paper aims at showing the potential benefits of such a STAM procedure by applying the methodology to distribute the demand of a sector located in the London Terminal Manoeuvring Area (LTMA). Experiments have considered regulated traffic scenarios where ETOT were allocated in order to reduce departure time uncertainties. Lastly, it is analysed the impact of the parameters used by the methodology to calculate the mitigation measures: safe separation criteria, look-ahead time and number of coordinated airports.

1. Introduction

The growth of passenger traffic observed in the last 20 years (UK Department for Transport, 2013) generated a forthcoming necessity to increase the airspace and airport capacity. The eventual distribution of the population around large cities and the capacity constraints on existing major airports led to build new airports and introduce the concept of Multi-Airport Systems (MAS) as a key mechanism to meet the future demand.

The European and US Air Traffic Management (ATM) systems are expected to be modernized based on the research and development activities coordinated by the Single European Sky ATM Research (SESAR) and the Next Generation Air Transportation System

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(NextGen) programmes (Next Gen Program, 2017; Sesar JU, 2017), respectively. The Trajectory-Based Operations (TBO) concept, in which the airspace user's (AU's) intentions are shared to all the interested parties, is the base of many proposed solutions. Regarding the Air Traffic Flow and Capacity Management (ATFCM) process, SESAR defined the Short-Term ATFCM Measures (STAM) as a mechanism that helps to improve the Demand and Capacity Balancing (DCB) activities by applying a set of pre-tactical measures few minutes before the departure time (Gatsinzi et al., 2017; Nosedal et al., 2014, 2015, 2018; Sesar, 2017). STAM measures could target to the flight plan (e.g. re-routing, speed changes, delay departure or slot swapping) or to the airspace (e.g. use of some military areas, level-capping, sector re-configuration).

This paper presents a STAM-based methodology to reduce the probability of the number of Air Traffic Controller (ATC) interventions “on air” and the loss of separation minima infringement in surrounding areas of the airports. The method proposes the application of minor changes in the Estimated Take-Off Time (ETOT) within the $-5/+10$ min window defined by the Calculated Take-Off Time (CTOT). Therefore, the proposed mitigation measures will not interfere the allocated ETOT in order to minimize the impact on Airspace User (AU) preferences once a regulated scenario has been put in place.

The terminal control areas are established in the vicinities of the airports and conform the junction between the control zones and the airways. The control area of a Multi-Airport System (MAS) is characterized by recurrent traffic that is distributed among the different airports of the zone. Short-term air traffic demand is established based on expected traffic crossing each ATC sector. Applying minor changes to the take-off time of selected flights is useful in a MAS for several reasons. Firstly, the mixed outbound traffic from different airports comprises the main sources of interdependencies that increase the traffic complexity and the ATC workload. Secondly, the traffic is more predictable for terminal airspace operations, which reduces the uncertainty levels and improves the effectiveness of the measures. The proposed methods would benefit the ATC activity in these areas by finding departure coordination opportunities on ground to remove the detected potential concurrence events. The reduced probability of a tactical intervention would also benefit the airspace user since the proposed mitigation measure will have less impact than other tactical measures.

The presented methodology is composed by three main functionalities: detection, analysis and mitigation, that are sensible to different parameters. Consequently, the research goal of this paper is to apply the STAM solution in a Terminal Manoeuvring Area (TMA) and understand the operating parameters of the methodology that are suitable to be applied in a representative multi-airport system. To this end, a set of tools have been developed using the method and a set of simulation exercises have been designed to analyse and study suitable working conditions for the proposed methodology.

The improvement of the pre-departure sequence must be seamlessly introduced at airport level without disturbing the ATCs strategy and using collaborative procedures. This paper analyses the possible benefits of such a STAM procedure by applying the methodology to a high traffic density airspace volume (EGTTAP) located in the London Terminal Manoeuvring Area (LTMA).

The paper is organized as follow: After a literature review in Section 1.1, a description of the mapping, detection, analysis and mitigation methodology is given in Section 2. The operational context and case of study are detailed in Section 3 and the obtained experimental results are discussed. Finally, Section 4 provides the conclusions and future research possibilities.

1.1. State of the art

Historically, the ATFCM activities have been based on metrics estimated at strategic level such as the *entry-count*, and more recently, the *occupancy* (EUROCONTROL, 2007). The number of aircraft that can be handled by the ATCs is limited by their workload. When the maximum capacity is about to be reached, the air traffic demand is limited by applying regulations to all the aircraft of the sector. Regulations produce delays or re-routings and have a direct impact on the environment and in the airline's strategy. From the ATM point of view, these measures are effective, because limiting the demand releases the system, but not efficient enough because it affects all the agents of the system. The results of limiting the demand is an eventual over-release of the airspace, which reflects that the measures taken to avoid a likely high-demand situation were not based on a good prediction of the system. The current metrics do not provide enough detail to determine the effects of the expected demand in the ATCs workload. At this point, the DCB process requires more realistic ways to determine how an increase of the demand in a sector affects the number of ATC interventions, i.e. using machine learning and big data technologies to improve the forecasts or introducing the use of complexity metrics in the regulation process.

Complexity metrics have been studied since many years by different authors (Delahaye and Puechmorel, 2010, 2000; Gianazza and Guittet, 2006; Masalonis et al., 2003; Netjasov et al., 2011). Additionally, Air Navigation Service Providers (ANSPs) could calculate their own complexity metrics to reconfigure the airspace according to the required capacity or to support the decision-makers to impose local restrictions, such as Minimum Departure Intervals (MDI) (EUROCONTROL, 2016). The effects of these measures tend to be efficient in areas where many airports feed a high number of aircraft to a common sector (e.g. London TMA). Although the MDI could be considered as a more dynamic process, the principle is based in limiting the demand of selected Standard Instrumental Departures (SID). Consequently, equally-distributed ground delays (e.g. “one each ten minutes”) are applied to all the flights that use the affected SIDs. To determine the required interval, the measure *groups* the affected flights by SID and its purpose is limiting the entry-count/occupancy to the target sector like performed at strategic level during the DCB process. The process does not identify what are the actual effects of selected flights in the target sector nor in the ATC workload.

The methodology presented is supported by the calculation of more dynamic metrics based on short-term trajectory predictions that identifies the effects of each AU as a stand-alone element of the system. This process determines the effects of individual AUs in the number of ATC interventions by detecting the imminent and potential concurrence events of each flight that crosses the target volume. Then, it is proposed a small changes of the Estimated Take-Off Time (ETOT) of selected flights in order to reduce the

probability of ATC interventions. The proposed methodology is based on the 4D-TBO concept (ICAO, 2015; SESAR Consortium, 2012), representing the current state of the art of this research sector. Instead of adjusting flights just in time, the overall flight performance can be improved significantly by performing more efficient avoidance manoeuvres assuming proper forecasts (Kuenz, 2015). Researchers have used the advantages of the 4D-TBO concept and studied, among other, conflict detection and separation observance approaches as in (Ruiz et al., 2014, 2013) or strategic trajectory planning approaches with uncertainty as in (Chaimatanan et al., 2018). Moreover, trajectory optimization focusing on the sensitivity of operational costs and efficiency have been carried out in (Vilardaga and Prats, 2015) and a coordinated multi-aircraft 4D trajectories planning, considering the buffer safety distance and fuel consumption optimization has been studied in (Qian et al., 2017). Machine learning techniques have been used recently to address the short-term trajectory prediction problem in TMA as in (Wang et al., 2017). The 4D-TBO concept, furthermore allows STAM involving measures like advancing or delaying aircraft by using the minor departure adjustments on the ground, referred to as green delays in (Castelli et al., 2011; Piera et al., 2014), flight level capping, minor re-routings e.g. in (Adacher et al., 2017), linear holding e.g. in (Xu and Prats, 2017), slot allocation and sequencing methods, e.g. in (Çınar and Demirel, 2017; Liang et al., 2017; Samà et al., 2017), headings or speed variations which apply to a limited number of flights to reduce the complexity of the anticipated traffic peaks (EUROCONTROL, 2017a). However, some manoeuvres are often not considered desirable measures by AUs due to high operational and fuel consumption costs as it is evaluated in studies of (Envisa, 2017; Ferguson et al., 2013). Green delays on ground flights is therefore a more acceptable alternative which is also the mitigation measure used in this work. The experimental part of this work considers regulated traffic scenarios, where predictability is higher since ATFM imposes calculated take-off times (CTOT). In Europe, these ATFCM slots are allocated by the computer-assisted slot allocation CASA (EUROCONTROL, 2018a) on the basis of a transparent set of rules and policies previously agreed and accepted by all the relevant ATM stakeholders, including AU's.

Nowadays, the systems strongly rely on AI and DA. During the last years, supported by the introduction of the 4D-TBO concept, the application and improvement of Decision Support Tools (DST) in ATM was advanced to support the global performance ambitions for air traffic planning and optimization. From an operational research perspective, some ATM problems can be seen as decision-making problems whose resolution consists of determining the domain values of the decision variables to reach feasible solutions. Furthermore, in case an objective function is formulated to describe the benefits of each feasible solution, there are some methods that could be applied to identify the best solution. However, since ATM problems (such as re-routing, flight-level changes, or ground-holding schemes) are usually complex problems of a large dimension, and highly combinatorial, there are few AI problem-solving technologies that can cope with that many different degrees of freedom. One efficient technique is Constraint Programming (CP), which has also been used in this work to determine which aircraft CTOT should be modified within the domain of $[-5, 10]$ minutes. CP is a powerful paradigm for representing and solving a wide range of combinatorial problems and offers a constrained version of real-world data analysis problems (Marriott and Stuckey, 1998; Rossi et al., 2006). In the last years, the paradigm has attracted much attention among researchers because it proposes on the one hand the modelling, using a high-level programming language, and on the other hand the solving, using various techniques from different areas such as mathematics, artificial intelligence, and operations research. Moreover, the nature of CP provides other important advantages such as a fast program development, an economic program maintenance and an efficient runtime performance. Other than metaheuristic or heuristic method, such as evolutionary algorithms, CP is used to solve complex combinatorial Constraint Satisfaction Problems (CSP). CSPs are expressed in terms of three entities: variables, their corresponding domains, and constraints relating them. Constraints can be considered as the main characteristics of CP. They are treated as logical relations among several unknowns (or variables), each taking a value from a set of accepted values called domain, which can be a range with lower and upper bounds or a discrete list of numbers. Solving a CSP consists in assigning a value to each variable in such a way that every constraint is satisfied.

The application of CP is used both in scientific and industrial sectors for many kinds of application, such as scheduling or resource assignment problems. Furthermore, it has been successfully used in many research studies in the ATM field, as reported in (Allignol et al., 2012; Barnier and Allignol, 2012). A CP model in the ATM context that would consider all degrees of freedom (3D geometry and time) to generate an optimal set of conflict-free 4D trajectories at a continental scale is out of scope reach for the current combinatorial problem-solving technologies. In this work, the use of CP to reduce the probability of ATC interventions by profiting of time stamps (i.e. RBTs) as a degree of freedom is proposed. Furthermore, the degree of freedom is constrained to a time window of -5 to $+10$ min of the assigned departure time and, in comparison to existing works, this approach considers a fixed part which is determined by those aircraft that are already in the air and cannot be modified. Therefore, the large-scale space of solutions is reduced to a size in which CP models could provide feasible and even quasi-optimal solutions.

Existing literature shows that CP in ATM is used in rolling horizons in which the 'past' part of the current solution is fixed, and the decision variables are considered as constants. The 'future' part of the problem is resolved with the new horizon. Various CP models to improve air traffic services have been developed. For example, a CP model for flight-level allocation for a vertical separation was developed in (Barnier and Brisset, 2004) and a CP model that minimizes the number of required ATFCM regulations has been developed in (Kerlirzin et al., 2000). Models that focus on improving the ATC workload have been developed in (Trandac et al., 2005) where a CP model for an airspace sectorization is presented and in (Flenerà et al., 2007) a CP model to minimize and balance the traffic complexities of airspace of the adjacent sectors is proposed. Finally, (Chemla et al., 1994) laid the foundation for CP modelling of the slot allocation problems. In (Allignol et al., 2012) a better description of improvements to the slot allocation problems together with CP applications can be found. Further planning methods and decision support tools can be found in (Barnier and Allignol, 2009) where a CP model for a conflict-free planning method is introduced and (Van Leeuwen et al., 2002) where a CP model for decision support is presented to aid the controllers in planning the movements of flights within an airport and its airspace.

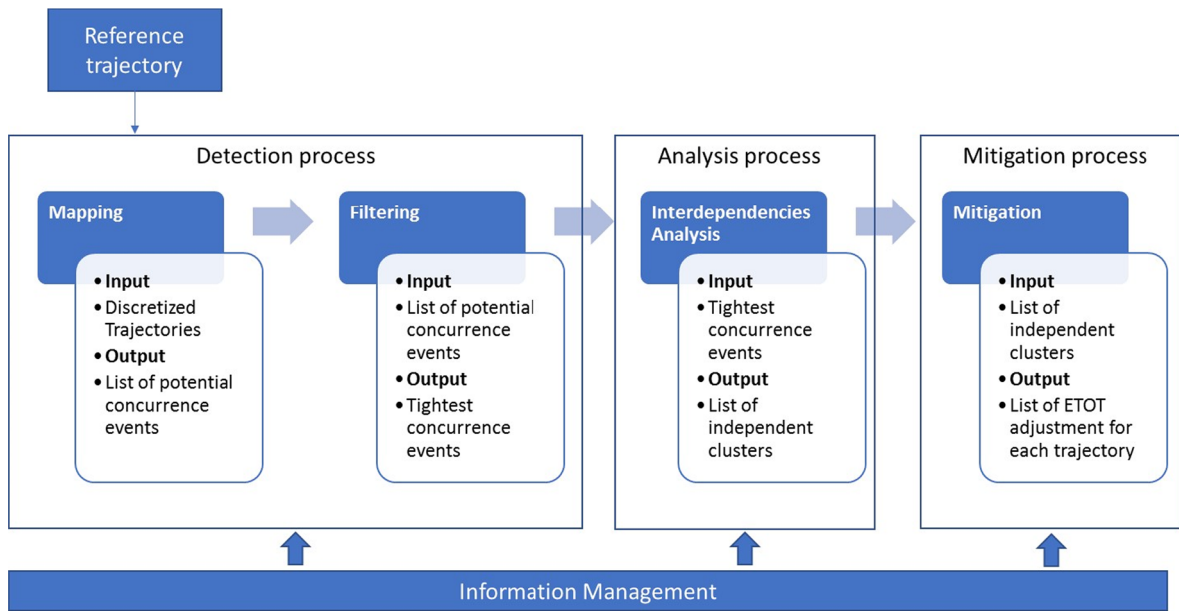


Fig. 1. Modular structure of the proposed methodology.

2. Methodology description

This section defines the methodology used to implement the consecutive set of tools as presented in [Schefers et al. \(2018\)](#) and [Schefers et al. \(2018\)](#). From a modular decomposition point of view, the main functional areas are detection, analysis and mitigation.

The detection functionality identifies the concurrence events and it is split into two sub-modules: the mapping process and the filtering process. The analysis functionality refers to the identification of topologies of interdependencies that cannot be removed by ground delays constrained by the CTOT time-window. This analysis will be helpful for identifying the trajectories that should be removed from the problem formulation in the mitigation functionality to provide a robust departure coordination. The mitigation functionality calculates feasible time stamp domains considering bi-objective criteria to resolve the trajectory clusters. The modular structure proposed for the development of the tools and their associated algorithms is shown in [Fig. 1](#).

2.1. Detection methods

The mapping process ([Schefers et al. 2018](#)) includes on one hand the mapping of the trajectories onto a grid of cells covering the determined airspace and the Spatio-Temporal (S-T) interdependencies to identify concurrence events (CE) and potential concurrence events (PCE) between trajectories that lose their safety buffer. The benefits of this methodology are the efficient way of identifying CE by partitioning the airspace and therefore being capable to promptly identify CE.

2.2. Mapping process

To detect concurrence events, the airspace is horizontally partitioned into square-cells with a size related to a lateral separation minima. The cell-size is a parameter that depends on the operational environment (e.g. Terminal Manoeuvring Area or en-route). Each horizontal layer of cells corresponds to a given flight level or altitude. A horizontal layer of cells is created according to the vertical separation criteria to be applied. This data structure conforms a 3D discretization of the airspace volume under consideration. In this work, different operational parameters are tested to understand the behaviour of the tools and the correlation to the detected CE. 4D trajectories provide the benefit that the aircraft can fly on a practically unrestricted trajectory for as long as possible in exchange of being obliged to meet accurately any Target Time of Arrival (TTA) over a designated point ([SKYbrary, 2017](#)). To ensure the reliability of the concurrence event identification, the traffic in the surrounding cells is analysed using an intelligent neighbourhood check algorithm. After the initial mapping on the trajectories 3D grid, cells that have an occupancy rate equal or greater than two (2) aircraft simultaneously and/or neighbouring cells where two or more aircraft lose separation minima are identified and stored for further temporal analysis.

The second step is the temporal mapping process that registers the entry and exit times of each aircraft trajectory into the cells having an occupancy greater than one. [Fig. 2 \(a\)](#) illustrates this process. With this information, the calculation of the temporal looseness (“clearance time” or “overlap time”) between pairs of aircrafts using the same cell can be determined. “Clearance time” refers to any time in which two aircraft do not share a cell in the same time frame. Logically, the smallest “clearance time” would be that one aircraft is just about to leave the cell and another aircraft is about to enter the cell. The temporal looseness H of two aircraft

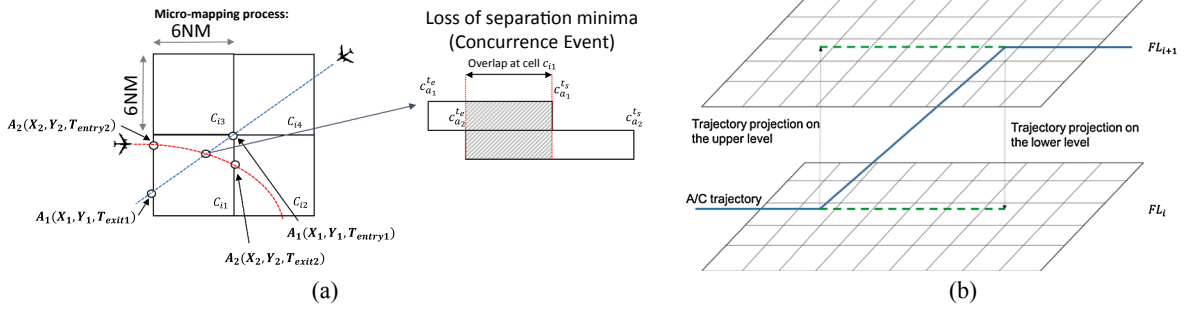


Fig. 2. S-T Interdependency (a) horizontal and (b) vertical projection.

can be calculated by determining the minimum value of the exit time of the two aircraft and subtract the maximum entry time from this value. Therefore, to be considered as a potential concurrence event the temporal looseness H of a pair must satisfy:

$$H = \min(c_{a_1}^{t_e}, c_{a_2}^{t_e}) - \max(c_{a_1}^{t_s}, c_{a_2}^{t_s}) \geq -h_m = (\delta_M - \delta_m) \quad (1)$$

where δ_M is the maximum time shifting that can be applied during the mitigation process (e.g. 10 min), and δ_m is the maximum advanced time (e.g. -5 min), $c_{a_i}^{t_s}$ refers to the time of an aircraft a_i entering into the cell and correspondingly, $c_{a_i}^{t_e}$ refers to the time of the aircraft leaving the cell c . When $H \leq 0$ there is a clearance (Potential Concurrence Event or PCE), and when $H > 0$ there is an overlap (Concurrence Event or CE).

To deal with vertical uncertainties, an aircraft a_j that changes its flight level from FL_i to FL_{i+1} is considered to be at both flight levels during the evolution time. By applying this method, it might occur that a concurrence event for aircraft a_j is registered in several flight levels because it is performing a climbing or descend manoeuvre, so it might happen that several concurrence events involving the same aircraft are detected simultaneously at the different flight levels. This is a rather conservative but safe approach which is the most important factor in air traffic management. A graphical illustration of the method used to map the vertical profile of the trajectory is represented in Fig. 2(b).

2.3. Filtering process

Since not all the potential concurrence events are of interest for the mitigation process, the detected concurrence events are filtered by their temporal looseness. The domain for rescheduling the ETOT is restricted to the CTOT window of $[-5, 10]$ minutes. Therefore, the list of the tighter S-T interdependencies must be filtered with $h_m = 15$ min, the maximum CTOT shifting window which would not endanger the safety separation even if the shift at each interval end is applied to each aircraft. This temporal filter ensures that no concurrence event is induced when the mitigation measures are calculated since all potential concurrence events with a temporal looseness lower or equal to 15 min will be included as no-overlapping constraints during the mitigation phase.

The idea behind this process is to focus on the tightest pair of aircraft that could lose separation minima when a shifting is applied to a flight. This process makes it feasible to develop a pre-tactical conflict detection methodology, capable of outperforming algorithms such as pairwise oriented detection or even Spatial Data Structure (SDS) methods (Lara, 2005), with a performance sensible to scalability problems.

2.4. Analysis methods

The second module of the methodology is the Analysis tool, executed after the mapping and filtering processes. This phase aims at analysing the interdependencies among the flights showing potential concurrence events. The analysis process has two main objectives: to determine clusters of trajectories that are interrelated because of the conflicts they are involved in; and to improve the problem solvability during the mitigation process. The first objective enables a separated mitigation process for each of the identified clusters. Consequently, the proposed mitigation measures applied to flights located in one cluster will not impact the trajectories at the other clusters. A relevant consequence is a significant reduction in the computational burden in the mitigation process. The second objective enables the definition of new interdependency metrics that, among other benefits, could be used to support decision making in complex situations where, for instance, the conflicts cannot be removed with the mitigation measures proposed in this paper.

To achieve these objectives, this work introduces the concepts of *Concurrent* and *Coupling* interdependencies and the analysis tool that is based on a graph representation of the potential and actual concurrence events detected and filtered at the previous phase (see Fig. 3).

2.5. Analysis of concurrent and coupling interdependencies

This process builds the so-called interdependency graph $G\langle N, E \rangle$ where the set N of nodes represents the *Concurrent* interdependencies, and the set E of edges represents the *Coupling* interdependencies. A Concurrent interdependency is defined as the set of

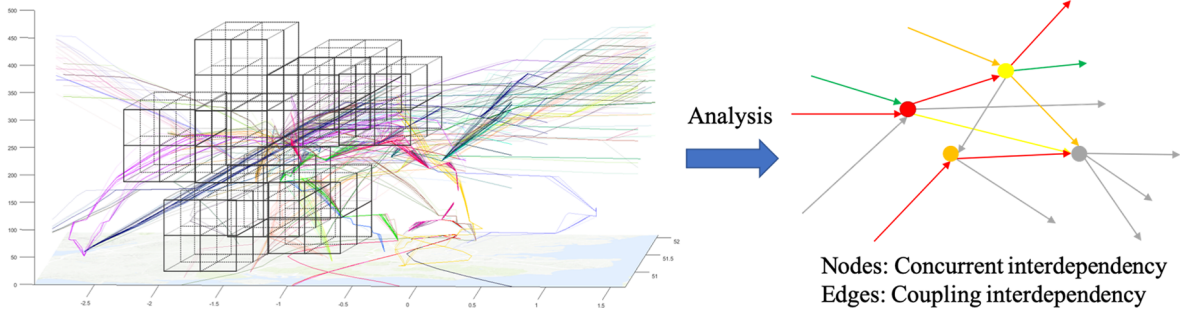


Fig. 3. Illustration of interdependencies using graph representation where nodes represent concurrent interdependencies and edges represent coupling interdependencies.

pairwise concurrence events happening at the same cell when they involve, at least, one common flight. Fig. 4 illustrates this concept. The flight a_2 is involved in two concurrence events at the same cell, so flights a_1 , a_2 and a_3 are grouped into one node representing the coupling interdependency among them.

A Coupling interdependency is defined as the set of concurrent interdependencies happening at different cells when they involve, at least, one common flight. Fig. 5 illustrates this concept. The flight a_4 is involved in three concurrent interdependencies at cells C_1 , C_2 , and C_3 , so there exists a coupling interdependency between all four aircrafts. A coupling interdependency is represented in the graph G by an edge connecting the interrelated coupled nodes.

As a first result, the graph G provides a formal representation of the system state: the mitigation algorithm will go through each graph node in order to generate the no-overlapping constraints that will define the space of feasible solutions to the separation problem. The graph edges are used to create the link constraints that will ensure that no concurrence events are induced when a solution is created for mitigating the concurrent interdependencies.

Moreover, Graph Theory (Chartrand et al., 2006; Gibbons et al., 1985; Trudeau, 2013) can be used to extract very useful analytical properties from this interdependency graph G . In the experimental part of this work, two of them have been used. The first one is the detection of the graph disconnected components or subgraphs. According to the interdependency graph G definition, each of the found subgraphs is a cluster of trajectories that do not show S-T interdependencies with the other trajectories at the traffic scenario. Therefore, the mitigation time adjustments for the trajectories of each cluster can be determined without side effect on the trajectories outside the cluster. Fig. 6 illustrates this concept. The mitigation measures for clusters 1, 2 and 3 can be calculated as separate optimization problems, which significantly benefits the computation burden of the mitigation phase.

Furthermore, the information contained in the interdependency graph G is being used to determine situations where the mitigation measures proposed in this work cannot remove a particular concurrence event. Fig. 7 illustrates this case. Assume aircrafts a_1 and a_2 are already flying (so no ETOT adjustment can be applied to them) and the mitigation solver is asked to determine the δ_{a_3} shifting to remove the concurrence events with a_3 . It may happen that δ_{a_3} does not exist in the allowed adjustment interval $[\delta_{min}, \delta_{max}]$. If no action is taken, the optimization solver determines that no solution exist for the whole cluster where these trajectories are present. However, the analysis of the node representing the coupling interdependency between flights, determines analytically this situation and other measures could be applied before the mitigation mechanisms proposed in this work are calculated. In the experimental part of this paper, situations analogous to a_3 in Fig. 7 are logged and the flight is removed from the mitigation process, so the remaining concurrence events can be solved.

2.6. Mitigation method

The mitigation algorithm has been formulated as an optimization problem using the Constraint Programming paradigm (Rossi

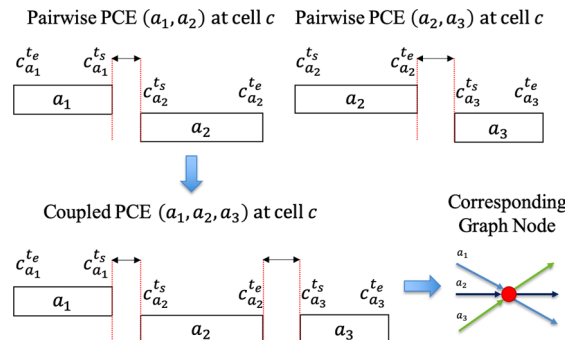


Fig. 4. Grouping two potential pairwise conflicts at the same cell to form one *Concurrent* interdependency node.

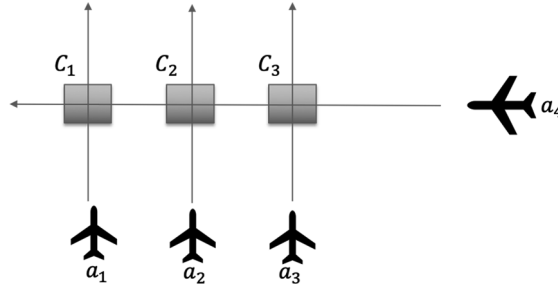


Fig. 5. Potential coupling interdependencies.

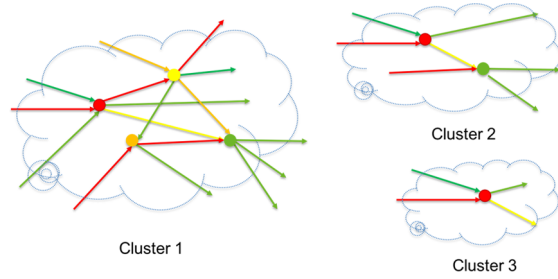


Fig. 6. Independent clusters of trajectories.

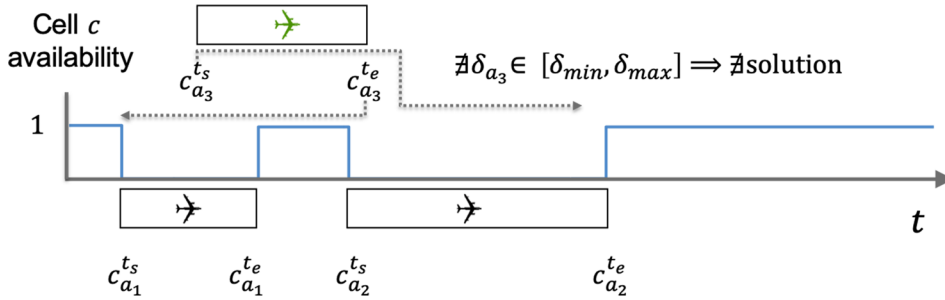


Fig. 7. Solvability analysis of a Concurrent interdependency.

et al., 2006). The mitigation measures are calculated as the solution to the optimization model listed in Table 1. The presented CP model is not considering equity nor AU's preferences since the proposed mitigation measures will not interfere the allocated CTOT once a regulated scenario has been put in place. Hence, we are assuming that equity and preference criteria have been already considered when CTOT's are imposed by ATFM slots calculated using CASA (EUROCONTROL, 2018a).

A description of the optimization model follows. Further details of this model can be found in (Schefers et al., 2018). The main data structures in the model, declared by Eqs. (2) and (3), are obtained from the detection and analysis processes. The elements at the set defined by Eq. (2) represent the time occupancy of the cell c by aircraft a at a given flight level f . Each element is obtained from the interdependency graph and it is characterized by the two parameters c_{af}^{ts} (cell entry time) and c_{af}^{te} (cell exit time). To meet the agreed target time of arrival (TTA), the model also needs to consider small speed adjustments since shifting the whole trajectory according to the applied slot time adjustment would not allow to meet the TTA. Therefore, data structures are introduced to model trajectory as a set of segments that will be used to obtain the suitable speed adjustments, whether possible. Let $\hat{g}_i^{af}$ be a segment of the aircraft a trajectory at a given flight level (FL). Therefore, the flight can be noted as the set of segments in Eq. (3) for each flight in the set of aircrafts A .

The decision variables at Eq. (4) models the time shifting to be applied and its domain ensures that the departure adjustment of the aircraft remains in the defined timeframe of $[-5, 10]$ minutes. Eq. (5) declares the interval decision variables for the occupancy of the cell c by an aircraft a at a given FL f and whose size is defined by the entry and exit times obtained at the detection process. These interval variables constitute the domain of the sequence decision variables declared for each cell having a potential concurrence event (Eq. (6)).

Eq. (7) declares a decision variable representing the entire flight trajectory, where s_a will be the actual take-off time and e_a the arrival time in the solution. This interval variable, along with δ_a , will be used in the model constraints for calculating the take-off shifting. The Eq. (8) declares the interval variables representing the segments g_i^{af} and their size. The segment size can be slightly modified in the solution with respect to the original trajectory according to the speed adjustment boundaries specified by the segment

Table 1
CP Model and data structure.

A set of aircraft	
C set of cells that have a concurrence event	
F set of Flight Levels	
$C_{AF} = \{ \langle c, a, f \rangle \mid \forall c \in C, \forall a \in A, \forall f \in F \}$	(2)
$RBT_a = \{\hat{g}_i^{af}\}, i = 1..p(a), \forall a \in A$	(3)
d. v. $\delta_a \in [\delta_{min}, \delta_{max}], \forall a \in A$	(4)
d. v. $P_{caf}: sz(P_{caf}) = (c_{af}^e - c_{af}^s), \forall c_{af} \in C_{AF}$	(5)
d. v. $O_c = \{P_{caf} \mid c_{af} \in C_{AF}, \forall c \in C, \forall f \in F\}$	(6)
d. v. $G_a = [s_a, e_a)$	(7)
d. v. $g_i^{af} = [s(g_i^{af}), e(g_i^{af})], \forall a \in A, \forall f \in F, \forall i \in 1..p(a):$ $sz(g_i^{af}) \in [sz(\hat{g}_i^{af}) - l(\hat{g}_i^{af}), sz(\hat{g}_i^{af}) + l(\hat{g}_i^{af})]$	(8)
d. v. $T_a = \{g_i^{af} \mid \forall a \in A, \forall f \in F, i \in 1..p(a)\}$	(9)
minimize:	
$w_1 \sum_{a=1}^n \delta_a + w_2 \sum_{a=1}^n L(G_a)$	(10)
$L(G_a) = \begin{cases} 1, & e(G_a) \notin [TTA_a - 1, TTA_a + 1] \\ 0, & \text{otherwise} \end{cases}$	
subject to:	
$\forall P_{c_i}, P_{c_j} \in O_c$	(11)
$NO(O_c) \Leftrightarrow \pi(P_{c_i}) < \pi(P_{c_j}) \Rightarrow e(P_{c_i}) \leq s(P_{c_j})$	
$s(G_a) = CTOT_a + \delta_a$	(12)
$span(G_a, \{g_i^{af}\}), \forall a \in A, \forall g_i^{af} \in T_a$	(13)
$\forall a \in A, \forall f \in F, \forall i, j \in 1..p(a)$	
$NO(G_a) \Leftrightarrow \pi(g_i^{af}) < \pi(g_j^{af}) \Rightarrow e(g_i^{af}) \leq s(g_j^{af})$	(14)
$e(g_i^{af}) \leq s(g_j^{af}), \forall i, j: i < j$	(15)
$e(g_i^{af}) = s(g_j^{af}), \forall i, j: j = i + 1$	(16)
$\begin{cases} s(g_i^{af}) = s(P_{caf}) & s(\hat{g}_i^{af}) = c_{af}^s \\ e(g_i^{af}) = e(P_{caf}) & e(\hat{g}_i^{af}) = c_{af}^e \end{cases}, \forall c_{af} \in C_{AF}$	(17)
$synchronize(g_i^{af_1}, \{g_i^{af_k}\}), \forall f_k \in F: f_k \neq f_1, \forall g_i^{af_1} \in T_a$	(18)

elasticity function $l(\hat{g}_i^a)$. The Fig. 8(a) illustrates the relationship between g_i^{af} and the trajectory interval G_a . The trajectory segments are required to set the link constraints between the trajectory and the occupancy intervals represented by the variables P_{caf} . Finally, the RBT segments at different FLs need to be synchronized to model the 3D concurrence event mitigation. Recalling the concurrence event detection process described in Fig. 2(b), the RBT exists in the lower and upper flight level during the FL change of the RBT. The sequence variable T_a is introduced to set later the proper synchronization between the trajectory segments g_i^{af} existing at the different flight levels and the entire trajectory G_a (Eq. (9)).

The bi-objective optimization goal in Eq. (10) combines the weights w_1 (minimizing the total aircraft delays) and w_2 (binding the Target Time of Arrival (TTA); where a refers to the aircraft, δ_a is the delay applied and $L(G_a)$ represents the speed adjustments of the RBT segments according to their allowed elasticity if the TTA cannot be met.

The constraint at Eq. (11) ensures that each of the cells is occupied by one single aircraft at a certain FL at a time. This no-overlap constraint (NO) imposes this condition over each interval variable P_{caf} at each cell c where potential concurrence events were

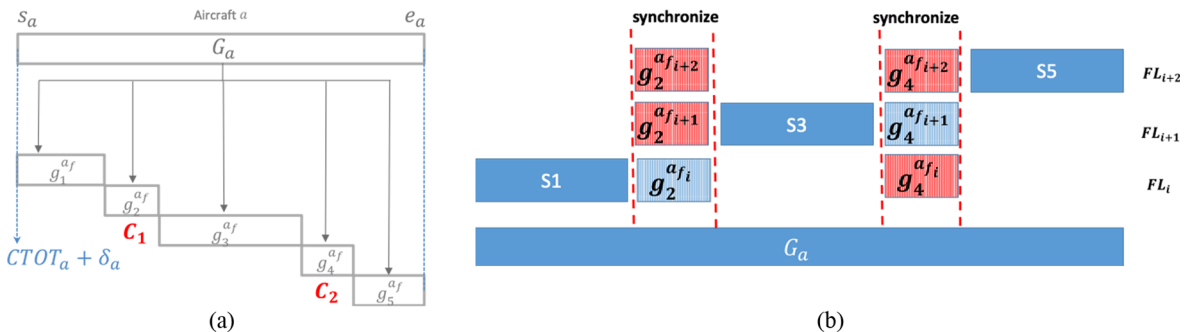


Fig. 8. Graphical representation of the RBT segments and the trajectory (a) and Flight Level synchronization (b).

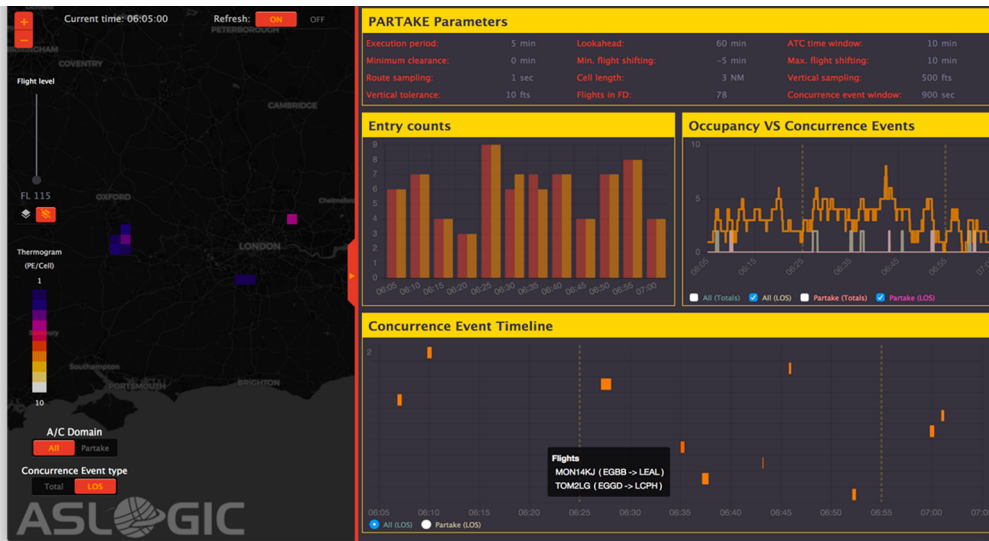


Fig. 9. Dashboard for interdependency metric visualization developed in the scope of the PARTAKE project.

detected. The constraint at Eq. (12) links the take-off shifting δ_a to be calculated and the interval variables representing the solution trajectory G_a . The constraints in Eqs. (13)–(16) ensure the proper temporal relationships between the trajectory segment intervals g_i^{af} and the trajectory interval G_a as a whole, as Fig. 8(a) illustrates. The constraint at Eq. (17) imposes the temporal links between the cell occupancy intervals $P_{c_{af}}$ and the trajectory segments g_i^{af} corresponding to the use of a cell where potential concurrence events are detected. For instance, the intervals g_2^{af} and g_4^{af} using cell C_1 and C_2 as shown in Fig. 8(a). Finally, the constraint at Eq. (18) is used to synchronize the start and end of interval segments g_i^{af} projected at different flight levels to model the 3D concurrence event mitigation, as shown in Fig. 8(b). This constraint makes all present intervals in the set to start and end together with interval g_i^{af} . To avoid temporal inconsistencies between constraints in Eqs. (13)–(16) and Eq. (18), just one g_i^{af} of the vertically projected segment is used to form the trajectory G_a . This is represented as the blue striped segments in Fig. 8(b).

2.7. Interdependency metrics

The presented tools have been tested and verified during the development of the PARTAKE project (SESAR JU, 2016; UAB et al., 2018). The mitigation measures are calculated on the basis of two new metrics: Concurrency and Coupling interdependencies. These metrics complement entry and occupancy counters by providing a prediction of the potential tactical intervention due to a separation infringement. A Concurrency interdependency shows where, when and how many flights can loss separation. Coupling interdependencies indicate the potential *domino* downstream effects of a tactical intervention. They are used to ensure that mitigation measures for removing concurrence events are not inducing those effects. A visual interface (see Fig. 9) has been designed for a quick understanding of the system performance, rising quickly and visually the situational awareness throughout the look-ahead time.

3. Application and experimental results

The developed methodology has been applied to a testing case involving a representative multi-airport system. Firstly, it is shown the operational environment and operational context considered for the experiments. Secondly, the testing case framework is outlined. Lastly, the section presents and discuss the obtained results.

3.1. Service in a TBO scenario

The methodology has been designed to be executed as a rolling time service that takes benefits of the Trajectory-Based Operations concept in which the airspace user intentions are known by all the interested parties (see Fig. 10). The input of the service is the set of reference trajectories that represent the instantaneous predicted S-T distributions of flights (on ground and on air) that crosses the target sectors. These trajectories are then used to detect, analyse and mitigate the concurrence events. The output of the service is a set of more effective ETOTs that mitigate the detected concurrence events.

The tuning of the different mitigation parameters is performed based on operational concerns relative, mainly, to safety criteria. The experiments developed in this section aims at evaluating the impact of the selected parameters on the capacity to solve the detected concurrence events.

The following terms are defined for understanding the main variables and parameters (all in minutes) of the execution timeline

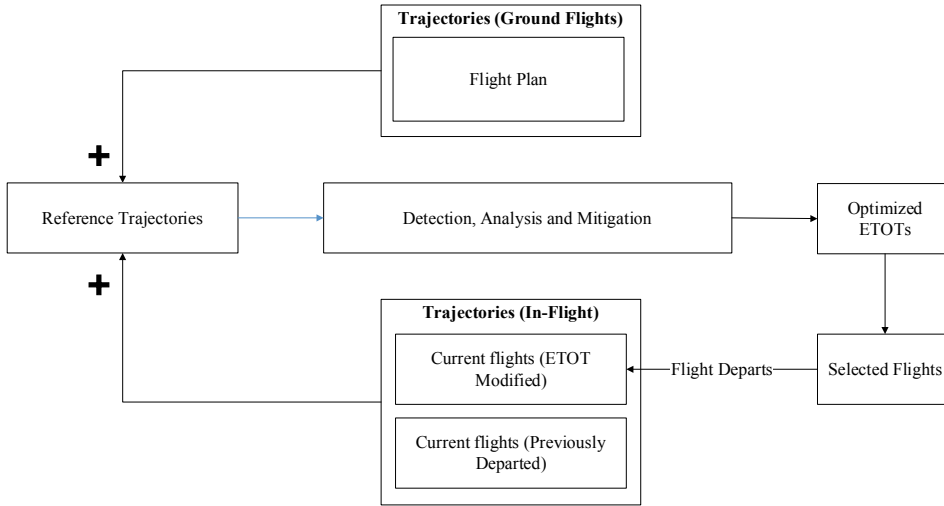
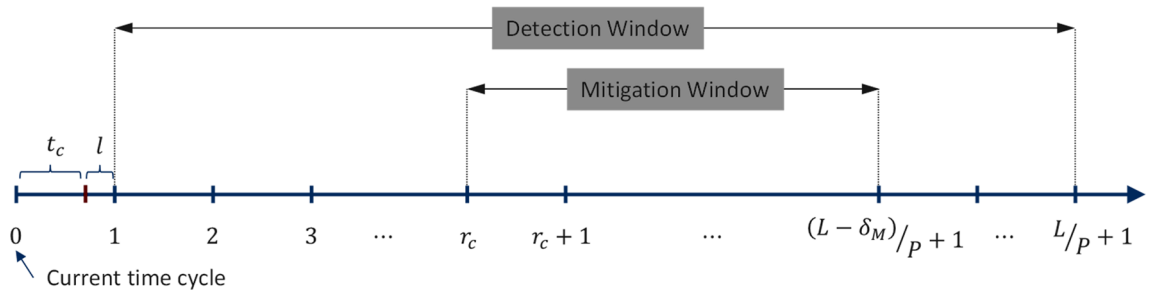


Fig. 10. Cyclic execution flow of the proposed tools.

(see Fig. 11):

- Execution Period (P): time period between consecutive executions.
- Look-ahead time (L): is evaluation period for detecting potential concurrence events among trajectories that are active during this period. It starts at cycle 1 (current time plus P)
- Cell-size (S_C): it is the size of the cell c .
- Shifting domain: $([\delta_m, \delta_M])$: minimum and maximum delay that can be applied to the ETOT.
- Offset: is the along track deviation present in a trajectory with respect to the original RBT. It can be caused either by an action (applied shifting delay) or by actual flying conditions.
- Required ATC reaction time (t_{ATC}): is the minimum time window between the time the ATC is informed about a possible departure shifting and the new assigned ETOT.
- Detection Window: timeframe where detection algorithm applies. It starts at current time plus P and ends L minutes later.
- Mitigation Window: is the time frame where departures are considered for mitigation actions. It starts at current time plus $r_c P$ and ends $L - \delta_M$ minutes later. Note that trajectories departing between $((L - \delta_M)/P) + 1$ and $(L/P) + 1$ intervals are considered for detection but not for mitigation.
- Minimum Clearance: it is the time in minutes of the minimum clearance to consider a potential concurrent event as a real conflict.



Parameters	P	Execution period
	L	Look ahead time
	δ_m	Minimum shifting delay
	δ_M	Maximum shifting delay
	r_c	Begin cycle of mitigation window
	t_c	Partake computational time of one cycle
	t_{ATC}	Required ATC reaction time
	l	Latency

Parameter Conditions:

$$P = \gcd(L, \delta_m, \delta_M, t_{ATC}) \text{ whenever possible}$$

$$t_c + l \leq P$$

$$L \geq t_{ATC} + 2P + \delta_m + \delta_M$$

$$r_c = \left\lceil \frac{t_{ATC} + \delta_m}{P} \right\rceil + 1$$

Fig. 11. Parameters available for tuning.

The following concepts are also introduced:

- **Selected Airports:** set of stations that are coordinated by the mitigation tool.
- **Detection domain:** all traffic that exists within the look-ahead time (L).
- **Mitigation domain:** all the flights whose departure is within the mitigation window in a given execution cycle and which depart from Selected airports.
- **Controlled domain:** set of flights departing from selected airports and whose departures have been regulated by actions at a given execution cycle. Once a flight becomes a member of this set it cannot belong to the mitigation domain in future execution cycles.

For the experimentation purposes, it is assumed that the actual flown trajectories have a high-adherence to the known input reference trajectories (flight intent in TBO context) being used in the execution loop illustrated in Fig. 10. The presented mitigation model is not considering time uncertainties since the actual 4D state of each flight is updated at each execution cycle. Nevertheless, further analysis of the methodology under time uncertainties conditions for ground operations or during flight is part of future research (preliminary results during flight were presented in (Schefers et al., 2018)). As to possible spatial deviations, the impact of such uncertainties can be reduced by increasing the cell-size used for detecting concurrence events. However, the bigger is the cell-size the greater is the generated latent capacity. Similarly, when the look-ahead time increases it is expected that the uncertainty level increases. However, the lower is the lookahead the smaller is the capacity to reduce the probability of concurrence events. Therefore, the effectiveness of the proposed methodology depends, among other factors (e.g. traffic or number of coordinated airports), on the proper trade-off between *cell-size* (S_C) and *look-ahead time* (L) parameters. In an operational scenario, it is expected that these values are fine-tuned depending on the traffic conditions and the uncertainty levels that are expected for the solution. The following experiments will illustrate the impact of these parameters on the capabilities of the proposed mitigation mechanism to reduce the concurrence event probability.

3.2. Case of study London TMA

The London Terminal Manoeuvring Area (LTMA) is a complex Multi-Airport System (MAS) (CAPITA, 2013). In 2015, it handled 155.2 millions of passengers and received more than 1.05 millions of flights (CAA, 2017).

LTMA traffic follows inbound and outbound standard routes to/from the five main airports (Stansted-EGSS, Luton-EGGW, Heathrow-EGLL, Gatwick-EGKK and City-EGLC, see Fig. 12). Some of these routes include alternative procedures in case of technical disruptions of nav aids or depending on the runway configuration (NATS, 2017).

For a sample of trajectories, it has been calculated the number of flights that crosses the most relevant waypoints of the TMA. Fig. 13 represents the waypoints areas with higher density in the LTMA: Brooksman's Park (BKP), Lambourne (LAM) and Compton (CPT) waypoints located at the North, North-East and North-West of London Heathrow Airport (EGLL), respectively.

The Capital sector (EGTTCAP), represents an often-regulated airspace volume. EGTTCAP is the result of *band-boxing* the elementary volumes Compton (EGTTCPT) and Vatn (EGTTVAT). Fig. 14 shows the hourly demand distribution of EGTTCAP. Regulations highlighted in red have been triggered in EGTTCPT.

Departure from the LTMA is often limited by the so-called Minimum Departure Intervals (MDI). The application of MDI rules involves that target airports (e.g. Stansted or Birmingham) are required to limit successive take-offs for a specific interval of time on the same SID (e.g. one flight each ten minutes). The rule aims at regulating the number of aircraft on air due to an unexpected

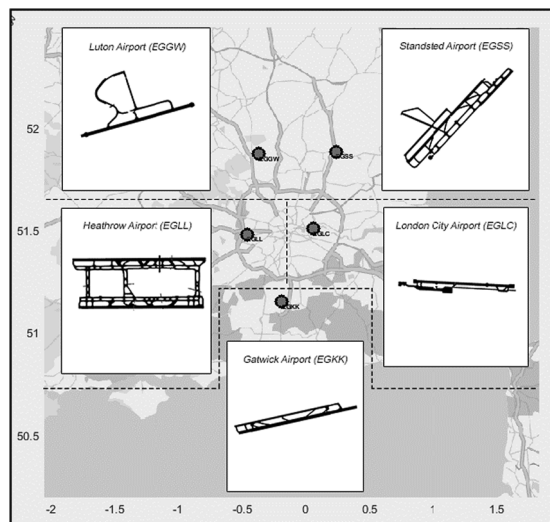


Fig. 12. London Terminal Manoeuvring Area (LTMA) Airports.

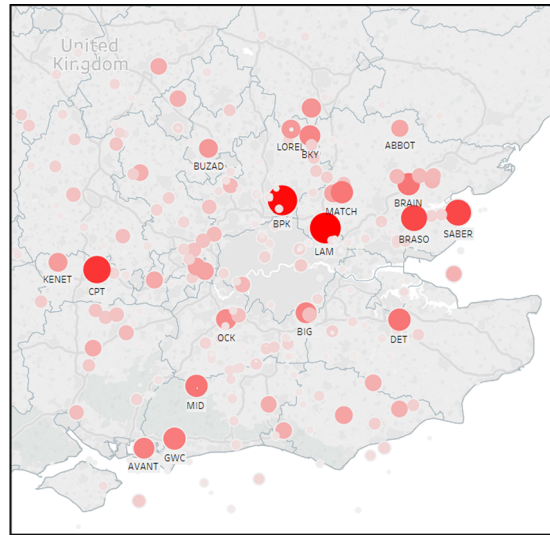


Fig. 13. High-density areas in London terminal airspace (data adopted from Eurocontrol DDR2 (EUROCONTROL, 2017b)).

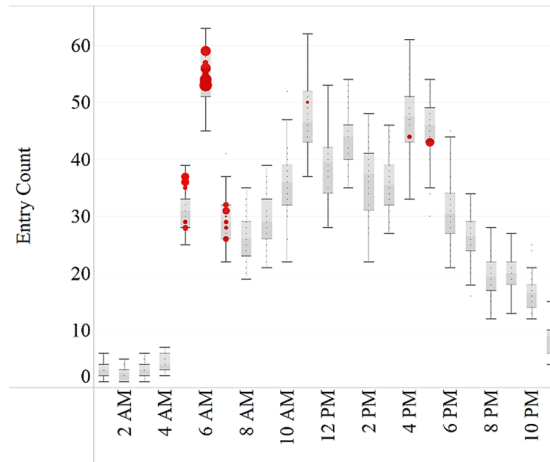


Fig. 14. Regulations in Capital (EGTTCP) during summer 2016 (EUROCONTROL, 2018b).

increase on the entry-count of highly congested sectors. The problems associated to these rules is that their application targets all the departures on the same SID. This effect produces that some flights in the departure queue could be affected but they do not cross the congested volumes or they do not have a significant impact in the ATC workload.

The idea of using the methodology is to determine a more efficient and logical departure sequence, *targeting only the flights that could produce concurrence events*, resulting in a more favourable demand distribution in the congested sectors. The ultimate goal is then reducing the number of ATC interventions on *air* while maintaining the airports throughput.

The algorithm presented in this paper was applied as a service to different realistic traffic samples obtained from Eurocontrol Demand Data Repository (DDR2) (EUROCONTROL, 2018b). Data provides a very accurate picture of pan-European air traffic demand, from several years ahead until the day before operations. It can be used to support the network collaborative planning process that include strategic, seasonal and pre-tactical planning as well as for the planning of special events or major ATM evolution projects.

Simulation exercises have been designed using the full LTMA volume (EGTTTC) to analyse and study optimal working conditions for the proposed methodology. Firstly, a traffic scenario was selected to analyse the three most relevant parameters: cell-size, number of coordinated airports and the look-ahead time. Once the appropriate operating parameters from this scenario are identified, they are applied to other days/times of traffic.

To test and evaluate the method towards the most relevant operating parameters, a variety of experiments using the developed framework were tested in a fast-simulation exercise, see Table 2. The simulation reflects upon the output of each module which is:

- **Detection:** number of potential concurrence events that could be removed.

Table 2

Performed experiments to demonstrate the behaviour of the methodology according to identified parameters.

Experiment	Cell-size					Airports		Look-Ahead Time (<i>L</i>)		
	2NM	3NM	4NM	5NM	6NM	2	4	45	60	75
1	✓					✓			✓	
2		✓				✓			✓	
3			✓			✓			✓	
4				✓		✓			✓	
5					✓	✓			✓	
6	✓						✓		✓	
7		✓					✓		✓	
8			✓				✓		✓	
9				✓			✓		✓	
10					✓		✓		✓	
11	✓					✓		✓		
12	✓					✓			✓	
13	✓					✓				✓
14		✓				✓		✓		
15		✓				✓			✓	
16		✓				✓				✓

- **Analysis:** number of clusters within the mitigation window
- **Mitigation:** number of removed potential concurrence events in the cycle together with the number of applied shifting.

The experiments 1–10 test the influence of the cell-size towards the percentage of CE that can be mitigated using the proposed methodology. The minimum horizontal separation for operations based on radar and/or ADS-B. The cell-size value ranges between 2NM and 6NM which are values selected close to the horizontal separation limits established in (ICAO, 2016) on operations based on radar and/or ADS-B. Also, given that the number of flights that could be affected in the departure sequence depends on the number of airports where the methodology could be applied, it has been decided to analyse the impact of implementing the methodology in 2-airport and 4-airport experiment setup based on preliminary observations of the traffic. Although the more airports are coordinated the more opportunities to find better solutions, the mitigation model presented in this work does not include constraints on the runway throughput. Therefore, the less congested airports supplying traffic to the LTMA have been selected for departure co-ordination in order to avoid possible negative impact on runway throughput in high-traffic airports (e.g. Heathrow and Gatwick).

The two main airports that feed traffic to the EGTTCAP (FL130-FL245) sector are London Luton (EGGW) and London Stansted (EGSS). Additionally, Birmingham (EGGD) and Bristol (EGBB) airports feed an important amount of traffic to EGTTCPT. Experiments 11–16 analyse the look-ahead time, considering the service definitions as explained in Fig. 11. Furthermore, an analysis of the variability of the entry-count with respect to the cell-size and an analysis of the relationship between the occupancy and the CE was performed to obtain information at an aggregated level regarding the system's sensitivity to network dynamics.

The parameters used in the fast simulation consider a rolling horizon with a cycle repetition (*P*) of every 5 min, a required ATC reaction time (t_{ATC}) of 10 min, and the mitigation CTOT window of [-5, 10] minutes.

3.3. Experimental results

As an initial step, a traffic scenario was selected to perform the fast simulation and to provide recommendations about the most relevant operating parameters: cell-size, number of operating airports and look-ahead time. It was used a sample traffic data of 19th of July 2017 from 6am to 7am. In this traffic scenario, 331 trajectories are found. The number of detected concurrence events decreases or increases depending on the separation criteria (cell-size). LTMA has been the target of an important number of regulations during summer of 2017 (including the 19th of July 2017), and most regulations occurred in the traffic peak period between 6:00am and 7:00am (EUROCONTROL, 2017b).

The experiments mentioned in Table 2 are performed to understand the systems behaviour with respect to the most relevant operating parameters. Later, these findings are compared and applied to other traffic scenarios to consolidate the results and generate a benchmark.

A graphical visualisation of the trajectories is shown in Fig. 15. The red lines indicate trajectories with CEs whereas the green lines indicate a CE-free trajectories during the indicated timeframe. The white geometric shapes surrounding the London area show the extent of the LTMA.

In the selected scenario, an average of 16% of PCE belongs to the solution space of the algorithm, meaning that the trajectories are flights that are still on the ground, belongs to one of the coordinated airports that are considered and therefore can be time-shifted by the mitigation process. This percentage indicates that for this traffic scenario the algorithm could apply mitigation rules in 16% of the traffic (at maximum) in order to reduce the amount of potential ATC tactical interventions on air.

Fig. 16 presents the amount of PCEs and CEs that have been detected. With an increased cell-size, the number of CEs and PCEs increase because more aircraft share a cell and therefore more flights are considered CEs. The amount of PCEs is directly proportional

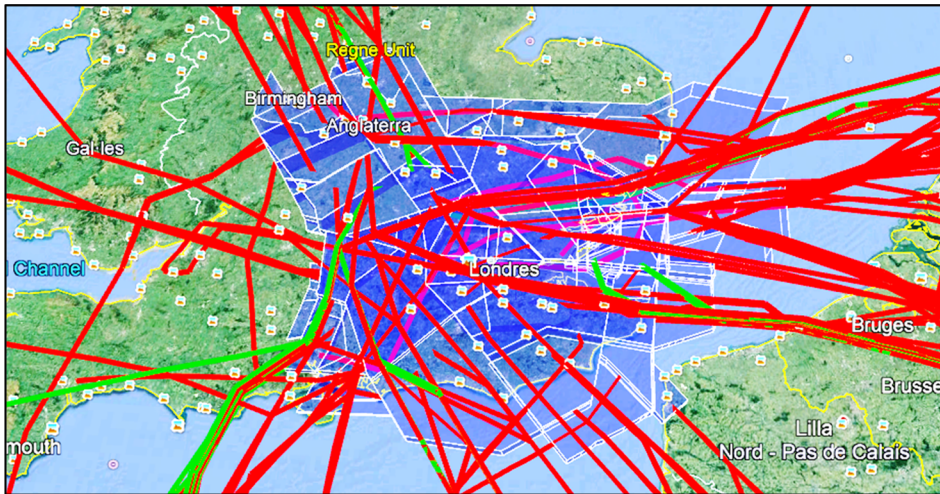


Fig. 15. Visualization of the RBTs of the selected traffic scenario.

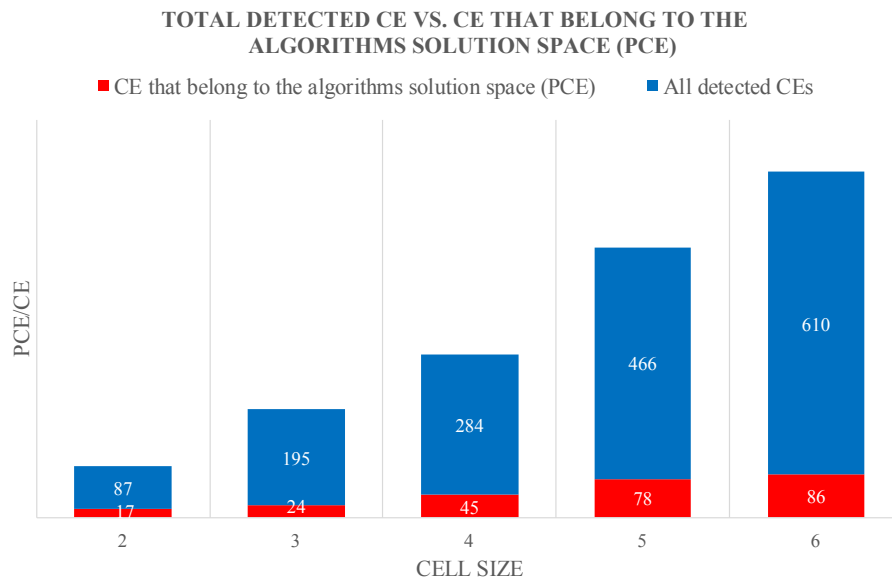


Fig. 16. Total detected CE and PCEs according to the applied cell-size.

to the number of selected airports where the mitigation process is applied. The 84% of concurrence events that does not belong to the algorithm solution space are produced by flights that departed from airports outside of the LTMA.

The most remarkable result to emerge from the **analysis of the cell-size** (experiments 1–10, Table 2) is that the percentage of solved PCEs and the absolute number of solved PCEs is maximum for cell-sizes of 2NM and 3NM. Starting from a cell-size of 4NM, the solvability decreases significantly as show in Fig. 17. Since LTMA is a very dense area with a high volume of traffic and many S-T interdependencies exist, there are cases when there is not enough capacity in the temporal dimension to change the ETOT without producing downstream effects. However, the number of CEs that cannot be solved during mitigation is very low using a cell-size of 2NM/3 NM (Fig. 17). The percentage of solved PCEs reaches almost 90% with a cell-size of 2NM and 75% with a cell-size of 3NM (grey line). Furthermore, when looking at the absolute numbers of PCEs that have been solved (orange bar), the highest number of PCEs are solved applying a cell-size of 2NM (15 CEs) and 3NM (18 CEs). This result furthermore shows that the percentage of overall solvable CEs (green bar) increases with a bigger cell-size until it achieves a saturation level at which no more concurrence events are detected.

Furthermore, to obtain information at an aggregated level regarding the system's sensitivity to network dynamics, an analysis of the effect of the cell-size on the occupancy has been performed. As it can be seen in Fig. 18, all three parameters, entry-count, exit-count and occupancy remain almost constant while the cell-size increases. The constant values throughout the different cell-size is an indicator that all trajectories are detected independent of the cell-size is. Besides the impact of the cell-size on the sector geometry (which is small), these indicators do not depend on the cell-size.

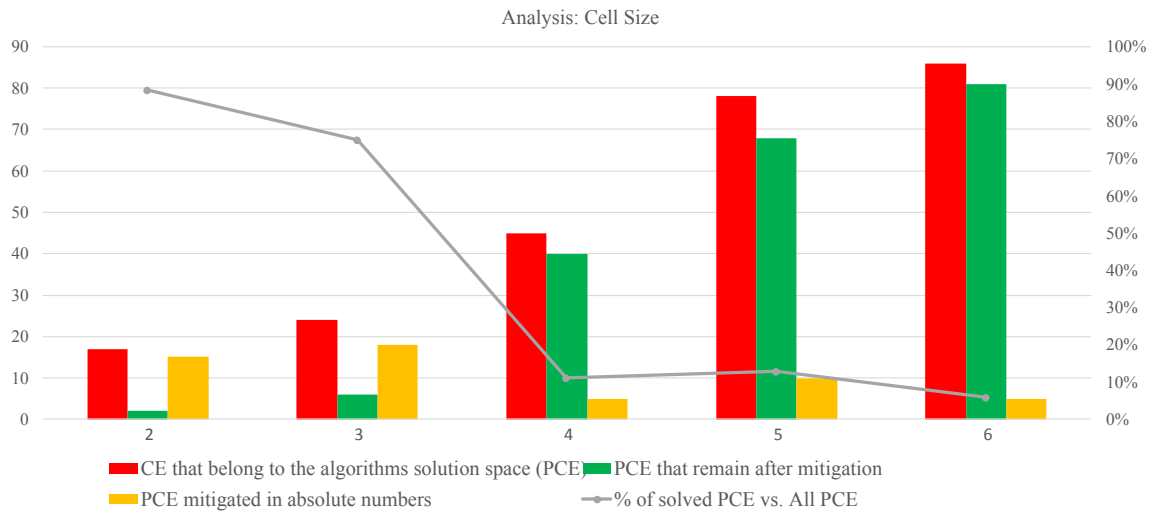


Fig. 17. Analysis of the cell-size. The red bar indicates the amount of CE that can be considered by the algorithm (PCE). The green bar indicates the amount of PCE that could not be removed. The grey line shows the percentage of solved PCEs with respect to all PCEs and the orange bar shows the mitigated PCEs in absolute numbers.

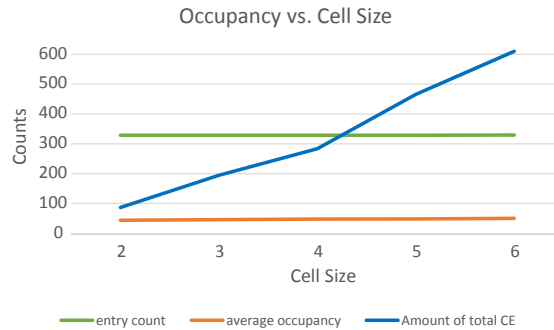


Fig. 18. Occupancy vs. Cell-size. It can be seen that the entry count and the occupancy remain stable with an increasing amount of CE.

The second parameter to analyse is **the number of operating airports**. The number of CE using either 2 (EGGW and EGSS) or 4 airports (EGGW, EGSS, EGBB and EGGD) seems not to influence significantly on the mitigation possibilities for small cell-sizes. When the cell-size increases, the difference between 2 or 4 operational airports increases and in the case of 6NM, 17 more CE could be solved, see Fig. 19. The reason for this is that for the sample of the experiment, EGGW and EGSS provide higher traffic volume than

2 VS. 4 AIRPORTS IN OPERATION

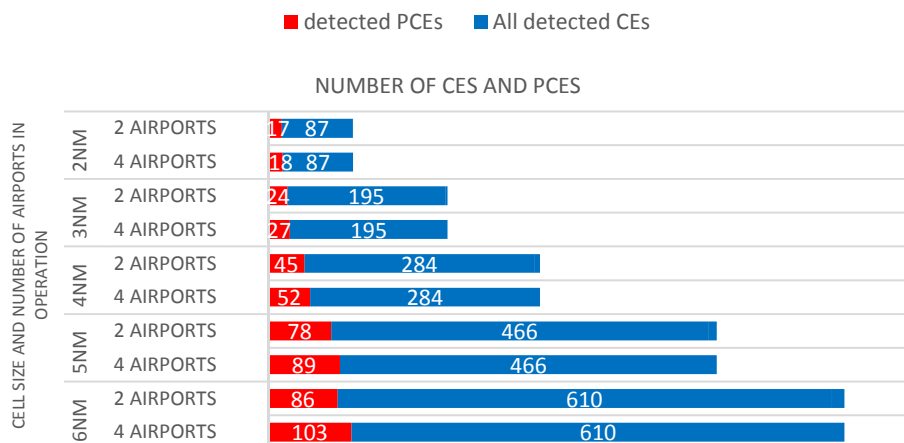


Fig. 19. Comparison of CEs with 2 operating airports and 4 operating airports.

EGBB/EGGD.

The third important operating parameter that has been analysed in the **look-ahead time** (experiments 11–16, Table 2). For these experiments, a series of different look-ahead times were tested to understand their influence on the amount of concurrence events. It is assumed that the possibility of CEs is lower with a smaller look-ahead time and grows as we increase it until a saturation level is reached. On one hand, with a very small look-ahead time the effectiveness of the method to solve CEs is very small and on the other hand, a big look-ahead time causes an increase of the uncertainty. Therefore, the analyses should reveal which look-ahead time has the best trade-off between effectiveness in solving CEs and uncertainty.

The smallest look-ahead time that has been chosen is 45 min. As detailed in Fig. 11, there are various parameters to determine the look-ahead time. The *look-ahead time* is the time that trajectories are predicted in advance. Usually, this time is calculated according to the average time of an aircraft inside the TMA, which in this case is around 20 min. The *ATC time* is the time, the ATC needs to provide the ETOT without being affected by ground operations. This parameter depends on different factors such as the skills of the ATC to match the proposed ETOT, the airport layout and/or the airport traffic/demand.

Finally, the *execution time* is the time needed to execute the algorithm. In this case, the execution time is multiplied by two (2), first to execute the algorithm and second to take into consideration the latency to submit the solution to the ATC. Therefore, for this simulation configuration the smallest look-ahead parameter is 20 min. (look-ahead time) + 15 min. (ATC time) + 5 min + 5 min (execution time) = 45 min. Note that the uncertainty associated to the first 15 min is expected to be absorbed at tactical level by the ATC capabilities to take-off the aircraft on the proposed ETOT. A sensitivity analysis is required to estimate the take-off time accuracy required to tackle the uncertainties associated to the trajectory until intercepting the concurrence event zone.

The test revealed that there was a correlation between the look-ahead time parameter, the cell-size and the execution time of the algorithm. The execution time increased according to the look-ahead time parameter applying a cell-size of 2 NM, whereas the execution time with 3NM seems to grow with a lower rate, see Fig. 20. The reason of this difference is that the time execution is related to the trajectory discretization and the amount of data the algorithm needs to process to achieve a valid solution.

The number of PCE before mitigation remains equal through all experiments, which is a positive indicator that the algorithm is capable to identify all CEs and PCEs of the selected traffic sample. The number of PCEs increases significantly applying a look-ahead time greater than 60 min.

Finally, for an improved visualization of the tool's effectiveness, a graphical illustration shows the reduction of the CEs before and after mitigation for the selected case. The chart in Fig. 21 shows the PCEs from the traffic scenario using a cell-size of 2NM, a look-ahead time of 60 min and considering 2 operating airports. A total of 88% of the PCEs are solved (meaning that from 100% of concurrence events that could have been solved, 88% were solved), which represents the 20% of the total CEs (the 88% of solved PCEs represent 22% of all flights). The concurrence events that could not be resolved belong to the case explained in Fig. 7, i.e. concurrence events that cannot be mitigated by simply applying a time shifting within the CTOT time window because of the cell occupancy intervals by the already flying aircrafts, whose trajectories cannot be modified by the proposed approach. These cases are detected but different mitigation measures should be taken in case of conflict (e.g. tactical intervention). For the scenario in Fig. 21, an ATC time of 10 min and a computational time of 5 min was assumed. Logically, the first concurrence events start to be resolved

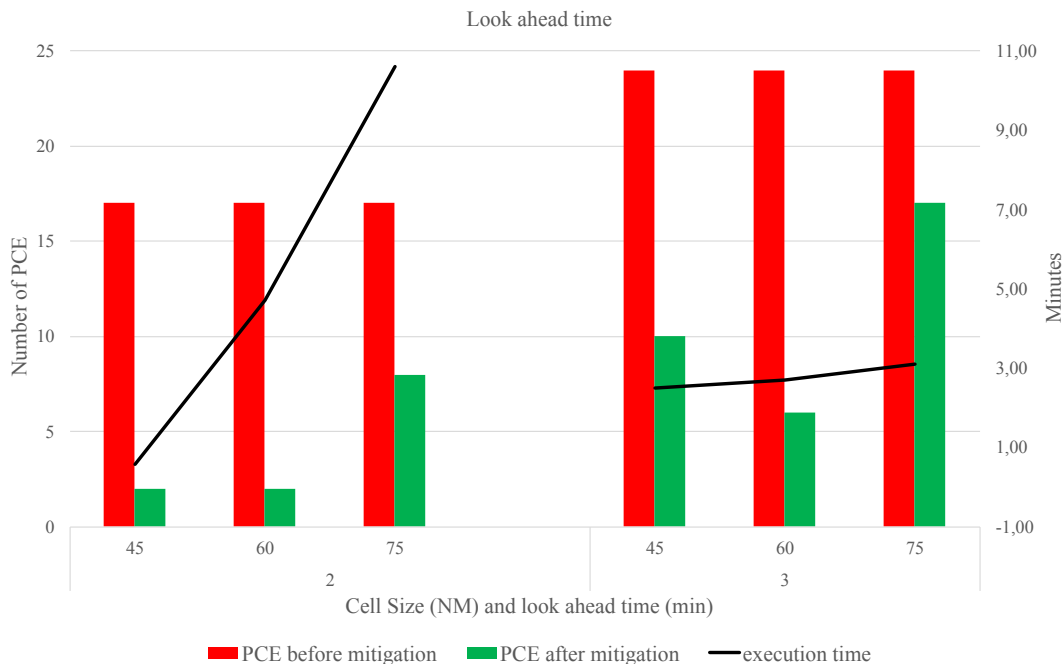


Fig. 20. Analysis of the look-ahead time parameter.

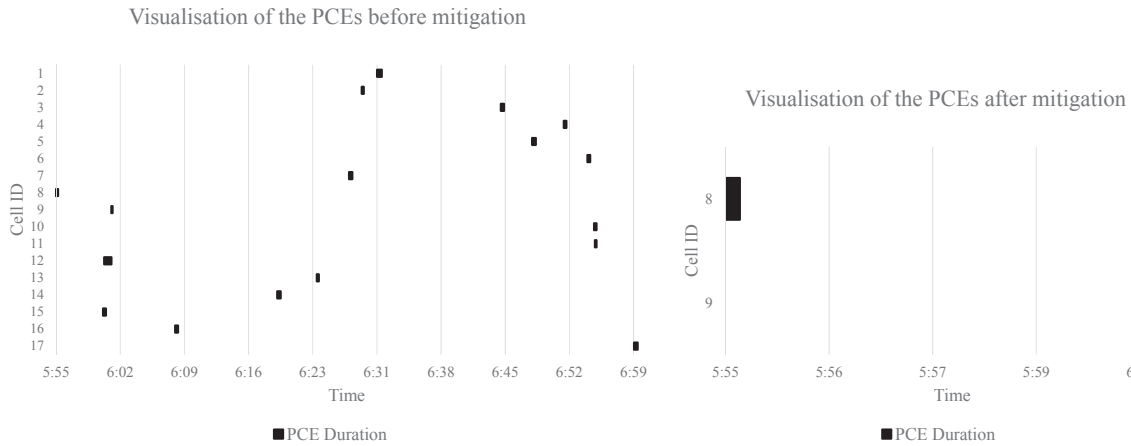


Fig. 21. Visualization of the PCEs. The Gantt chart shows the PCEs before mitigation and after mitigation. A total of 88% of the PCEs is solved, making it 20% less probable that there is an ATC tactical intervention.

from 6am onwards. The remaining concurrence event at 5:55am did not leave the ATC enough time to operate and therefore remains as a concurrence event after mitigation.

In summary, a first recommendation for operating parameters can be retrieved from these experiments. Considering the scenario of this study case, the cell-size should be set to 2NM or 3NM (depending on the available performance resources). The difference between operating with 2 airports or 4 airports in this case becomes significant with a larger cell-size, whereas the difference between resolved concurrence events is rather small at a lower cell-size. Finally, a 60-minutes look-ahead time achieves the best results applying a cell-size of 3NM.

A second set of experiments have been carried out using the recommended operating parameters. The traffic samples have been chosen to cover a wide range of demand values (e.g. day of the week and hour of operation). A summary of the tested realistic traffic scenarios is presented in the Table 3.

The experiments revealed that, on average, there are more PCEs that could be solved in the later afternoon, see Fig. 22. On Wednesday afternoon and on Saturday afternoon, the number of PCEs that could be solved reaches from 41% to 52%, meaning that in the latter half of the existing total CE could be solved by the proposed algorithm, reducing the possibility of an ATC intervention by over 50%.

During the morning hours, the traffic volume increases because air traffic is building up around the airports. As the demand increases, the air-traffic controllers delay flight departures and take longer to sequence arriving flights. For time slots where no such regulations are applied and a normal daily routine is performed, more possible CEs can be detected, and a greater number of CEs can be mitigated.

Further tests carried out to determine the most effective cell-size (S_C) for the parameter confirmed our initial findings. The results on the cell-size experiments are represented in Fig. 23. The figure shows a clear trend that the absolute number of solved PCEs is higher when applying a cell-size of 2NM or 3NM whereas a cell-size of 5NM or 6NM solves less PCEs.

Applying a cell-size of 4NM, some outliers can be observed. In some cases, the cell-size of 4NM solved many CEs whereas in other cases the results are unsatisfactory. Although the aircraft are separated with the determined safety distance, in a real context where the operations involving safety factors tends to be more conservatively, a distance of 2NM might reduce the time to prevent an ATC intervention. Therefore, it is proposed the use of a cell-size of 3NM as it gives steady good results throughout all experiments.

The results of the traffic scenarios with respect to the analysis of the number of operating airports can be seen in Fig. 24. The numbers shown below were calculated using the mean of all traffic scenarios. The findings confirm previous results that the difference of the number of PCEs is rather low operating in 2 or in 4 airports, however, contrary to expectations, for these experiments, these values remain low.

Finally, the analysis of the look-ahead time shows a steady, low amount of non-solvable PCEs after mitigation applying a cell-size

Table 3
Realistic traffic scenarios that were chosen for the experiments.

Day of traffic scenario	Date of traffic scenario	Hour of traffic scenario
Monday	17th of July 2017	6 am to 7 am
Monday	17th of July 2017	4 pm to 5 pm
Wednesday	19th of July 2017	6 am to 7 am
Wednesday	19th of July 2017	4 pm to 5 pm
Saturday	22nd of July 2017	6 am to 7 am
Saturday	22nd of July 2017	4 pm to 5 pm

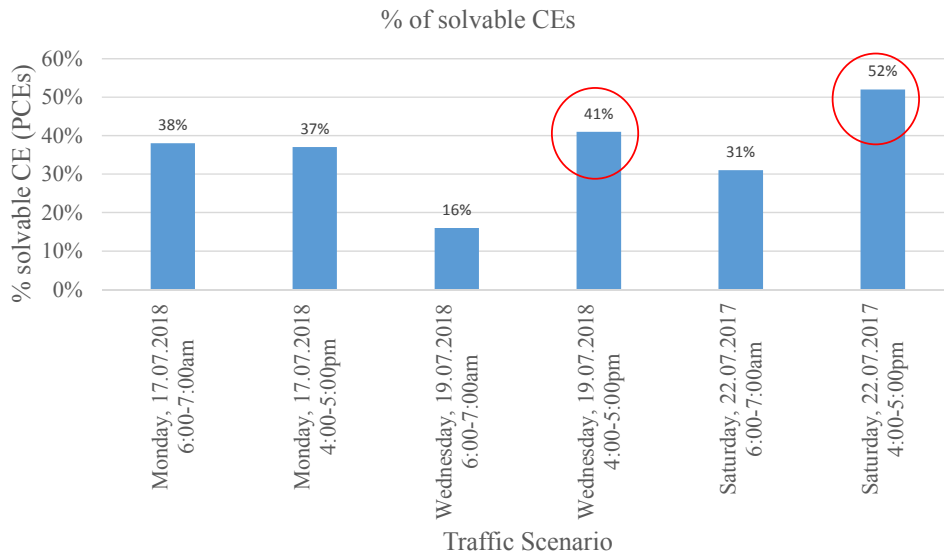


Fig. 22. Percentage of solvable CE (PCEs). The highest number of PCEs that could be solved is observed in the later afternoon hours whereas busy morning hours such as Wednesday morning provide less possibility to solve CE.

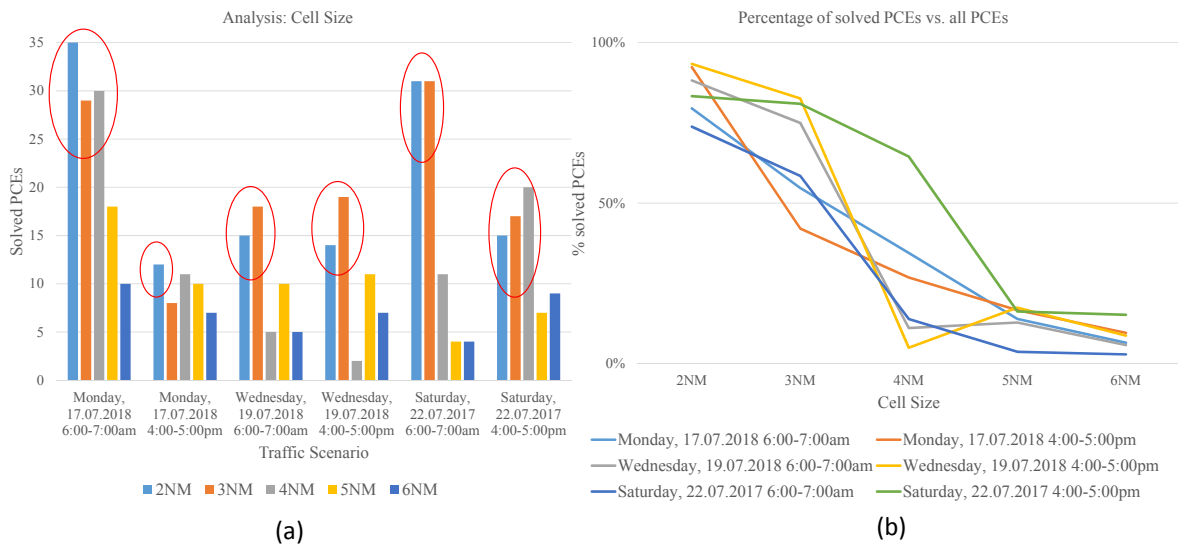


Fig. 23. Summary of results of the analysis cell-size. (a) It can be observed that a smaller cell-size leads to more solved CE whereas a larger cell-size resolved less CE in absolute numbers. (b) The percentage of solved PCEs reveal similar results. A smaller cell-size leads to more solved CE and a bigger cell-size to less solved CE. The cell-size 4NM is streaked by outliers.

of 2NM. Moreover, the execution time of the problem grows exponentially with the look-ahead time. In comparison with the cell-size of 2NM, applying a cell-size of 3NM cell-size, shows more non-solvable PCEs after mitigation. Furthermore, the number of non-solvable PCEs after mitigation is higher with a look-ahead time parameter of 75 min. The lowest number of non-solvable PCEs after mitigation can be found with a look-ahead time parameter of 60 s, however, the execution time with 5 min is rather high but still within the limits, see Fig. 25. The values have been determined using the mean of all traffic scenarios to see the trend. However, given that each traffic sample faces different environmental circumstances, the results from this analysis should also consider additional factors (e.g. time of the day, regulations etc.).

The analysis of the cell-size revealed that the number of possible CE increases with a bigger cell-size and the analysis of the cell-size showed that given a bigger cell-size and a greater look-ahead time parameter (L), more possible CE remain unsolved.

All the experiments were performed on a Windows 10 computer with an Intel Core I7 CPU 2,30 GHz and 8 GB RAM. The detection and analysis mechanism is implemented in JAVA and the mitigation mechanism is implemented in with the ILOG CP solver (IBM, 2015). The running time depends on the operating parameters however all experiments were solved within 5 min and therefore, remain within the cycle time of the experiment that is set to 5 min.

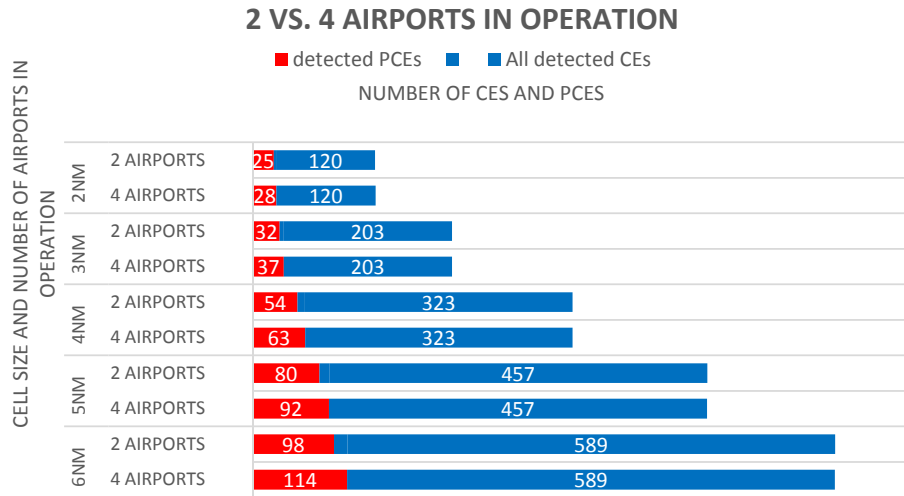


Fig. 24. Summary of results for operating in 2 or in 4 airports. The difference of detected PCEs is rather low.

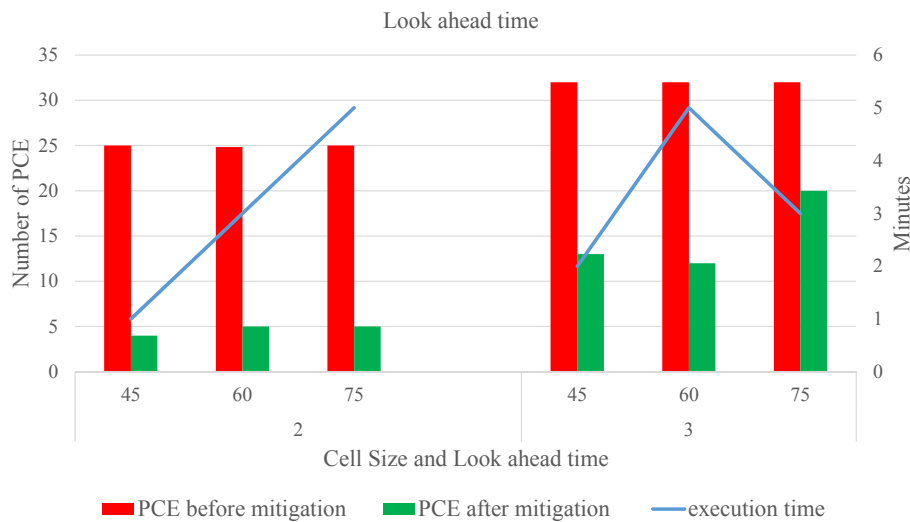


Fig. 25. Summarized analysis of the look-ahead time parameter.

4. Conclusion and future research

4.1. Conclusion

A STAM-based methodology to reduce the number of ATC interventions on air has been presented. The three-step methodology, composed by detection, analysis and mitigation, was used to develop a framework designed to be executed as a recurrent TBO service. The S-T interdependency analysis method provide a baseline to design new metrics that could support the application of alternative pre-tactical measures to the current MDI.

A sensitivity analysis resultant from the experiments has focused on determining suitable values for the cell-size (S_C), the look-ahead time (L), while analysing different scenarios defined by the day of the week, time intervals and number of operating airports.

The trend of the parameters throughout different traffic scenarios has been consolidated during all experiments. However, in some traffic scenarios the number of PCEs and CEs and the percentage of solvable CEs had a significant difference. During traffic peaks (early morning hours and/or with ATC regulations), the percentage of solvable CEs was 16% whereas the possibility of solving CEs raised to 52% in traffic scenarios with lower traffic demand (late afternoon).

Significantly, the cell-size parameter has showed best results when using 2NM or 3NM. However, since the cell-size of 2NM could be insufficient to prevent ATC interventions during real operations, it probably will trigger an ATC intervention before the concurrence event is mitigated. Therefore, the use of a cell-size parameter of 3NM shows the most appropriate value for the sample of data used if the priority of the decision-makers is to cover the most quantity of concurrence events while maintaining acceptable levels of uncertainty. The use of cell-sizes of 5NM or 6NM lead to a reduced number of solved CE in exchange of a lower uncertainty

values.

The experiments show that the difference between deploying the method in 2 or 4 airports has a smaller improvement on the mitigation of CEs. The effects of using different airports becomes significant when the number of departing flights (control variables) increases and when the number of interdependences between trajectories of the selected airports is reduced (e.g. to avoid redundancy in the solutions). This means that an analysis of the traffic is recommended prior selection of the airports in order to ensure a maximum number of independent control variables (PCE) is achieved. At this end, further experiments should be performed in order to understand the effects of different airports for different traffic samples.

Finally, the look-ahead time parameter has been evaluated. Considering the execution time needed to run the traffic scenarios with different look-ahead time parameters and the amount of PCEs that remain unsolved after the mitigation process, the experiments show that a look-ahead time parameter between 45 min and 60 min could be recommended. The uncertainty levels increase with the look-ahead time. However, this parameter is also associated to other factors that prevents its reduction. The ground ATC requires a minimum time to direct the flight to the stand-by/holding point, and depending on the taxi layout, once the push-back and start phase is completed, changing the sequence of take-off could not be possible. Therefore, the look-ahead time is directly linked to the airport taxi layout and the taxi times. Further analysis is required to understand the uncertainties associated to ground operations.

4.2. Future research

The methodology presented an ideal case that considered a high adherence nominal route for the reference trajectories. There are several sources of uncertainties that should be considered when including the human-in-the-loop. The application of the algorithm in a terminal manoeuvring area support a reduction of the look-ahead time and the uncertainties associated to the take-off and ascending phases. In a terminal airspace, exist nominal routes that provides a high 4D adherence. An analysis of the nominal routes of a multi-airport system will reduce significantly the uncertainty levels associated to the TMA operations and support the selection of the airports, routes and sectors for the application of this methodology. A key aspect is the use of reference trajectories that represent the actual traffic. The analysis of historical traffic samples that determine recurrent traffic patterns will improve the selection of cell-size and look-ahead time to guarantee reduced levels of uncertainty.

In a realistic operational scenario, the ground operation inputs an important amount of latency that is expected to be absorbed by the skills of the ground ATC while issuing take-off clearances at the proposed ETOT. Consequently, further research is required to understand the impact of the presented methodology on the human performance, including the push-back, taxi operations and uncertainties associated to the typical operations of an airport (e.g. last-minute passenger delays).

The proposed method could be used to redefine the capacity values of sectors based on quantifying the events associated to ATC interventions (e.g. a novel complexity metric targeting specific concurrence events). Further analysis is required to determine the parameters of the algorithm that actually reduces the number of ATC interventions while including the human in the loop (a very small cell-size could still trigger an ATC intervention on air).

The experiments presented in this paper uses the London terminal airspace as study case. However, it has been determined that the sensitivity of the parameters and the amount of solutions are impacted by the configuration of the scenario and the traffic sample. The application of the methodology in other multi-airport systems could help to determine the effects of the amount of traffic and the airports involved in the effectivity of the solution.

Finally, the presented mitigation model has not included AU nor Airport preferences. Nevertheless, the Constraint Programming paradigm will allow to enhance the existing model by adding new constraints representing these preferences. However, the impact on problem solvability of the new constraints must be further investigated in order to find the right trade-off with the main purpose of reducing the probability of tactical interventions.

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Appendix A

Acronyms

ANSP	Air Navigation Service Provider
ATC	Air Traffic Controller
ATFCM	Traffic Flow And Capacity Management
ATM	Air Traffic Management
AU	Airspace User
CTOT	Calculated Take-Off Time
CE	Concurrence Event (loss of defined separation minima)
CEs	All Concurrence Events that have been detected with the detection tool

DCB	Demand And Capacity Balancing
DDR2	Demand Data Repository
DFS	Depth First Search
EGBB	Bristol Airport
EGGD	Birmingham Airport
EGGW	London Luton Airport
EGLL	London Heathrow Airport
EGSS	London Stansted Airport
EGTTCAP	LTMA Capital Sector
EGTTCPT	LTMA Compton Sector
EGTTTC	LTMA
EGTTVAT	LTMA Vatou Sector
ETOT	Estimated Take-Off Time
FL	Flight Levels
LTMA	London Terminal Manoeuvring Area
MAS	Multi Airport System
MDI	Minimum Departure Intervals
PCEs	Potential Concurrence Events (CE) that could be mitigated with the mitigation tool since they fulfil the requirements e.g. are still on the ground and could be delayed, belong to one of the airports that have been chosen, etc.
RBT	Reference Business Trajectory
SATM	Aerospace Transport And Manufacturing
SDS	Spatial Data Structure
SESAR	Single European Sky ATM Research
SID	Standard Instrumental Departures
STAM	Short Term ATFCM Measures
TBO	Trajectory Based Operations
TMA	Terminal Manoeuvring Area

List of variables and operators used in the CP Model and data structure.

Variable	Role	Description
A	Set of flights	Set of flights that could be selected to a potential change of ETOT
C	Set of cells	Set of cells that have at least one concurrence event
F	Set of flight levels	Set of flight levels that define the airspace volume
RBT_a	Parameter	Reference Business Trajectory of flight a that the airspace user agrees to fly, and the ANSP/airport agrees to facilitate
$CTOT_a$	Parameter	Calculated Take-Off Time window where ETOT must lie
TTA_a	Parameter	Target Time of Arrival
$l(\hat{g}_i^{af})$	Parameter	Elasticity of the segment that results from bounded speed adjustments
w_1	Parameter	Weight value assigned to minimizing the total aircraft delays
w_2	Parameter	Weight value assigned to binding the Target Time of Arrival
$s(\hat{A}\cdot)$	Function	Start time of an interval variable
$e(\hat{A}\cdot)$	Function	End time of an interval variable
$sz(\hat{A}\cdot)$	Function	Size of an interval variable: $sz(\hat{A}\cdot) = e(\hat{A}\cdot) - s(\hat{A}\cdot)$
$p(\hat{A}\cdot)$	Function	Number of segments required for describing the trajectory
P_{af}	Decision variable	Interval variable representing the occupancy of the cell c by an aircraft a at a given FL^f
O_c	Decision variable	Sequence variable representing a cell at a given flight level used by two or more flights
G_a	Decision variable	Interval variable representing the entire flight a
g_i^{af}	Decision variable	Interval variables representing the segments of the flight interval G_a at each mapped flight level
T_a	Decision variable	Interval decision sequence variable setting the relationship between the trajectory segments g_i^{af} and the entire trajectory G_a
NO	Constraint	Constrains the involved interval variables to no overlap in time
$span$	Constraint	States that the interval flight spans over all present intervals from the set segments
$synchronize$	Constraint	Constrains the given set of interval variables to start and end together with the interval set as first argument

List of general parameters

Variable	Name	Description
S_C	Cell-size	The size of the cell c
L	Look-ahead time	The evaluation period for detecting potential concurrence events among trajectories that are active during this period
P	Execution Period	Time period between consecutive executions
$[\delta_m, \delta_M]$	Shifting domain	Minimum and maximum delay that can be applied to the ETOT.
δ	Offset	The along-track deviation present in a trajectory with respect to the original RBT. It can be caused either by an action (applied shifting delay) or by actual flying conditions
t_{ATC}	Required ATC reaction time	Minimum time window between the time the ATC is informed about a possible departure shifting and the new assigned ETOT

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