Aircraft departure synchronization to reduce ATC en route interventions

Jenaro Nosedal-Sánchez

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by

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Thesis advisor
Dr. Miquel Àngel Piera Eroles

DISSERTATION

Submitted in Partial Fulfillment of the
Requirements for the Degree of

Doctor in Philosophy
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February 2016

Dr. Miquel Àngel Piera Eroles, Associate professor at School of Engineering at Universitat Autònoma de Barcelona,

CERTIFIES:

That the doctoral thesis entitled "**Aircraft departure synchronization to reduce ATC en route interventions**", presented in partial fullfilment of the requeriments for the obtention of the degree of Doctor in Philosophy, embodies original work done by **Jenaro Nosedal-Sánchez** under his supervision.

Dr. Miquel Àngel Piera Eroles.
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Dedication

To my beloved wife Gabriela, to my lovely sons Efrén and Luis and to my devoted parents Dolores and Víctor.

"I was blessed twice with the greatest treasure: my family,
all what I am is because of them and for them".
–Jenaro Nosedal Sánchez

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Sabadell, Barcelona
February, 2016

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ABSTRACT OF DISSERTATION

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Abstract

The research work presented in this thesis focuses on the micro and macro analysis of the untimed en route waypoints of aircraft trajectories obtained after applying a bi-dimensional (i.e. latitude and longitude positions) D - transform [45] and on the application of causal modelling and constraint programming (CP) techniques to simulate and validate a departure-time-bounded adjustment process that preserves the scheduled slots while relaxing tight 4DT interdependences (for instance, reducing or solving airspace demand - capacity imbalances).

The research developed instead of a fragmented look at the Air Traffic Management (ATM) system, in order to generate synergies between airspace users (AUs) while reducing Air Traffic Control (ATC) interventions, proposes an innovative framework supporting a comprehensive analysis of interdependencies between Air Traffic Flow and Capacity Management (ATFCM), Departure Management (DMAN) and the agreed Reference Business Trajectories (RBTs).

The overarching goal of this dissertation is to contribute to the literature about the use of robust combination of RBT's time stamps preserving the 3D agreements into a set of collaborative-competitive trajectories under a global scope with minimum ATC interventions.

Furthermore, the proposed approach allows the linkage of land side with air side operations, and enables the connection between AUs requirements within the traffic network, thus provides a framework to deploy new Decision Support Tools (DSTs) towards more collaborative and competitive ATFCM services.

Resumen

La investigación que se presenta en esta tesis, se enfoca en el análisis a nivel micro y macro de la posiciones atemporales de trayectorias aéreas en la fase de ruta, obtenidas a partir del uso de una transformación bidimensional (posiciones de latitud y longitud) transformación D [45] y de la aplicación de modelos causales y técnicas de programación por restricciones para simular y validar un proceso de ajuste acotado de tiempos de despegue que conserva las ventanas de salida programadas y al mismo tiempo relaja las interdependencias tensas entre trayectorias 4D (e.g., reduciendo o resolviendo desequilibrios entre demanda y capacidad en el espacio aéreo).

La investigación desarrollada, con la finalidad de producir sinergias entre los Usuarios del Espacio Aéreo (AUs) y simultáneamente para reducir las intervenciones de Control de Tráfico Aéreo (ATC), en vez de revisar el sistema de Gestión de Tráfico Aéreo de manera fragmentada, propone un marco innovador que soporta una análisis exhaustivo de las interdependencias entre Gestión de Flujo de Tráfico Aéreo y Gestión de la Capacidad (ATFCM), Gestión de Despegues (DMAN) y las Trayectorias Comerciales de Referencia (RBTs) acordadas.

El objetivo general de este trabajo es aportar a la literatura con el uso de combinaciones robustas de marcas temporales de las RBTs que preservan los perfiles 3D acordados dentro de un conjunto de trayectorias competitivas y colaborativas bajo un enfoque global que reducen al mínimo las intervencin de ATC.

Adicionalmente, el enfoque propuesto permite la vinculación de parte de tierra con las operaciones del lado aire, y habilita la conexión entre los requerimientos de los AUs dentro de la red de tráfico, por lo que proporciona un marco para implementar nuevas herramientas de apoyo en las decisiones (DST) para el desarrollo de servicios ATFCM más competitivos y colaborativos.

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Chapter 1

Introduction

1.1 Background

The objective of Air Traffic Management (ATM) is to ensure safe and efficient flights, from departure to arrival. This mission is carried out by a number of national and international organizations that provide different services to the airspace users (AUs). [18]

Air Traffic Flow and Capacity Management (ATFCM), is a service complementary to Air Traffic Control (ATC), the objective of which is to ensure an optimum flow of air traffic through defined areas assuring that available capacity of the ATC system will not be exceeded. [20]

Accordingly with [6], ATFCM procedures try to resolve local demand-capacity mismatches by adjusting the aggregate traffic flows to match scarce capacity resources (e.g. runways, sectors and air traffic controllers (ATC's)).

ATFCM presents 3 levels of decision-making actions [21]:

Strategic: activity taking place during the period from several months until a few days before a flight. During this phase, comparison is made between the expected air traffic demand and the potential ATC capacity. Objectives are set for each ATC unit in order to provide the required capacity for them.

Pre-tactical: action taken during the few days before the day of operation of a flight. Based on the traffic forecasts, the information received from the Flow Management positions at every ATC centre in Europe and the Central Flow Management Unit (CFMU) statistical data.

Tactical: the work carried out on the current day of operation of a flight. Flights taking place on that day may be affected by ATFCM regulations, actions to assure the ATC demand capacity balance, which includes the re-allocation of individual aircraft departure times, re-routing to avoid bottlenecks and alternative flight profiles.

At tactical level, these regulations are applied as a method of matching traffic demand to available capacity by limiting the number of flights planned to enter an airspace or aerodrome, achieved by the issuing of new departure slots (CTOTs) [24]. When the lack of airspace capacity is predicted in a certain sector, regulations are applied by holding flights on the ground prior to departure [34].

This management is carried out in Europe by the Eurocontrol Network Management Operations Center (NMOC) that enforces ATFCM regulations when required so by ATC units predicting or anticipating overloads. Meanwhile in the United States these regulations take the form of Ground Delay Programs (GDPs), this ATFCM initiative currently in use attempt to address airport arrival capacity reductions. Under this mechanism, departure delays are applied to flights at their origin airports that are bound for a common destination airport which is predicted to suffer from reduced capacity or excessive demand. Besides GDPs, other strategies can also be initiated in order to solve capacity-demand imbalance problems, such as the airspace flow program (AFP), an equivalent slot allocation initiative implemented when a capacity demand imbalance is predicted in an airspace sector.[16]

The premise for these initiatives, coordinated by the Air Traffic Control Strategic Command Center (ATCSCC), is that it is better to absorb delays for a flight while it is grounded at its origin airport rather than incurring air-borne delay near the affected destination airport which is both unsafe and more costly (in terms of fuel costs) [5].

The current method of organizing airspace and balancing demand and capacity relies on partition of airspace into sectors. This fragmentation of airspace configurations into several air traffic control (ATC) boundaries for ATM directly limits the airside capacity utilization [12].

Nowadays, the demand - capacity airside (i.e., in ATC sectors) balance is determined by a simple aircraft counter for a time interval. Each sector has a capacity threshold in the form of the maximum number of aircraft at a given time slot. This threshold has been used by ATFCM as a controller workload limit indicator for each sector. However this indicator does not take into account the traffic complexity [31][38].

The traditional approach to improve predictability by constraining flexibility is no longer viable in many cases. This regulation approach usually tends to induce latent capacity problems, because relies on incomplete information (e.g. lack of traffic complexity indicators and lack of understanding of the interdependences between trajectories).

The current layered planning approach fragments the ATM system both at functional level and at operational level due to a lack of flexible synchronization (i.e., Trajectory Based Operations (TBO) mechanism) that could deal with a trade-off solution considering the optimization targets of each stakeholder subject to infrastructure capacity and safety constraints.

This fragmented decision making scope hides disturbances that become source of emergent dynamics, these dynamics lead the introduction of operational complexity for integration for a flexible and predictable ATM system under this approach.

Free routing, soft flight level capping constraints, integration of Remotely Piloted Aircraft (RPAs) are just some examples that claim for a truly integration at ATM service system level in which present layered ATM planning could exploit the freedom gaps between the strategic /pre-tactical/ tactical ATFCM [23], to move one step forward to a competitive ATM system in which present resources are used to attend AUs demands avoiding resources idleness and saturations that foster regulations, holdings and poor efficient trajectories.

In addition to those former facts, the predicted growing trends of air traffic reinforce evidence of the necessity of new operational and managing policies for more efficient use of existing airside capacity [27].

Among other new approaches to reduce latent capacity, one of the most important and challenging paradigms of the Single European Sky ATM Research (SESAR) [57] and Next Generation Air Transportation System (Next Gen) [60] programs is the introduction of trajectory-based operations (TBO), which involve the use of 4D trajectories (i.e. consecutive waypoints in three spatial dimensions and their corresponding time-stamps), also known as business trajectories (BTs) according to SESARs terminology for civil flights. It is expected that the use of 4D trajectories will be the seed for new demand and capacity balance tools relying on the synchronization and predictability of the air transportation system. [40].

While TBO concept enhance the design of new DSTs that could deal with present demand - capacity balance in ATM, relying on a technological framework for information sharing (System Wide Information Management (SWIM), [25]), a word of caution come into view at practical level: ATM stakeholders realize that technological flexibility is not synonymous of better performance. It is well accepted that a major limitation of current ATM system is the loss of effectiveness due to the limited integration between the layered planning Decision Support Tools (DSTs) [54].

A comprehensive analysis of hard and soft interdependencies between sector capacities defined at ATFCM level, priority sequence of departure at DMAN (Departure Manager) level and the agreed flight plan at RBT (Reference Business Trajectory) level provides the framework to exploit an extra degree of freedom to address AUs demands with the available capacity. This TBO freedom gap provides an advanced approach to coordinate trajectory changes and constraints generating synergies between AUs while reducing ATC interventions.

Hence, allowing small changes in the time stamp component of the agreed 4DT with a pre-processing of the hotspots predicted at micro level using ATFCM macro level information obtained from SWIM can cope with large amount of disturbances and frequent poor adherence trajectory problems, compared to traditional and Airport Collaborative Decision Making (A-CDM) methods. This TBO freedom gap facilitates implementation of changes without affecting the AUs operational costs and could be straightforward applied to smoothly fit to AUs preferences characterized by a high diversity of choices.

The concept of combining trajectories is of course not new, it has been widely studied; consider for example the agreement approaches from SBTs (Shared Business Trajectory) to RBTs. Despite these efforts, there is still little concrete evidence of convergence to stable solutions because AUs cannot share the right information due to a fierce market competition and diverse business models, the lack of a feedback loops between ATM strategic and tactical DSTs and the uncertainties that affect the time component of the trajectories agreed.

The work presented in this research focuses on the micro and macro analysis of the untimed waypoints of the trajectories obtained after applying a bi-dimensional (i.e. latitude and longitude positions) D - transform [45] and on the application of causal modelling and constraint programming (CP) techniques to simulate and validate a departure-time-bounded adjustment process that preserves the scheduled slots while relaxing tight 4DT interdependences (for instance, reducing or solving demand - capacity imbalances).

The research developed instead of a fragmented look at the ATM system, in order to generate synergies between AUs while reducing ATC interventions, proposes an innovative framework supporting a comprehensive analysis of interdependencies between ATFM, DMAN and the agreed RBT.

The overarching goal of this dissertation is to contribute to the literature about the use of robust combination of RBTs time stamps preserving the 3D agreements into a set of collaborative-competitive trajectories with minimum ATC interventions.

1.2 List of publications

This dissertation thesis is based on a collection of peer - reviewed and published research papers listed below.

Paper I. **Nosedal, J.**, Piera, M. A., Ruiz, S., and Nosedal, A. (2014). An efficient algorithm for smoothing airspace congestion by fine-tuning take-off times. Transportation Research Part C: Emerging Technologies, 44, 171-184.

Paper II. **Nosedal, J.**, Piera M.A., Solis A.O, and Ferrer C. (2015). An optimization model to fit airspace demand considering a spatio-temporal analysis of airspace capacity. Transportation Research Part C: Emerging Technologies, 61, 11-28.

In addition to the above, the following papers have been elaborated and submitted during the period of research (included as appendices).

Paper III. **Nosedal, J.**, Piera M.A. and Lebbink D. (2015). Revisiting the impact of flights' arrival variability on departure punctuality: a causal analysis of earliness landing. Journal of Air Transport Management: An International Journal of Research, Policy and Practice. Status: Under Review.

Paper IV. **Nosedal, J.** and Piera M.A., (2015). Causal analysis of aircraft turnaround time for process reliability evaluation and disruptions identification. Transportmetrica B: Transport Dynamics. Status: Under Review.

Moreover other conference articles were published during the research; these are listed below as a reference but are not included as a part of this thesis.

V. A demand shifting algorithm to smooth the peaks at the airport security screening checkpoint (SSC) facilities, **Nosedal-Sánchez J.**, Piera-Eroles M.A., Martinez R., Alsina N., I3M: The 12th International Multidisciplinary Modelling and Simulation Multiconference, 21-23 September, 2015. Bergeggi, Italy.

VI. Asignación de puertas de embarque considerando restricciones espacio - temporales mediante modelado con redes de Petri coloreadas, **Jenaro Nosedal Sánchez** y Miquel Àngel Piera Eroles. XXXVI Jornadas De Automática, September 2015. Bilbao, Spain.

VII. Passenger Slot Assignment for Airport's Security Screening, **Nosedal-Sánchez J.**, Piera-Eroles M.A., Martinez R., Alsina N., I3M: The 11th International Multidisciplinary Modelling and Simulation Multiconference, 10-12 September, 2014. Bordeaux, France.

VIII. Use of Colored Petri Nets to Model Aircraft Turnaround at an Airport, Fernandez de Liger, Piera Eroles M.A., **Nosedal-Sánchez J.**, 6th International Conference from Scientific Computing to Computational Engineering (6th IC-SCCE), 9-12 July, 2014. Athens, Greece.

IX. A Causal Model to Schedule Efficient Ground Delays in present Air Traffic Management Systems, Modeling and Simulation for Complex Networks Management. **Jenaro Nosedal**, Miquel A.Piera and Sergio Ruiz. Summer Computer Simulation Conference (SCSC 2013), July 2013. Toronto, Canada.

X. Concurrent and Distributed Systems Analysis Using Colored Petri Nets, **Jenaro Nosedal**, Olatunde Baruwa and Miquel A. Piera. XXXIV Jornadas De Automática, September 2013.Terrassa, Spain.

XI. Causal Decision Support Tools for Strategic Trajectory De-Confliction to Enable Seamless Aircraft Conflict Management (STREAM) Clustering And Interaction Causal Solver Models. **Jenaro Nosedal**, Sergio Ruiz, Miquel A.Piera and Andrea Ranieri. 2nd Sesar Innovation Days, November 2012. Braunschweig, Germany.

XII. Modelo Causal Para La Simulación De La Gestión Del Tráfico Aéreo (ATM) A Nivel Pretáctico Y Estratégico., **Jenaro Nosedal**, Sergio Ruiz and Miquel A. Piera. XXXIII Jornadas De Automática, September 2012. Vigo, Spain.

1.3 Thesis structure

The remaining sections of this work are organised as follows. Chapter 2 provides the literature review and introduces the research motivation and objectives. Chapter 3 and 4 include the peer reviewed publications. The first paper exposes an algorithm that facilitates macro and micro analysis along the entire en route path for 4D trajectories, considering the entire European airspace and reducing the combinatorial explosion problem during the detection of collective micro regions (pair-wise comparison) by spatial data structure (SDS) analysis. In this paper are also introduced several challenging results by properly tuning the Calculated Take-Off Times

(CTOTs) for mitigating the propagation of perturbations between trajectories. The second paper, included in Chapter 4, by means of discrete event simulation, describes and formalizes the spatio-temporal interactions between trajectories and presents an optimization model for airspace capacity- demand management by applying an efficient departure time bounded adjustment configuration. Chapter 5 includes the research results summary, conclusion and possible future lines of research.

Finally, two additional under review publications related with the analysis of the Arrival variability and the Turnaround processes are included as annex A and B respectively.

Chapter 2

State of the art

In Europe, all aircraft must respect so called CFMU-slots, which are 15 minutes time windows during which they are allowed to take off. If they miss their slot, they have to apply for another slot, this slot re-scheduling request can imply a long time waiting (i.e. delay with respect to original departure time), especially during the peak hours. These new slots are issued by the CFMU for whole Western Europe based on the predicted capacity of the ATC sectors, in U.S. similar restrictions exists to avoid air traffic congestion at airports.[26]

From the airport ground management perspective, slot re-allocation usually implies some problems because aircraft must be assigned to a specific position for this waiting time. If an aircraft reaches the runway threshold too soon, it will have to hold on until it slot comes, and other aircraft can be stuck in the queue. Conversely, if the aircraft reaches the runway too late, the slot is missed again.[33]

Currently, if an imbalance is predicted on the day of operations between the traffic demand and the available airspace capacity, the ATM authority (i.e., the ATFCM) issues a regulation to reduce the rate of flights entering the ATM sectors at a given time. When the regulation modifies the flight departure slot [11], the delays are often known as green delays [52].

As alternatives to the ATM regulations, air traffic controllers (ATCOs) frequently issue maneuvers at a tactical level consisting of holding stacks, headings, flight level changes or speed variations [22]; unfortunately, such maneuvers are often not considered desirable measures by AUs due to high operational and fuel consumption costs (i.e., airborne delays, when incurred, dominate ground delay costs [28]). Green delays are therefore deemed more acceptable alternatives [9].

The purpose of this ground-holding scheme is to respect the en route capacity constraints provided by each ATC center (ATCC) as the number of aircraft that can coexist in the same sector within a given time frame, based on their daily schedule. The number of aircraft in a sector is the air traffic characteristic that has been most cited, studied and evaluated in terms of its influence on workload [53]. However, a limitation of this regulation model is that the definition of the sector's capacity (i.e., the hourly rate of aircraft entering a sector) is poorly related to traffic complexity [3]. To capture ATC complexity more accurately, it is necessary to consider the flight characteristics of each individual aircraft and interactions between aircraft pairs [17] and the surrounding traffic.

Air traffic local complexity can be measured by the control activity required to accept an additional aircraft entering a sector [41], however from a network perspective, due to the high degree of connectivity in air traffic networks [42] it is expected that only if global traffic complexity is considered (i.e., all en route potential conflicts) all potential interdependencies can be identified and in consequence, the real impact of accepting one additional aircraft can be evaluated.

Domino effects [59], together with a lack of complete understanding and a suitable formalism for modeling these interdependencies, are key elements that often lead to the introduction of negative network effects (i.e., ground holding based solely on local information) and the impossibility of taking advantage of positive network effects (i.e., ground holding to improve the network's robustness).Thus, even small delays can easily propagate through trajectories [56], leading to regulations that could be avoided (e.g., the application of unnecessary delays and/or airborne holding procedures) and the underuse of sectors capacity [12].

Traffic assignment techniques have been developed to reduce congestion in transportation networks by distributing traffic demand across time and space [13]. Because congestion indicates that several aircraft are requiring the same space at the same time, congestion could be tackled by shifting flight trajectories in time (slot re-allocation) or in space (route re-allocation). The following approaches have been developed to solve this general route-time allocation problem: spacetime network [66]; variational inequality [47]; optimal control [35]; simulation [10]; integer and dynamic programming (ground-holding problem) [32] [44]; and more recently, the collaborative en route resource allocation model (Combined Trajectory Options Program) [36] and airspace planning and design based on conflict risk assessment [49] have been investigated. Slot allocation problems focused on controllers workload using constraint programming (CP) technology are discussed in [3]. Multi-sector complexity planning resolution using CP technology is presented in [30]. In [50], some of the most relevant dynamic traffic assignment (DTA) methods are analyzed, and path processing modeling approaches are addressed as the core of future DTA development. In [13], the application of multi-objective stochastic methods (i.e., genetic algorithms) on real traffic data, not by using the flow network concept but by simulating the flight of each aircraft, for one day over the French airspace is presented.

Based on the TBO paradigm [19], an airspace user's demand is represented by the BTs, and the airspace capacity constraints will be given by the spatial and temporal interdependencies between these trajectories. To analyse these spatio-temporal interdependencies between trajectories, the recognition of all of the potential proximate events per pair of trajectories in a given traffic scenario must first be performed. Then, by the analysis of the occupancy time windows, it is possible to analyse the airspace demand - capacity balance or imbalance.

Theoretical and experimental results for a new air traffic system, based on the moving point paradigm, are reported in [55], where air traffic is completely organized by a 4D-sequencing (i.e., an allocation of flights to multi-directional lattices is proposed). In [43], Monte Carlo simulations and reachability analysis are applied to assess the 4D trajectory concept.

The above mentioned approaches partially solve the bi-allocation problem and propose solutions for slot allocation only, route allocation only or both for extremely minor instances of the problem. Furthermore they fail to tackle the congestion problem from a global scope, because do not consider the air traffic complexity at global level. Note that the reduced saturation problem of specific sectors could lead the introduction of regulations that generate reallocation of the congestion downstream or upstream or raise higher congestion because negative domino effects are produced in the whole network.

Some other airspace analyses and partitioning (or repartitioning) methods based on superimposing traffic flows over a fine grid have been used by several researchers. Dynamic airspace configuration (DAC) is a new operational paradigm that proposes migrating from the current structured, static airspace to a dynamic airspace [39]. In DAC research, dynamic airspace sectorization (DAS) represents an initial approach to restructuring airspace to achieve capacity-demand balance, while managing air traffic controllers workload and ensuring an orderly flow of traffic [61].

The sectorization problem, considered as NP-hard problem, has been studied most recently as a global optimization problem using integer programming [4]. Other proposed approaches to the sectorization problem include the use of genetic algorithms [15] and graph partitioning [63]. A survey of the algorithmic aspects of airspace sectorization tools developed up to 2012 is provided in [29]. In [2], the Australian airspace is modeled as a hyper-rectangular discrete space (i.e., cells of 10 NM).

All of the formerly cited works focus mainly on the sectorization problem at a macroscopic level, addressing only one country's airspace or, in the most general cases, a single ATC area, and therefore, they do not consider a microscopic representation of traffic at the network level, which would be aligned with 4DT concepts and TBO procedures. In this research, 4DT is considered as a precise description of an aircraft path in space and time which includes the centerline of the path, using WPTs to represent specific steps along the path, together with appropriate buffers to describe the associated position uncertainty. The path contains altitude descriptions for each WPT and suitable indications about the time(s) at which the trajectory will be executed, in some of the WPTs in a 4DT path may be associated with Controlled Time of Arrivals (CTAs). Each CTA is defined by a Target Time of Arrivals (TTAs) requirement that must be met by the aircraft within a specified time tolerance. Therefore, CTAs actually represent time windows for the aircraft to cross specific waypoints and are used when needed to regulate traffic flows entering congested en route or arrival/departure airspace.

Under TBO approach, airspace users should fly precise 4-dimensional trajectories (4DTs), involving 3 spatial dimensions plus time, previously agreed upon with the network manager. A 4DT, otherwise known as BT, represents a contract between the airline and the network manager such that the aircraft should fly the trajectory, preserving the time stamps specified in the BT.

Regarding the challenges for the implementation of the TBO approach, while many trials around the world have demonstrated that aircraft equipped with Flight Management System (FMS) are capable of performing a TBO to very tight tolerances, other research results suggest that additional work is needed to mature the concept [14]. One of the major factors is the wind [62], which leads to longitudinal uncertainty that affects the execution of RBTs and their respect time stamps. However the theoretical time separation analysis reported by Klooster and De Smedt in [37], provide evidence that horizontal spacing of 105 s or, greater would avoid separation problems even in the presence of longitudinal deviations because of wind. But other factors can affect adherence significantly, some ATC directives for instance (based on predictive time horizon and tactical level) affect the adherence of the original RBTs but also is a source of downstream adherence problems due to domino effects constraining, at the same time the airspace capacity.

At land side, the surface traffic automation systems [46][58] enhance the management of airport surface operations to provide shared situational awareness and to control taxi times through the use of virtual queues. The collaborative departure queue management (CDQM) concept manages the length of the runway departure queues so that aircraft experience minimal physical queuing while ensuring that the runways are used at their maximum capacity, while also adhering to the departure slot allocation [51].

The trajectory-based surface operations concept has been proposed to improve surface movement efficiency while maintaining safety. The proposed systems guide surface movements and monitor their conformance with assigned trajectories. Whether the time-based trajectories can be effectively followed so that the expected benefits can be achieved [67].

From an optimisation point of view, ground movement is one of the key operations at the airport as it links other airport processes such as departure sequencing, arrival sequencing and gate/stand allocation and its performance can affect each of these

[64] Thus aircraft ground movement is a key element that could enable the RBT adherence since departure. For that reason ground movement reliability become an important component of research and development [7][8].

The airport ground movement management involves directing aircraft to their destinations in a timely manner, with the aim being to meet some target time windows (i.e. CTOTs). Ground movement links the various operations together: arrival sequencing, departure sequencing and the gate/stand allocation planning. In that sense, aircraft turnaround is a key factor to enhance the airport ground movement reliability and in consequence to achieve TBO adherence. Aircraft turnaround complexity arises due to the effects of interdependencies between different actors that are able to generate an event that could block, freeze, delay, or disable/ enable other activities programmed in the same or in another sub-process [65][1]. Since aircraft turnaround is a time critical process with several interdependent sub processes running sequential and in parallel, it is often a significant contributor to departure delays with direct impact in air traffic operations. Aircraft departure delays not only consume the scheduled turnaround time of an aircraft, but can also disrupt the slot planning (i.e. CTOTs), while aircraft arrival delays affect the gate assignment scheduling of an airport and might lead to a longer aircraft ground service times than scheduled [48], becaming a relevant source of disturbances affecting the TBO adherence.

2.1 Motivation and research objectives

The aim of this research is to empower TBO as a flexible synchronization mechanism that will support an efficient and competitive use of the ATM services by linking the land side operation with the air side. The proposed approach relies on an intelligent cooperative combination of the time stamp component of the RBT agreed by the

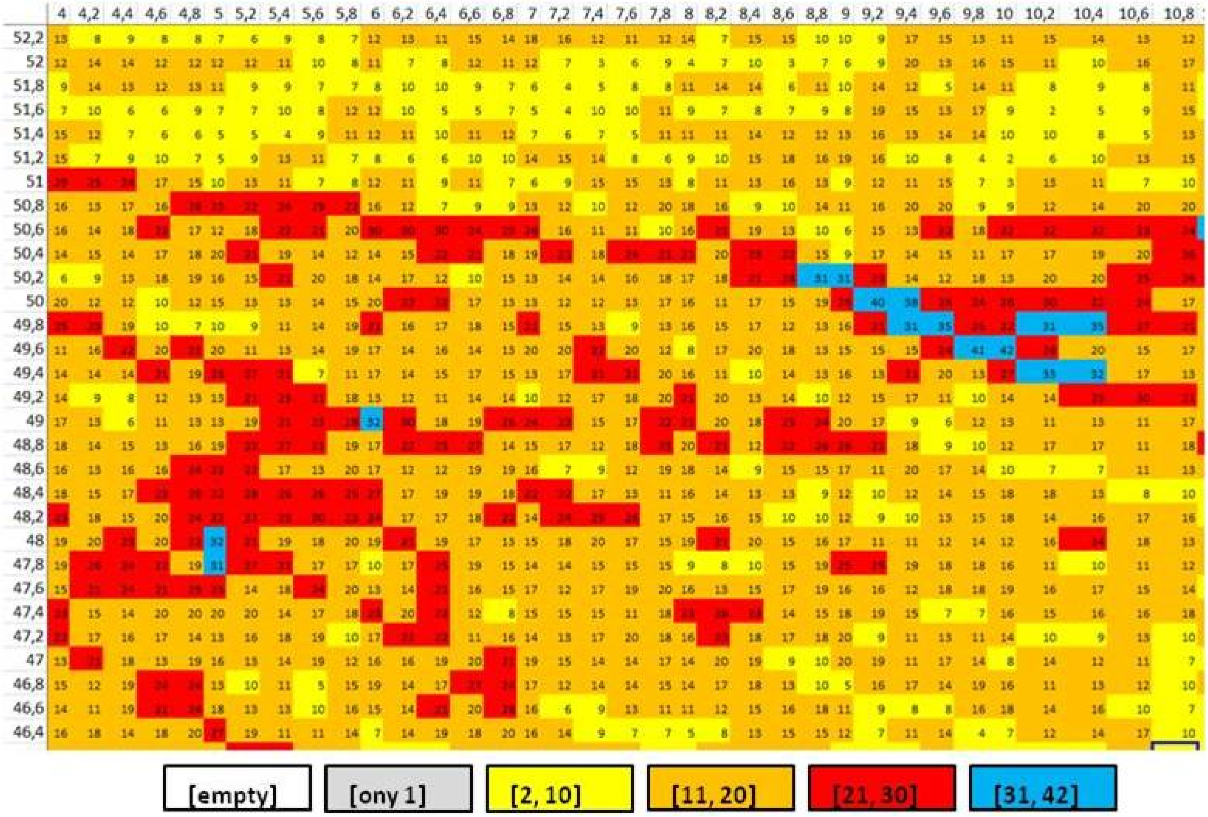

Figure 2.1: Airspace hotspots identification

AUs taking into account the global interdependencies.

To achieve this, the research is focusing on several innovation strands which are the main objectives pursued:

- Development of models and tools to enable the detection of all the potential spatial interdependencies between trajectories through efficient methods, at macro level by means of the traffic analysis under a global scope (i.e. with a 12 NM granularity) to detect airspace hotspots (Fig.2.1).

- Development of models and tools to enable the analysis at micro level (i.e. with 6NM granularity) of all spatio-temporal interdependencies between trajectories

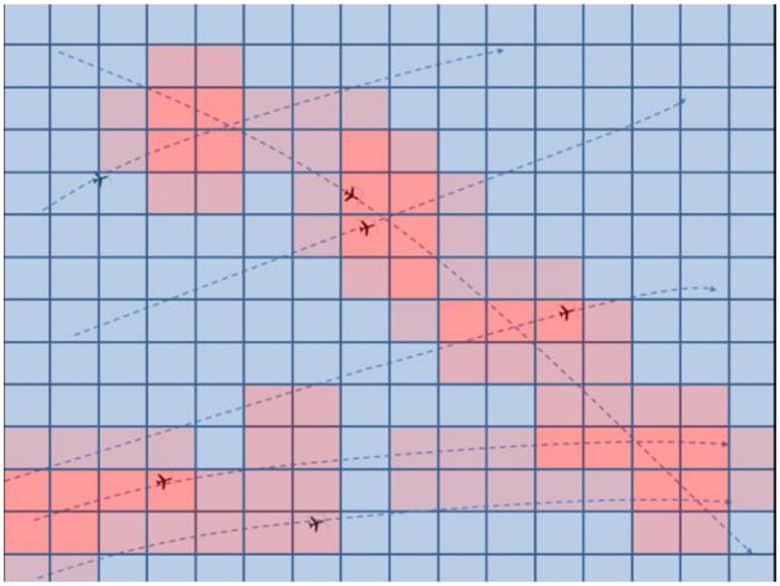

Figure 2.2: Airspace potential proximate event identification

within detected hotspots to determine potential proximate event (Fig.2.2).

- Analysis and measurement of the potential proximate events overlap or clearance time at micro level (Fig.2.3).
- Development of causal models to predict and simulate the system interdepen-

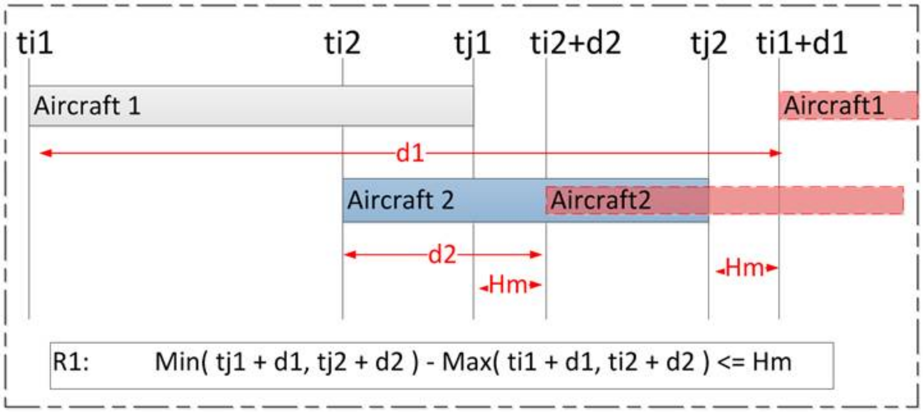

Figure 2.3: Potential proximate event clearance analysis and measurement

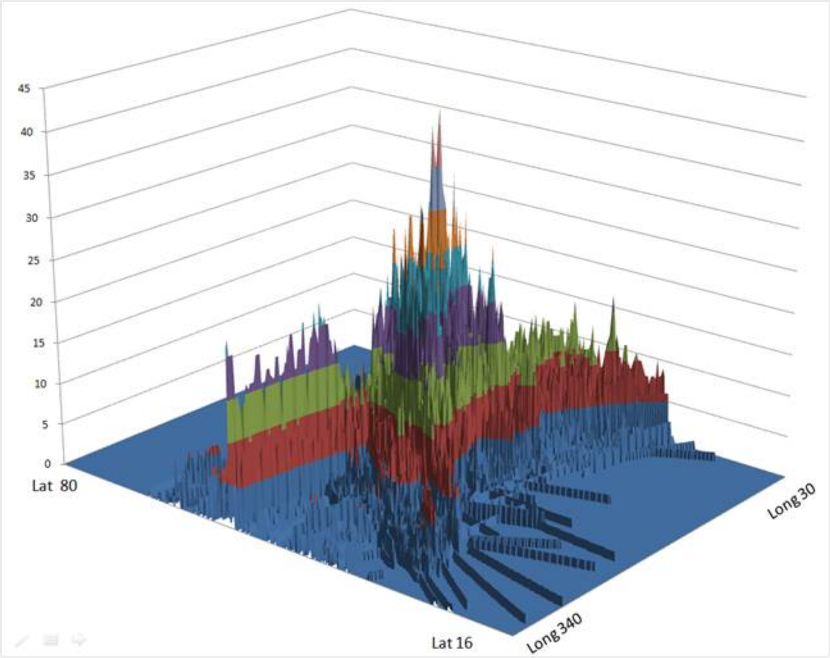

Figure 2.4: Airspace hotspots distribution over Europe

dencies and enable the analysis and solution of congested scenarios, where the obtained solutions allow the maximization of the clearance time between potential proximate events without incurring in departure slots re-scheduling.

- Development easily extendable and adaptable robust cooperative DSTs to deal with feasible time stamp agreements considering the TBO interdependencies.

- Propose and obtain new indicators based on the hotspots and potential proximate event identification. New indicators that provide relevant information about the airspace use (i.e. hotspots spatial distribution (Fig.2.4)) and robustness of traffic scenarios (i.e. clearance time distribution for potential proximate events (Fig.2.5)).

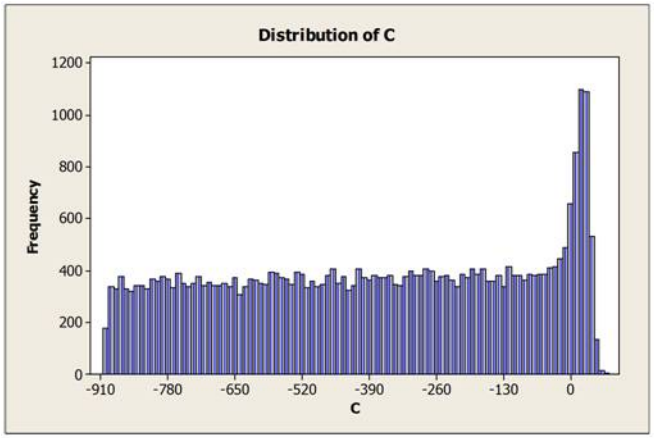

Figure 2.5: Clearance time distribution for potential proximate events

Chapter 3

Paper I

In this paper, several challenging results are presented by properly tuning the Calculated Take-Off Times (CTOTs) as a tool for mitigating the propagation of perturbations between trajectories that can readily appear in dense sectors. Based on the identification of collective micro regions, a tool for predicting potential spatio-temporal concurrence events between trajectories over the European airspace was developed, together with a CTOT algorithm to sequence the departures that preserve the scheduled slots while relaxing tight trajectory interactions. The algorithm was tested by considering a realistic scenario (designed and analyzed in the STREAM project) to evaluate relevant ATM KPIs that provide aggregated information about the sensitivity of the system to trajectory interactions, taking into account the system dynamics at a network level. The proposed approach contributes to enhancing the ATM capacity of airports to mitigate network perturbations.

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An efficient algorithm for smoothing airspace congestion by fine-tuning take-off times

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ABSTRACT

Current technological advances in communications and navigation have improved air traffic management (ATM) with new decision support tools to balance airspace capacity with user demands. Despite agreements achieved in flying reference business trajectories (RBTs) among different stakeholders, tight spatio-temporal connectivity between trajectories in dense sectors can cause perturbations that might introduce time or space deviations into the original RBTs, thus potentially affecting other 4D trajectories. In this paper, several challenging results are presented by properly tuning the Calculated Take-Off Times (CTOTs) as a tool for mitigating the propagation of perturbations between trajectories that can readily appear in dense sectors. Based on the identification of "collective microregions", a tool for predicting potential spatio-temporal concurrence events between trajectories over the European airspace was developed, together with a CTOT algorithm to sequence the departures that preserve the scheduled slots while relaxing tight trajectory interactions. The algorithm was tested by considering a realistic scenario (designed and analyzed in the STREAM project (Stream, 2013)) to evaluate relevant ATM KPIs that provide aggregated information about the sensitivity of the system to trajectory interactions, taking into account the system dynamics at a network level. The proposed approach contributes to enhancing the ATM capacity of airports to mitigate network perturbations.

1. Introduction

The level of saturation at different periods in some air traffic sectors in the European airspace, together with the predicted growth in air traffic demand, requires a new design for decision support systems (DSSs) to improve certain procedures of air traffic management (ATM).

One of the most important challenges of the SESAR (Sesar program, 2013) and Next Gen (Next Gen program, 2013) programs regarding current ATM is the introduction of trajectory-based operations (TBO), which involve the use of 4D trajectories (defined by consecutive waypoints in three spatial dimensions and their corresponding time-stamps), also known as business trajectories (BTs) according to SESAR's terminology for civil flights. It is expected that the use of 4D trajectories and the underlying new ATM procedures will improve the synchronization and predictability of the air transportation system (Korn et al., 2006).

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Currently, if an imbalance is predicted on the day of operations between the traffic demand and the available airspace capacity, the ATM authority (i.e., the ATFCM) issues a *regulation* to maximize the rate of flights entering the ATM sectors at a given time. When the *regulation* delays flight departures (Castelli et al., 2011), the delays are often known as *green delays* (Piera et al., 2014).

As alternatives to the ATM *regulations*, air traffic controllers (ATCOs) frequently issue maneuvers at a tactical level consisting of holding stacks, headings or speed variations (ATFCM Services, 2013); unfortunately, such maneuvers are often not considered desirable measures by AUs due to high operational and fuel consumption costs (i.e., airborne delays, when incurred, dominate ground delay costs (Ferguson et al., 2013). *Green delays* are therefore deemed more acceptable alternatives (Carlier et al., 2007).

The purpose of this ground-holding scheme is to respect the en route capacity constraints provided by each ATC center (ATCC) as the number of aircraft that can coexist in the same sector within a given time frame, based on their daily schedule. The number of aircraft in a sector is the air traffic characteristic that has been most cited, studied and evaluated in terms of its influence on workload (Prandini et al., 2011). However, a limitation of this *regulation* model is that the definition of the sector's capacity (the hourly rate of aircraft entering a sector) is poorly related to traffic complexity (Barnier et al., 2001). To capture ATC complexity more accurately, it is necessary to consider the flight characteristics of each individual aircraft and interactions between aircraft pairs. (Djokic et al., 2010)

Air traffic complexity can be measured by the control activity required to accept an additional aircraft entering a sector (Lee et al., 2007) (i.e., local complexity). From a network perspective, global complexity is related to the interactions between trajectories (i.e., all en route potential conflicts).

Due to the high degree of connectivity in air traffic networks (Lu and Shi, 2007), it is expected that only if global traffic complexity is considered can all potential interactions be identified.

Domino effects (Ruiz et al., 2014), together with a lack of complete understanding and a suitable formalism for modeling these interactions, are key elements that often lead to the introduction of negative network effects (i.e., ground holding based solely on local complexity information) and the impossibility of taking advantage of positive network effects (i.e., ground holding to improve the network's robustness).Thus, even small delays can easily propagate through trajectories (Pyrgiotis et al., 2013), leading to regulations that could be avoided (e.g., the application of unnecessary delays and/or airborne holding procedures) and the underuse of sectors (European Commission, 2013).

In this paper, by identifying "collective microregions" (square cells of six NM used by two or more flights at the same Flight Level (FL), independent of occupancy time window) and the analysis of occupancy time windows (i.e., temporal-longitudinal looseness (Ruiz et al., 2012), the volume of potential concurrence events that could require controller intervention is determined. Furthermore, an algorithm that can mitigate the effect of potential spatio-temporal concurrence events (i.e., congestion) between any two interacting trajectories is proposed. This algorithm preserves all pre-assigned slots by computing and applying "fine-tuning" (i.e., time offsets of [0,15] minutes) on the Calculated Take-Off Times (CTOTs).

The proposed algorithm allows for the analysis of the interactions among en route trajectories (i.e., loss of due safety distance between the geometric description of flight paths) to calculate "clearance" and "overlapping" time windows along the complete flight paths, thus predicting potential "concurrence events" (i.e., conflicts) and/or the longitudinal looseness for each trajectory (assuming TBO). With this approach, the proposed algorithm seeks to help ATM incorporate new strategies based on complete interaction-causal analysis to improve decision-making processes.

The paper is organized as follows. Section 2 provides a literature review. Section 3 describes the algorithm. Experimental results for a realistic scenario are reported in Section 4, and conclusions and opportunities for further work are discussed in Section 5.

2. Literature review

Traffic assignment techniques have been developed to reduce congestion in transportation networks by distributing traffic demand across time and space (Delahaye et al., 2005). Because congestion indicates that aircraft are occupying the same space at the same time, it can be reduced by shifting flight trajectories in time (slot re-allocation) or in space (route re-allocation). The following approaches have been developed to solve this general route-time allocation problem: space–time network (Zenios, 1991); variational inequality (Nagurney, 1998); optimal control (Janson et al., 1993); simulation (Cascetta, 1987); integer and dynamic programming (ground-holding problem) (Glover and et al., 2013; Maugis, 1996); and more recently, the collaborative en route resource allocation model (Combined Trajectory Options Program) (Kim et al., 2013) and airspace planning and design based on conflict risk assessment (Netjasov et al., 2013) have been investigated.

Slot allocation problems focused on controllers' workload using constraint programming (CP) technology are discussed in Barnier et al. (2001). Multi-sector complexity planning resolution using CP technology is presented in Flener et al. (2007). In Peeta and Ziliaskopoulos (2001), some of the most relevant dynamic traffic assignment (DTA) methods are analyzed, and path processing modeling approaches are addressed as the core of future DTA development. In Delahaye et al. (2005), the application of multi-objective stochastic methods (i.e., genetic algorithms) on real traffic data, not by using the flow network concept but by simulating the flight of each aircraft, for one day over the French airspace is presented. In Margellos (2012), Monte Carlo simulations and reachability analysis are applied to assess the 4D trajectory concept. Theoretical and experimental results for a new air traffic system, based on the moving point paradigm, are reported in Prot et al. (2014), where air traffic is completely organized by a 4D-sequencing (i.e., an allocation of flights to multi-directional lattices is proposed).

The abovementioned approaches partially solve the bi-allocation problem and propose solutions for slot allocation only, route allocation only or both for extremely minor instances of the problem. They also fail to offer a global scope of air traffic complexity because they do not consider the full European ATM network.

Some airspace analyses and partitioning (or repartitioning) methods based on superimposing traffic flows over a fine grid have been used by several researchers. Dynamic airspace configuration (DAC) is a new operational paradigm that proposes migrating from the current structured, static airspace to a dynamic airspace (Kopardekar et al., 2007). In DAC research, dynamic airspace sectorization (DAS) represents an initial approach to restructuring airspace to achieve capacity-demand balance, while managing air traffic controllers' workload and ensuring an orderly flow of traffic (Tang et al., 2012).

The sectorization problem, considered an NP-hard problem, has been studied most recently as a global optimization problem using integer programming (Basu et al., 2009). Other proposed approaches to the sectorization problem include the use of genetic algorithms (Delahaye et al., 1994) and graph partitioning (Trandac et al., 2005). A survey of the algorithmic aspects of airspace sectorization tools developed up to 2012 is provided in Flener (2012). In Alam et al. (2008), the Australian airspace is modeled as a hyper-rectangular discrete space (i.e., cells of 10 NM).

All of the cited works focus mainly on the sectorization problem at a macroscopic level, addressing only one country's airspace or, in the most general cases, a single ATCC area, and therefore, they do not consider a microscopic representation of traffic at the network level, which would be aligned with 4DT concepts and TBO procedures.

The proposed algorithm facilitates a microanalysis along the entire en route path, can consider the entire European airspace and reduces the combinatorial explosion problem during the detection of "collective microregions" (pair-wise comparison) by spatial data structure (SDS) analysis. The post-processing of a state space stored in the SDS to perform sensitivity analysis of temporal/longitudinal looseness is described in Ruiz et al. (2012). The application of a spatial data structure for the efficient analysis of interactions in large scenarios is described in Ruiz et al. (2013, 2014), and in Ruiz et al. (2013), a CD&R platform-based SDS for a simplified 4D nominal model is proposed.

3. Algorithm description

To detect the different "collective microregions" throughout the entire European airspace, each en route trajectory is initially projected onto a discrete grid (100,000 square macrocells of 12 NM) spanning longitudes of −20 to 30 degrees and latitudes of 0 to 80 degrees.

In Fig. 1(a), a three-dimensional view of a traffic scenario is shown, whereas in Fig. 1(b), a planar projection of the corresponding flight's trajectories is provided. In Fig. 1(b), some regions in which potential concurrence events are identified (red/dark cells) can be observed; these cells are identified after macro-mapping each flight trajectory path.

After the initial mapping, macrocells with an occupancy rate equal or greater than two are partitioned for the identification of "collective microregions" (square cells of 6 NM in use by at least two aircraft simultaneously; FL independent of occupancy time window). Then, for each aircraft pair, the probability of sharing a "microregion", "clearance time" or "overlap time" is computed, and finally, constraint programming (CP) calculates time adjustments ("fine-tuning") on the CTOTs to avoid all potential concurrence events. The algorithm's flowchart is presented in Fig. 2, and the next subsections will briefly summarize each process.

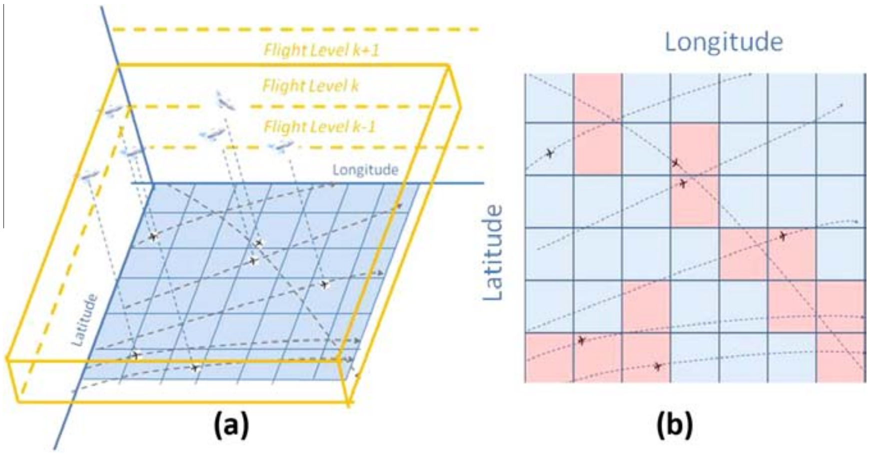

Fig. 1. (a) 4D trajectories and (b) macro-mapping and concurrence events in *FL k*.

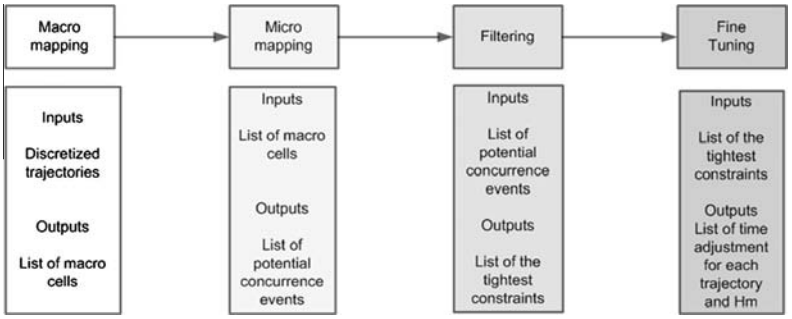

Fig. 2. The algorithm's flowchart.

3.1. Macro-mapping process

All en route trajectories are loaded and mapped onto a grid (100,000 square cells of 12 NM) by FL, and all trajectories must be discretized (time-equidistant waypoints). Position information, indicated by geographical coordinates, is supplemented with a time stamp to form the following 4×1 vector: *[longitude, latitude, flight level, time stamp]*. CTOT is known for each trajectory.

Fig. 3 graphically represents the elements involved in macro-mapping a single trajectory. For illustration purposes, a grid with 16 macrocells is presented with the corresponding position tracking vector and tracking time vector. These elements allow for the tracking of the position and the time at which the aircraft occupy each position.

Each trajectory is discretized into a sequence of waypoints (separated at constant time steps) mapped on the grid (100,000 square cells of 12 NM), which spans longitudes of −20 to 30 degrees and latitudes of 0 to 80 degrees. Fig. 3(a) presents each cell's geometry and size. Position tracking (Fig. 3(c)) is stored as a vector. Each position in the vector can assume a binary value of 0 or 1. Presence in a cell is represented by 1 and absence by 0. All of these vectors are used to form a matrix. Each row in this matrix corresponds to one trajectory and each column to one macrocell.

After mapping all trajectories in the grid, initial detection is implemented by calculating the sum of the elements in each column of the matrix. Those columns whose sum is greater than one indicates the presence of macrocells that may contain "collective microregions".

3.2. Micro-mapping process

Each macrocell (square bin of 12 NM) with potential concurrence events is divided into four microcells, or *quadrants* (named *I*, *II*, *III* and *IV*). The partition procedure is illustrated in Fig. 4(a and b). To determine whether a trajectory occupies each of the four microcells (square bins of 6 NM), positions within the macrocell are analyzed. Then, a microcell in use by two or more trajectories is identified (i.e., a collective microregion) independent of the corresponding occupancy time window registered.

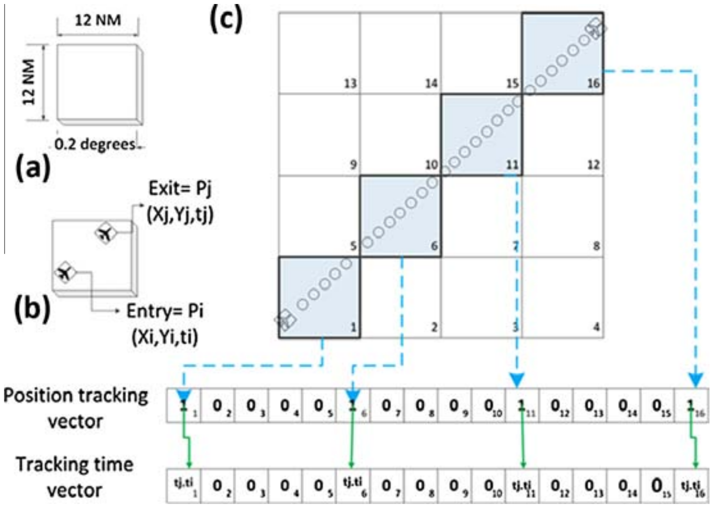

Fig. 3. (a) Macrocells, (b) macro-mapping and (c) occupancy tracking time.

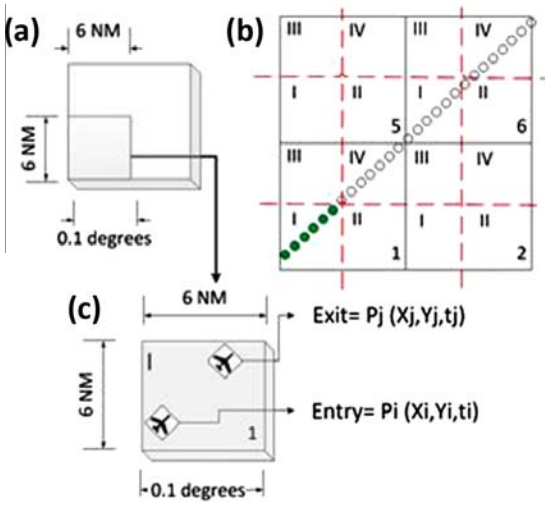

Fig. 4. (a) Microcells, (b) micro-mapping and (c) occupancy tracking time.

In Fig. 4(b), solid circles represent the trajectory segment contained in quadrant *I* of macrocell 1. This segment occupies the microcell over a time window *[ti,tj]*, where *ti* represents the time of entry and *tj* the time of exit. This period is the temporal domain of occupancy of a microcell for an aircraft (Fig. 4(c)).

For "collective microregions", entry times and exit times are used to determine the temporal looseness, *H*, i.e., the size of the overlap or clearance between aircraft pairs, and later to compute the time adjustments for CTOTs (i.e., fine-tuning) to avoid all potential concurrence events in the detected "collective microregions".

The calculation of *H* between time windows of aircraft *x* and *y* in "collective microregions" is expressed as follows:

$$H = Min(tj_x; tj_y) - Max(ti_x; ti_y) \tag{1}$$

where *Min* is a function that yields the minimum exit time between flights *x* and *y*, i.e., tj_x and tj_y, and *Max* is a function that yields the maximum entry time, i.e., ti_x and ti_y.

Fig. 5 shows a diagram of time window usage by three aircraft in a "collective microregion" and lists the three potential concurrence events and the calculation of *H* for each aircraft.

The micro-mapping allows for pair-wise comparisons between aircraft within each microcell. Subsequently, to improve the reliability of the "collective microregion" identification, for segments located on the boundaries of surrounding cells, macro- and micro-mapping processes are applied on nominal and "shifted" trajectories. The shifted trajectories are obtained by moving each aircraft's "nominal" position (by the addition of 0.025, 0.05 and 0.1 degrees to the latitudes and longitudes) before mapping them on the grid.

Fig. 6(a) shows trajectories mapped with a 0.05-degree shift with respect to the "nominal" position, presented previously in Fig. 1(b). Fig. 6(b) illustrates the integration of potential concurrence events based on the macrodetection of the "nominal" and 0.05-degree-shifted trajectories in the same lattice, where darker microcells represent overlapped "collective microregions" and those slightly less dark cells represent additional "collective microregions", as detected by the trajectories'

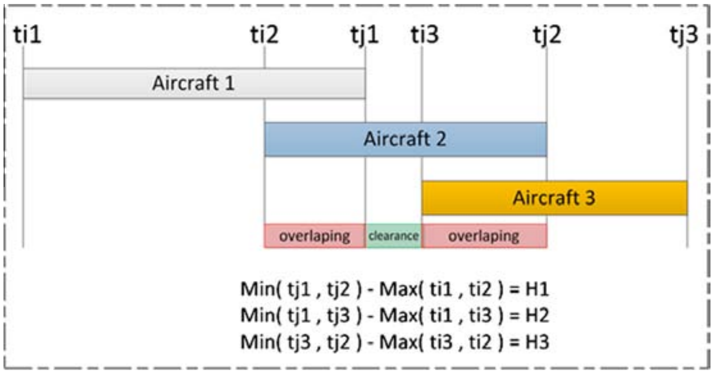

Fig. 5. Time window diagrams and calculation of *H*.

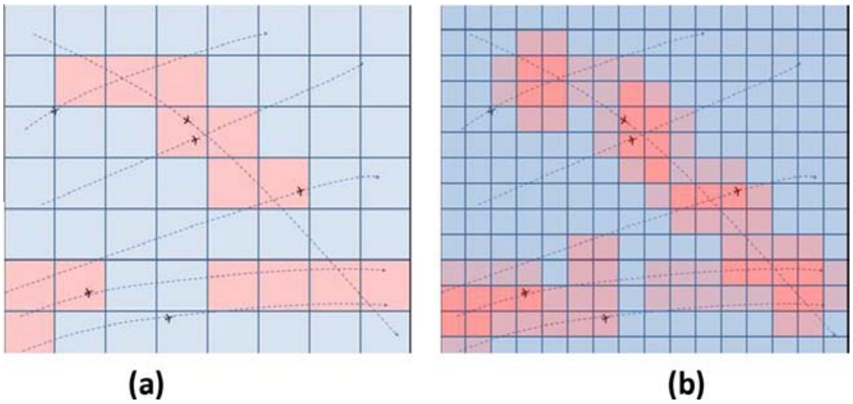

Fig. 6. (a) Macro-mapping of trajectories shifted by 0.05 degrees and (b) overlapped macrodetection (for nominal and shifted trajectories).

displacements. After microdetection, the resulting "collective microregion" lists are integrated into one list. This overall list is used as an input for the filtering.

3.3. Filtering process

For each pair of aircraft, the several potential concurrence events, i.e., instances in which both trajectories share more than one "collective microregion", can be detected. Events with a positive H indicate an overlapping; if H is negative, events have a clearance time. Based on the calculation of H (the size of an overlap or clearance), it is possible to identify the "tightest" potential concurrence events for each pair of aircraft. Hence, to shorten the overall list, all redundant or highly slack events between pairs of aircraft are eliminated, whereas the most critical or closed interactions are retained.

Because departure slot allocation times must be respected, the maximum value for a time adjustment (i.e., fine-tuning) on CTOTs is considered 900 s; therefore, potential concurrence events with a clearance time longer than -900 s have sufficient time separation to be avoided, even when the maximum adjustment time is applied. Moreover, potential concurrence events with a value of H less than -1200 s (safety buffer of 300 s) are eliminated from the list. Based on this reduction or filtering process, a complete list of the most constrained conditions (tightest events) between trajectories is obtained. This reduced list comprises the restrictions for the fine-tuning process.

3.4. Fine-tuning process

The list of potential concurrence events provides a global scope of interactions between trajectories. This information makes it possible to define the constraints required to represent all potential concurrence events in the network. Because of the strong complexity associated with solving time adjustment allocation problems and to find solutions within a reasonable computational time, the fine-tuning process is implemented as a constraint programming (CP) model. CP is an emergent modeling technology for the declarative description and the effective solution of large combinatorial optimization problems (Milano, 2012).

The CP model is defined by the following objective function:

$$Minimize\ H_m \tag{2}$$

H_m represents the maximum clearance time for the tightest concurrence events or the minimum overlap time after applying the set of time adjustments on the CTOTs (fine-tuning).

The restrictions (expressions 3 and 4) provide information about all potential temporal interactions (i.e., potential concurrence events) between trajectories. Based on these constraints, emergent downstream conflicts (i.e., negative domino effects) are avoided. Variables' domains (expression 5) correspond to the time values of adjustments for the CTOTs.

$$R1:\ Min(tj_1 + d_1; tj_2 + d_2) - Max(ti_1 + d_1; ti_2 + d_2) \leqslant H_m \tag{3}$$

$$Rn:\ Min(tj_m + d_m; tj_n + d_n) - Max(ti_m + d_m; ti_n + d_n) \leqslant H_m \tag{4}$$

$$Dom\ 0 \geqslant d_1 \ldots d_n \leqslant d_{max} \tag{5}$$

During the solution search process, constraints between different variables are propagated to derive a simpler problem (reducing domain space) until a complete solution is found (Kumar, 1992). Thus, the solution is one among all feasible solutions explored during the search process; in our model, it is the result of a minimization problem because, based on the information presented in Fig. 5, negative values of H indicate clearances, and positive values indicate overlaps.

The fine-tuning computed for each aircraft's CTOT corresponds to variables d_1 to d_n. The maximum value for adjustments "d_{max}" is 900 s; after solving this minimization problem, we obtain values spanning *[0,900]* seconds.

By applying these adjustments, the maximum clearance time of H_m for the tightest concurrence events detected in all "collective microregions" is obtained. Thus, for the tightest concurrent events, the clearance time will be equal to at least H_m.

Fig. 7 graphically represents the constraint specification based on time windows. This constraint specification is derived to avoid overlaps between any pair of aircraft. To be more realistic and to improve the speed of resolution of the CP model, in the implemented model, adjustments are defined in minutes.

3.5. Technological framework

Macro- and micro-mapping processes and a partially filtering process were implemented in R 64-bit version 2.15.1 for Windows (Team, R. Development Core, 2013).

The fine-tuning model is an OPL constraint programming script and was introduced and implemented in ILOG-CPLEX 12.2 for the 32-bit version by IBM (Cplex, 2010).

For the described processes, an Intel 5-Core laptop with a 64-bit architecture and 4 GB of RAM was used.

Fig. 8 presents an integrated system architecture proposed for the real implementation of the algorithm (i.e., rolling network operation plan (NOP)).

In Fig. 9, the reported times by process correspond to the run times for completing the analysis, as executed by a single computer for a realistic densified scenario (detailed in Section 4) of 4010 trajectories (4DT) across the European airspace.

The reported time for the macro-mapping process includes the loading time of all nominal trajectories, and outputs (i.e., number of "collective microregions") by process are also presented in Fig. 9.

The micro-mapping process (pair-wise analysis within macrocells) can be executed in parallel by several computers; therefore, the duration of the process may decrease proportionally with an increase in the number of available CPUs.

4. Application and experimental results

4.1. Realistic scenario

The algorithm was applied to an over-stressed realistic scenario. The scenario was composed of a set of 4010 real 4D trajectories in the European airspace for a time window of 2 h. In this work, we assumed TBO without uncertainties. In this context, the trajectories were discretized at each second, and each position was specified in terms of geographic coordinates and a time stamp.

This scenario was designed and analyzed in the STREAM project, a Eurocontrol SESAR WP-E project (Ruiz et al., 2014; Stream, 2013).

To stress the scenarios under consideration, all trajectories were assigned to the same FL, and all correspond to a direct route trajectory calculated using the Trajectory Predictor from Boeing Research and Technology Europe.

4.2. Experimental results

The algorithm was tested with a realistic and stressed scenario to evaluate relevant ATM KPIs. Density and occupancy have been broadly applied in transportation as parameters of traffic performance (Zi Xiao et al., 2013), these parameters provide information at an aggregated level regarding the system's sensitivity to network dynamics from trajectory interactions.

4.2.1. Density

The macro-mapping identified that only approximately 30% of the (3D) airspace considered is used by at least one of the flights, whereas 20% of the airspace (i.e., 67% of the used airspace) is used by several trajectories that might potentially conflict.

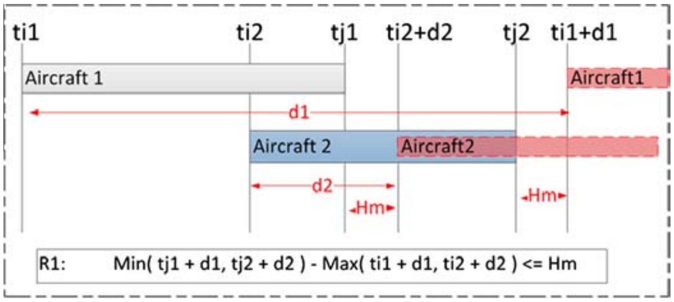

Fig. 7. Constraint specification.

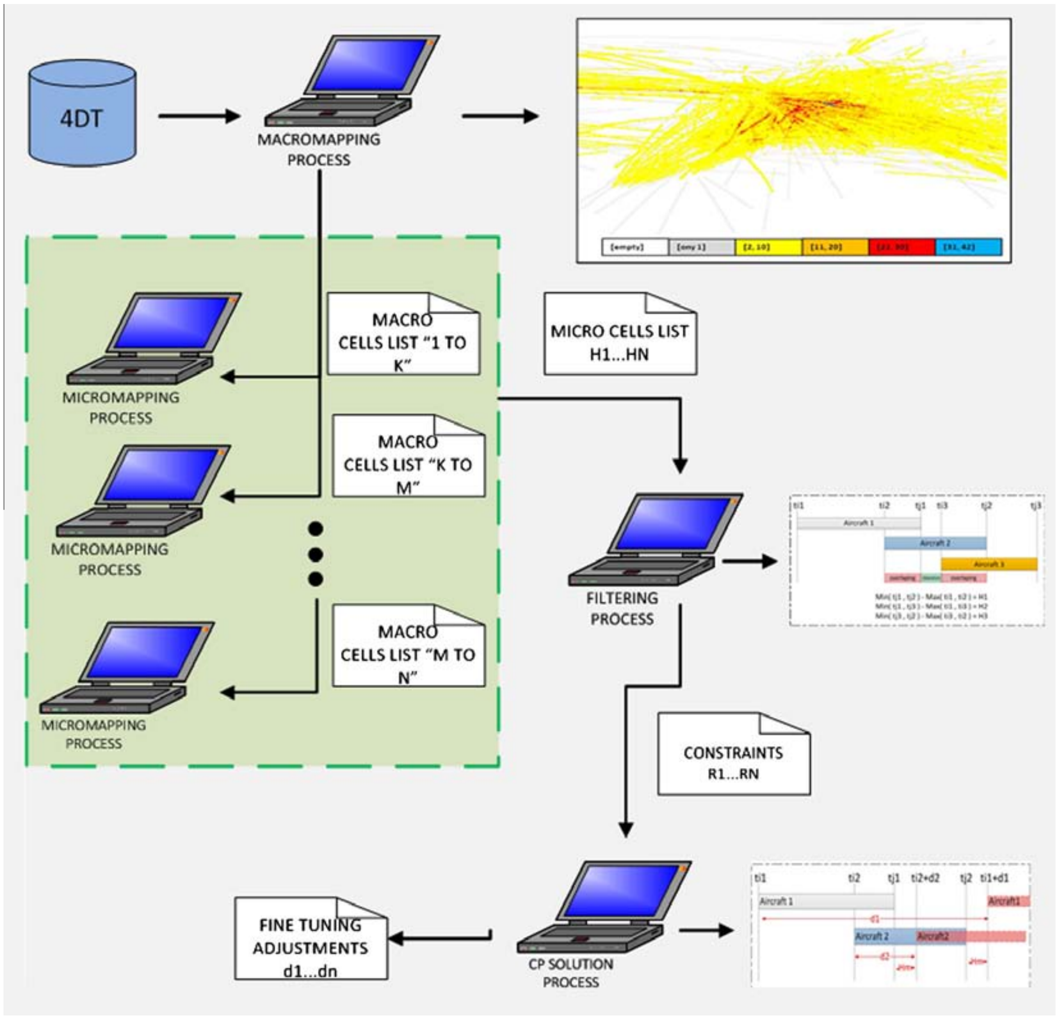

Fig. 8. Technological framework.

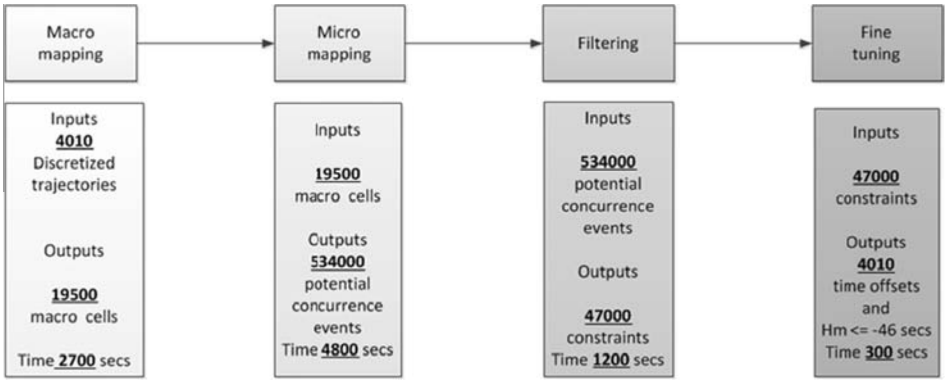

Fig. 9. Algorithm outputs and run time by process.

Fig. 10 illustrates the frequency distribution of the number of trajectories that were mapped in each single macrocell. The highest inter-temporal occupancy of trajectories in a single cell is 42 (not necessarily simultaneously), and the number of cells with a potential interaction between two trajectories (i.e., a potential conflict in the case of a potential variability of the longitudinal dimension of the trajectories) is 4079.

As indicated by the histogram, the direct route traffic used in the Stream project is neither distributed randomly through the airspace (i.e., a uniform pdf) nor concentrated in airways (i.e., a normal pdf); rather, the traffic exhibits a well-balanced

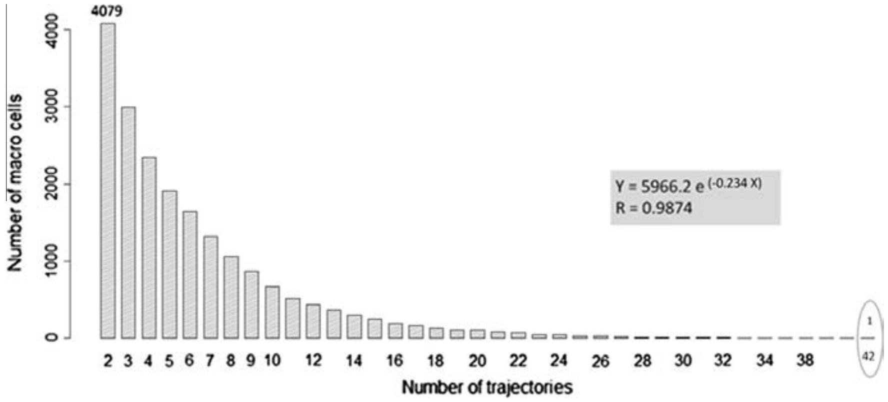

Fig. 10. Frequency distribution of the number of trajectories mapped per macrocell.

use of resources given a stochastic demand (i.e., an exponential pdf), as occurs in surface highways tolls or customer call centers in which random demand is balanced with capacity by considering the cost of queues.

4.2.2. Airspace hot spots

The spatial distribution of the potential concurrence events for the 4010 trajectories in Europe generated by macrodetection is illustrated in Fig. 11. The results correspond to the analysis of the European airspace area delimited by *[−20,30]* degrees longitude and *[0,80]* degrees latitude. The middle of the figure indicates how some airspace regions, which are not overcrowded, interact with "congested regions" by crossing trajectories.

A more detailed representation of the macrodetection and hot spot identification for the region spanning *[4,10]* degrees in longitude and *[46,52]* degrees in latitude is presented in Fig. 12, wherein it is possible to locate "highly congested regions". The value in the cell represents the number of trajectories over a time window of 2 h.

The number of times a trajectory crosses other trajectories is relevant for designing an indicator for an RBT's tightness with respect to surrounding traffic.

The implemented micro-mapping functionality provides information about the number of interactions by trajectory (i.e., potential concurrence events with H longer than −1200 s are excluded).

Fig. 13 illustrates the number of interactions discretized in groups of 60. As shown, 204 trajectories do not interact with surrounding traffic, thus boosting the network robustness in the nominal scenario (i.e., lack of uncertainty). It can also be noted that approximately 95% of the trajectories have one or more interactions, thus representing possible candidates for spurring positive or negative domino effects (Krozel et al., 2001).

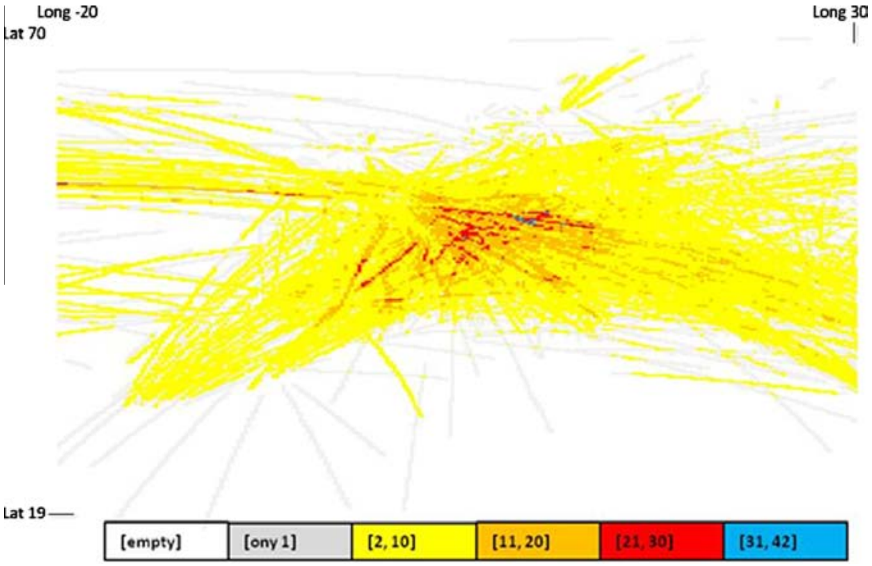

Fig. 11. Spatial distribution of the number of trajectories mapped per macrocell.

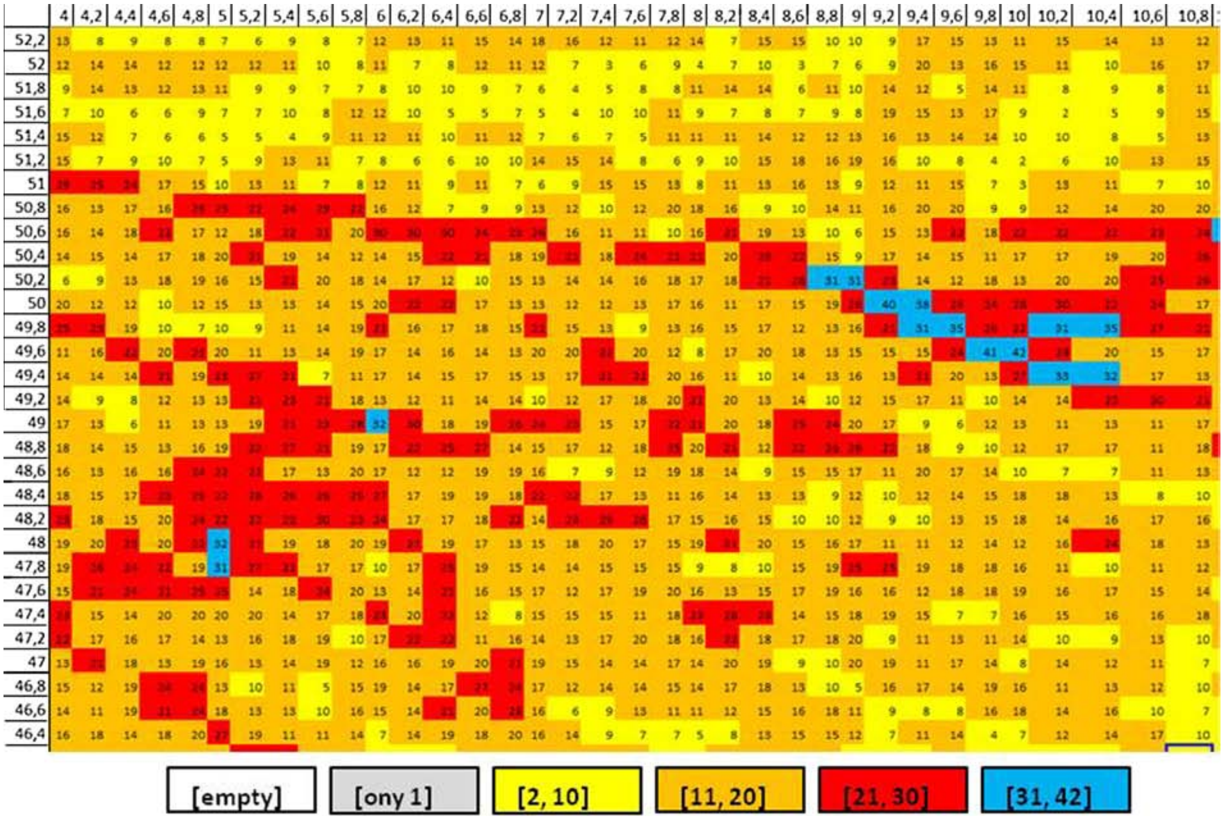

Fig. 12. Hot spot identification.

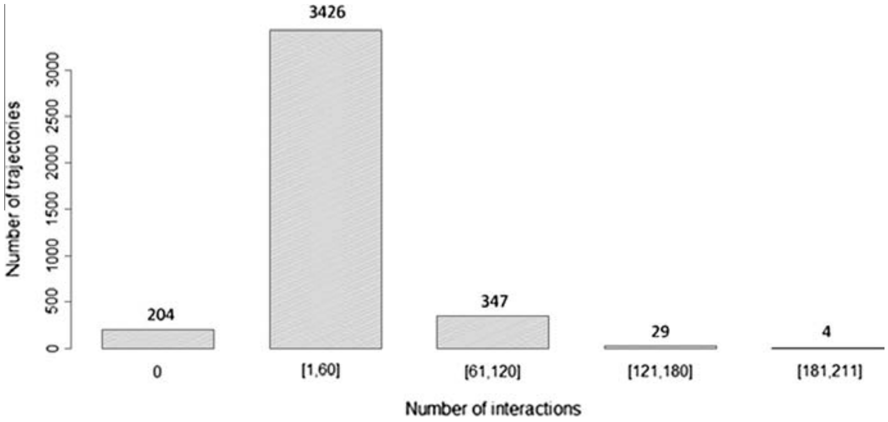

Fig. 13. Histogram of interactions per trajectory.

Fig. 14 presents a more detailed analysis of trajectories with fewer than 60 interactions (i.e., rank *[1,60]*), or 85% of all trajectories. The densification of certain areas is consistent with an exponential pdf of the number of interactions between the trajectories.

4.2.3. Overlapping and clearances

Fig. 15 illustrates the distribution pattern of the *H* (overlapping and clearances) computed by considering the tightest concurrence events in the “collective microregions” obtained after the filtering process. The uniform pdf obtained represents the scenario’s potential to assimilate a “tightening process” by slightly modifying the time dimension of the 4DT (i.e., time stamp offset) and redistributing the overlaps “absorbing” clearances by considering the less constrained events.

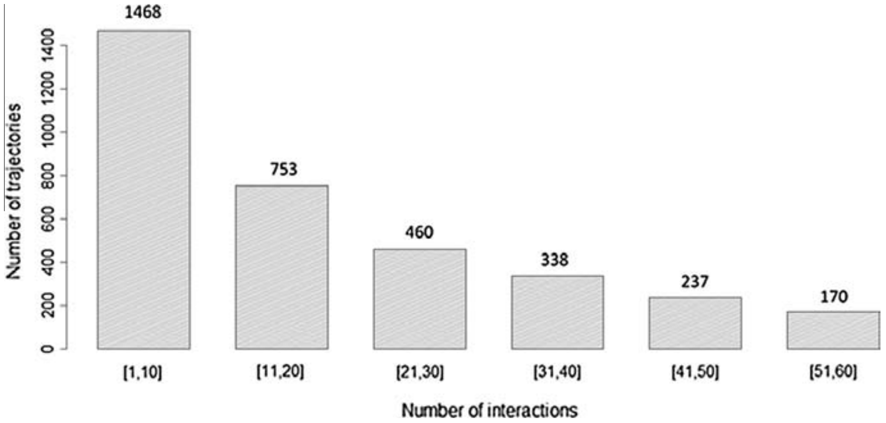

Fig. 14. Histogram of interactions per trajectory *[1,60]* cases.

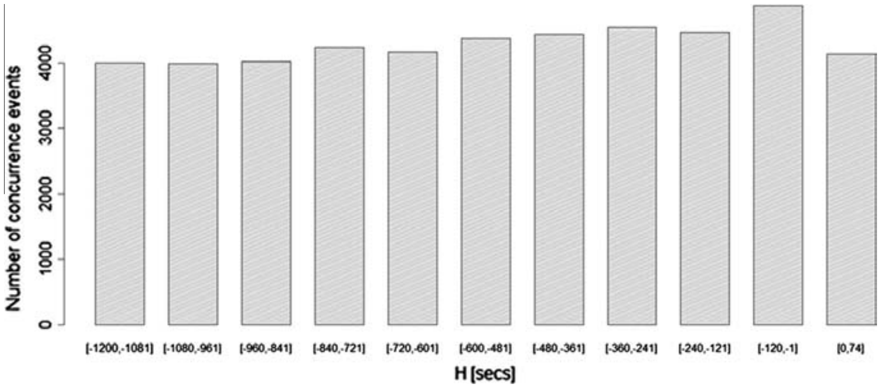

Fig. 15. Distribution pattern of looseness, *H* (overlapping and clearances).

4.2.4. Fine-tuning

The constraint programming model implemented generates several feasible solutions in which minor delays on the CTOTs inside the allocated slot (i.e., less than 15 min) are used to maximize the looseness of the potential concurrence events in the “collective microregions” and to improve the robustness of the en route trajectories with respect to the surrounding traffic in the presence of sources of uncertainty that affect a flight’s longitudinal dimension (i.e., wind prediction errors (Tastambekov et al., 2014). Robust schedules in the ATM system should incorporate uncertainties with alternatives or buffer bottleneck points to prevent significant capacity losses. Furthermore, the schedules should absorb randomly arising uncertainties to maximize the efficient use of the available capacity (Heidt and Gluchshenko, 2012).

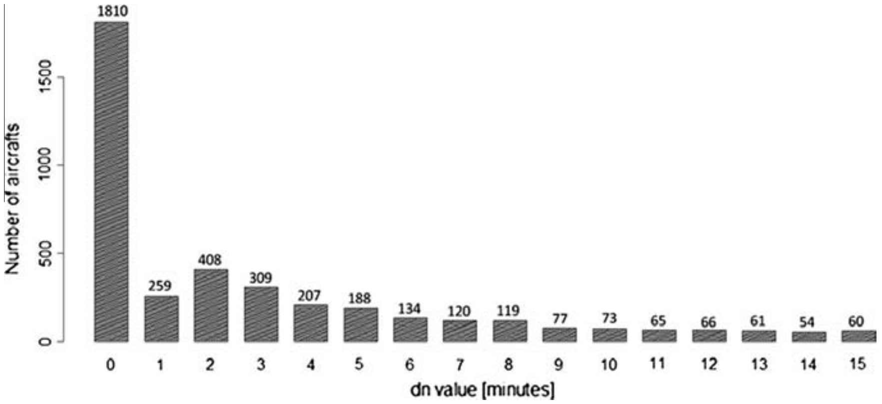

Fig. 16. Distribution of computed fine-tuning values “d_n” based on the CP model solution.

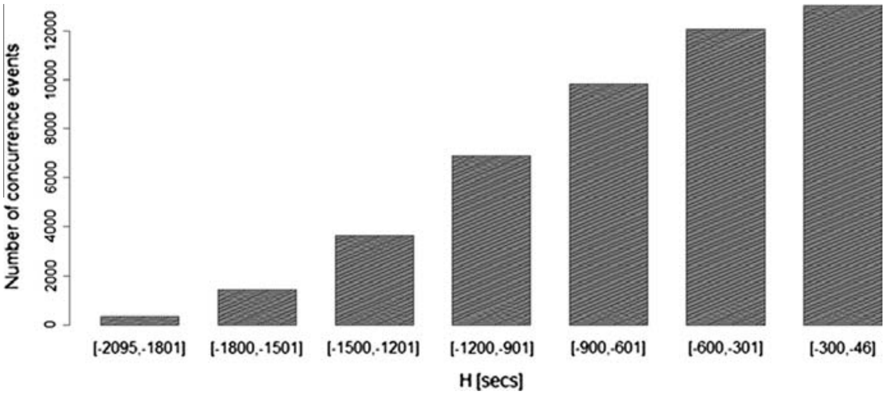

Fig. 17. Histogram of H after applying the fine-tuning based on the CP model solution.

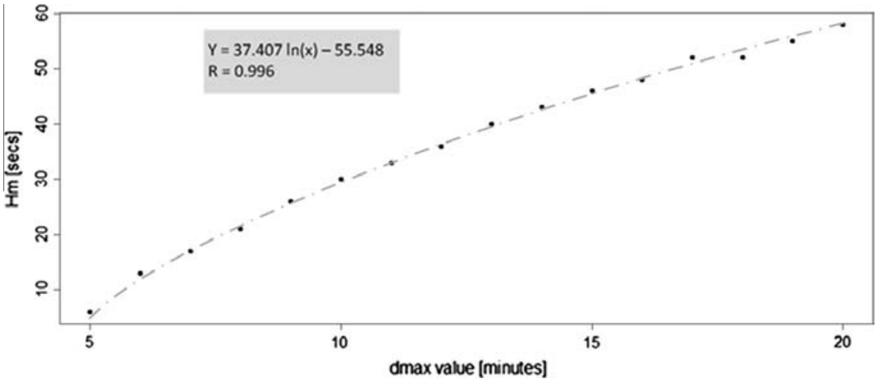

Fig. 18. Correlation between d_{max} and H_m.

Fig. 16 illustrates the CTOTs' fine-tuning for a particular feasible solution in which 1810 trajectories (45%) can preserve their RBT and less than 8% require a time offset greater than 9 min to preserve their slot time, while removing any (nominal) predicted interactions. For this particular solution, the minimum clearance obtained in the most constrained events was 46 s.

The new distribution pattern for the clearances obtained, H, is represented in Fig. 17. The distribution of the clearances provides an aggregated value of network dynamics that could be fostered if airports are operating with delays within a certain time frame.

One direct way to add "looseness" to the system is to raise the maximum offset value. To demonstrate the system's sensitivity to this strategy, Fig. 18 graphs the correlation between d_{max} and H_m. This curve fits an inverse exponential function (where the function is denoted by Y and the quadratic error by R), and the extra delay time marginally contributes in terms of "looseness".

Therefore, without a maximum limit value for offsets, the CP solution may effect a "shifting" for the entire scenario, thus providing a solution that maximizes robustness but minimizes air space capacity.

5. Conclusion and further research

5.1. Conclusion

In this paper, an efficient algorithm for the macro and microdetection of "collective regions" over Europe for a realistic and overstressed scenario was presented. The proposed algorithm generates a microanalysis of interactions between trajectories for large scenarios, thus providing a global fine-tuning solution to improve the robustness of en route trajectories with respect to the surrounding traffic.

In terms of ATM-relevant KPIs, the algorithm

- Enables the analysis of sensitivity and robustness.
- Provides sensitivity information to airports to prevent delays or to prioritize departures in tight network flights.
- Proposes a robust scheduling system by maximizing clearance times in the most conflicted "collective microregions" without affecting pre-programmed slots.

- Avoids potential concurrence events without modifying the trajectories' path geometry nor flight's speed.
- Computes fine-tuning of the CTOTs, thus preserving airports' pre-programmed time slots.
- Provides fine-tuning for ATM that grants an extra degree of freedom to mitigate over-densified scenarios.

5.2. Further research

Future research will be dedicated to developing and implementing the following:

- Comparisons between direct and structured routes to evaluate both routes in terms of robustness.
- Metrics for obtaining optimal solutions in terms of fairness, equity and robustness.
- Improved numerical efficiency to reduce computational time, a key factor for delivering fine-tuning results in real time.
- Additions to the CP model to allow for constraint relaxation for over-densified scenarios to combine better strategic planning tools with tactical operations.
- Additions to the algorithm to consider uncertainties from airside and landside operations.

Acronyms

4DT	trajectory described in terms of three spatial dimensions and time stamps
ATC	air traffic control
ATCO	air traffic controller
ATCC	air traffic control center
ATM	air traffic management
AUs	airspace users
BT	business trajectory
CD&R	conflict detection and resolution
CP	constraint programming
CTOT	Calculated Take-Off Time
DSS	decision support systems
FL	Flight Level
KPI	key performance indicator
Next Gen	next generation air transportation system
NOP	network operation plan
NP	nondeterministic polynomial time
OPL	optimization programming language
pdf	probability distribution function
RBT	reference business trajectory
SDS	spatial data structure
SESAR	single European sky ATM research
TBO	trajectory-based operations
WP-E	work package E

Acknowledgments

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Chapter 4

Paper II

This paper presents an optimization model for airspace capacity - demand management that performs an efficient departure time bounded adjustment configuration for trajectory based operations. This optimization model is supported by the 4D trajectories paradigm, in which a discrete event model has been developed to formalize the trajectories spatio-temporal interdependencies. Based on the elements and parameters declared on the validated coloured Petri net model, a set of constraints is obtained. By means of constraint programming, feasible solutions for demand - capacity imbalances are proposed for a case study scenario, while the original departure slots are preserved in addition to the airspace users preferences. The results obtained show the advantages in terms of capacity and robustness that can be achieved by applying an efficient departure time bounded adjustment configuration.

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An optimization model to fit airspace demand considering a spatio-temporal analysis of airspace capacity

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ABSTRACT

The European and U.S. airspace systems are highly congested at certain peak time intervals. Controllers' workloads have reached generally accepted limits; therefore, many highly demanded sectors are subject to traffic regulations and restrictions during many hours of each day. A lack of a spatio-temporal analysis of the airside capacity management tools generates airside delays at the destination airport in the form of holding or path-stretching in terminal manoeuvring areas, or even during the cruise by re-routing. These emergent dynamics are demonstrated every day by the urgent need for new and better tools for analyzing and making strategic and tactical decisions that neither induce delays nor negatively impact daily operations. This paper presents an optimization model for airspace capacity–demand management that performs an efficient departure time bounded adjustment configuration for trajectory based operations. This optimization model is supported by the *4D* trajectories paradigm, in which a discrete event model has been developed to formalize the trajectories' spatio-temporal interdependencies. Based on the elements and parameters declared on the validated *coloured Petri net* model, a set of constraints is obtained. By means of constraint programming, feasible solutions for demand–capacity imbalances are proposed for a case study scenario, while the original departure slots are preserved in addition to the airspace users' preferences. The results obtained show the advantages in terms of capacity and robustness that can be achieved by applying an efficient departure time bounded adjustment configuration.

1. Introduction

Growing air traffic trends necessitate the identification of operational and managing policies for better performance of existing airside capacity (Farhadi et al., 2014). The current method of organizing airspace and balancing demand and capacity is to partition airspace into sectors. This fragmentation of airspace configurations into several *air traffic control* (ATC) boundaries for *air traffic management* (ATM) directly influences the airside capacity utilization, among other impact factors (European Commission Memo, 2013).

Presently, the demand–capacity airside (i.e., ATC sectors) problem is detected by a simple aircraft counter for a time interval. Each sector has a capacity threshold in the form of the maximum number of aircraft at a given time slot. This threshold

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serves as a controller workload limit indicator for each sector without taking into account the traffic complexity (Kopardekar et al., 2008).

At a tactical level, when the lack of airspace capacity is predicted in a certain sector, regulations are applied by holding flights on the ground prior to departure (Helme, 1992). Currently, there are two main ground-delay based tools to tackle the demand–capacity problems:

- *Airspace flow program* (AFP), which applies delays to a subset of flights predicted to fly through a designated flow-constrained area (including one or several sectors) (Business Aviation Association, 2015).
- *Ground delay program* (GDP), in which delays are applied only to a set of flights destined for a single airport (Manley and Sherry, 2010).

A detailed survey of ground-holding policy models for the *air traffic flow management* (ATFM) problem can be consulted in Agustín et al. (2010) and the current European slot allocation system in Castelli et al. (2011). By delaying departures in present GDPs, new problems can be induced:

- *At Airport*: Usually, in congested airports, runways are considered to be one of the main bottlenecks to preserve the programmed landing and departure operations (Idris et al., 1999; Mori, Mar. 2013; Montoya et al., Feb. 2014). Therefore, delaying a certain number of flights due to airspace congestion will generate extra delays once regulations are cancelled, by trying to schedule the departure of the programmed flights along with the previously delayed flights (Delgado and Prats, 2011).
- *At Airspace*: Congestion in sectors depends mainly on the programmed traffic, in terms of spatial and temporal distribution. Thus, a sector B that was properly balanced considering the programmed traffic could become congested when the delayed trajectories expected in the interval [Ts_1 .. Te_1] fly through sector B in the interval [Ts_2 .. Te_2]. (Here, *Ts* and *Te* refer to start and end time stamps, respectively.)

Under existing GDPs, the airlines' operations are often disrupted, which results in a state of 'irregular operations' or route failure (Wei et al., 2014). These may be characterized by significant delays, many cancellations and a large number of disrupted passengers, which are recognized to be highly detrimental to airline profit and passenger welfare (Xiong and Hansen, 2013). Thus, more stringent scheduling procedures may be necessary (Deschinkel et al., 2002), including some form of resources management (i.e., intelligent decision support tools (D'Ariano et al., 2012) to adapt the demand to the available capacity with bounded collateral effects on the airline's operation or narrow passenger disruptions.

In presence of highly demanded airspace spots (Nosedal et al., 2014) (i.e., regions with demand consisting of several trajectories that coexist during the same time frame), the air traffic controllers' intervention (i.e., holding and heading manoeuvres) to handle potential conflicts easily propagates and increases induced ATC workload. The high degree of connectivity in air traffic networks could affect overall network performance with leading to higher operational and fuel consumption costs for the airlines.

To achieve needed capacity, it is necessary to improve ATM procedures to ensure a better synchronization of all air traffic flow (Ruiz et al., 2013; Rodionova et al., 2014). Considerable research efforts have been undertaken, and several operational systems have been developed around the world to address airspace *demand–capacity* imbalances. The underlying principle in each is that *demand–capacity* imbalances should be addressed before the affected flights depart from their originating airports (Churchill and Lovell, 2012).

The technology modernization of *communication, navigation and surveillance* (CNS) through international programs, such as SESAR (SESAR, 2015) and NextGen (NEXTGEN, 2015; Brooker, 2008), has enabled a key change in ATFM to a *trajectory based operations* (TBO) approach. Under this approach, airspace users will fly precise *4-dimensional trajectories* (4DTs), involving 3 spatial dimensions plus time, previously agreed upon with the network manager (Wandelt and Sun, 2015). A 4DT, otherwise known as a *business trajectory* (BT), represents a contract between the airline and the network manager such that the aircraft should fly the trajectory, preserving the time stamps specified in the BT (Berechet et al., 2009; Castelli et al., 2011; Enea and Porretta, 2012).

With respect to the airspace, the TBO paradigm (Prevot et al., 2003) enhances the design of new tools to evaluate the demand–capacity balance by the amount of potential controller interventions that can be required in each particular traffic scenario. Thus, the demand–capacity balance of a region – e.g., en route European airspace or the *National Airspace System* (NAS) of the U.S. – can be estimated by considering the amount of potential proximate events (such as loss of safety distances between trajectories with time stamp concurrency) that could emerge due to all the programmed traffic (based on airspace users' preferences). The proximate event zone can be represented by a square cell of 6 NM (0.1 latitude × 0.1 longitude degrees) and height 1000 feet, values in which aircraft are perceived to pass far enough away from each other to ensure a safe distance (otherwise referred to as 'protected zones' (Huang et al., 2014).

At the airport, the surface traffic automation systems (Mori, 2013; Roling and Visser, 2008) enhance the management of airport surface operations to provide shared situational awareness and to control taxi times through the use of 'virtual queues'. This approach has become an important component of ATM research and development in both Europe and the U.S. (Bhadra et al., 2012; Brinton and Lent, 2012).

The *collaborative departure queue management* (CDQM) concept manages the length of the runway departure queues so that aircraft experience minimal physical queuing while ensuring that the runways are used at their maximum capacity, while also adhering to the departure slot allocation (Pellegrini et al., 2012). The *calculated time of take-off* (CTOT) is allocated by Eurocontrol and corresponds to a 15-min window, running from 5 min before the allocated time until 10 min afterwards (Greenwood, 2001).

Regarding the challenges for the implementation of the TBO approach, while many trials around the world have demonstrated that some modern aircraft (e.g., those equipped with *Flight Management System* (FMS)) are capable of performing a TBO to very tight tolerances, other research results suggest that additional work is needed to mature the concept (De Smedt, 2015). One of the major factors is the wind (Tastambekov et al., 2014), which leads to longitudinal uncertainty that affects the execution of *reference business trajectories* (RBTs) and their respect time stamps. Based on the theoretical time separation analysis reported by Klooster and De Smedt (2011), we assume in the current work that using a spacing of 105 s or, greater should not cause separation problems even in the presence of longitudinal deviations because of wind.

Based on the above, this paper presents a spatio-temporal model, driven by discrete events, to simulate and validate the departure-time-bounded adjustment process that preserves the scheduled slots while relaxing tight 4DT interactions (for instance, reducing or solving demand–capacity imbalances). The simulation model is extended and implemented as a constraint programming model applied to solve a case study scenario (which is a large and congested one).

By means of the distribution of time clearances, the robustness of different solutions is analyzed. Time adjustments of up to 15 min are referred to as '*fine tuning*' or '*bounded adjustments*' (i.e. '*short delays*' (Cook et al., 2004), to differentiate them from 'delays', which pertain to departure postponements of more than 15 min (Eurocontrol, 2005).

This paper is organized as follows. Section 2 describes the problem. Section 3 focuses on the discrete event modelling approach. Section 4 presents the model developed using *coloured Petri nets* (CPN) and also reports on simulation results. In Section 5 the optimization models and the solutions obtained for a case study scenario are provided. Finally, Section 6 presents our conclusions.

2. Problem description

Based on the TBO paradigm (Enea and Porretta, 2012), an airspace user's demand is represented by the BTs, and the airspace capacity constraints will be given by the spatial and temporal interactions between these trajectories. To analyse these spatio-temporal interactions between trajectories, the recognition of all of the potential proximate events per pair of trajectories in a given traffic scenario must first be performed. Then, by the analysis of the occupancy time windows, it is possible to analyse the demand–capacity balance or imbalance. In this work we show the benefits of using a departure time adjustment mechanism as an extra degree of freedom to develop demand–capacity balance policies, without affecting the trajectories' geometric profiles or *airspace user* (AU) preferences. In this section, both the problem and the solution approaches are described by way of a conceptual example.

Fig. 1 shows the en route segments of two aircraft's trajectories in a proximate event, in which a fine tuning in the departure time of aircraft A is applied as a resolution in such a way that, by time t_{j+3}, aircraft B arrives at waypoint B(X_{j+3}, Y_{j+3}, Z_{j+3}) while aircraft A is located in a 4D waypoint far enough from aircraft B (i.e., preserving safety distances in crossing waypoints

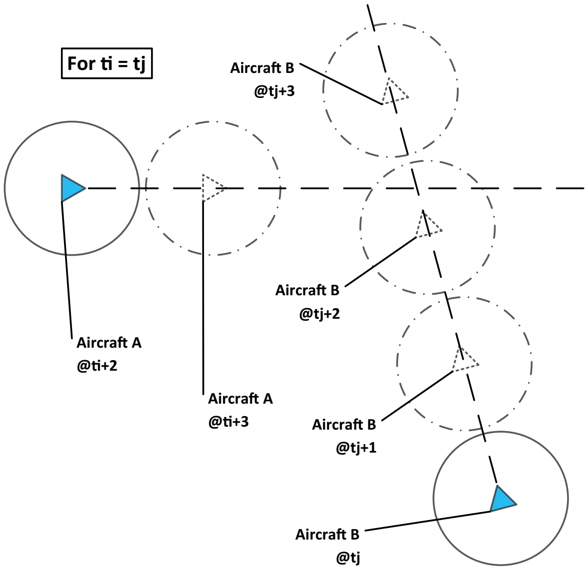

Fig. 1. Safety distance preservation by fine tuning A.

(Cai et al., 2012). Here the distance of separation can be expressed as the clearance time, *S*, for this proximate event between aircraft A and B. A similar, though essentially opposite, resolution could be obtained by fine tuning the departure of aircraft B long enough to preserve the safety distance, as shown in Fig. 2.

When the traffic density increases, each trajectory can have several proximate events. It can easily be understood that, by fine tuning the departure time, the time stamps associated with each waypoint in the path will experience a modification. Thus, some of the time window overlaps could be avoided, while some new time window overlaps would be enabled (network or synergy effects (Everdij et al., 2011). As a result, the computation of the departure fine tuning should consider not only the local proximate event with the time overlap detected but also the impact of the shift with the remaining positions for the entire path, avoiding transforming other proximate events into time-overlapped events. One also must avoid any disruption in terms of adherence to the planned departure time slots. Hence, the departure's fine tuning computation is deployed as a globally-bounded adjustment process (with an adjustment within the interval [0, 15] min).

To exemplify the network effects being referred to, a scenario with four aircraft (A1, A2, A3 and A4) and their respective nominal trajectories (*Tr10*, *Tr20*, *Tr30* and *Tr40*) are illustrated in Fig. 3. For the spatio-temporal analysis of the trajectories'

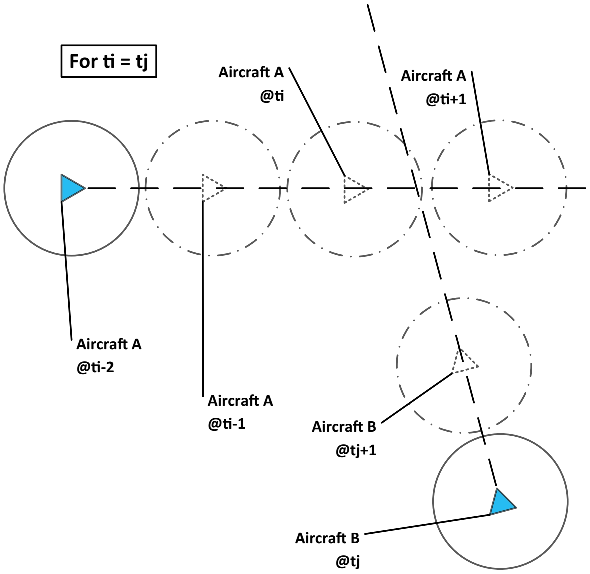

Fig. 2. Safety distance preservation by fine tuning B.

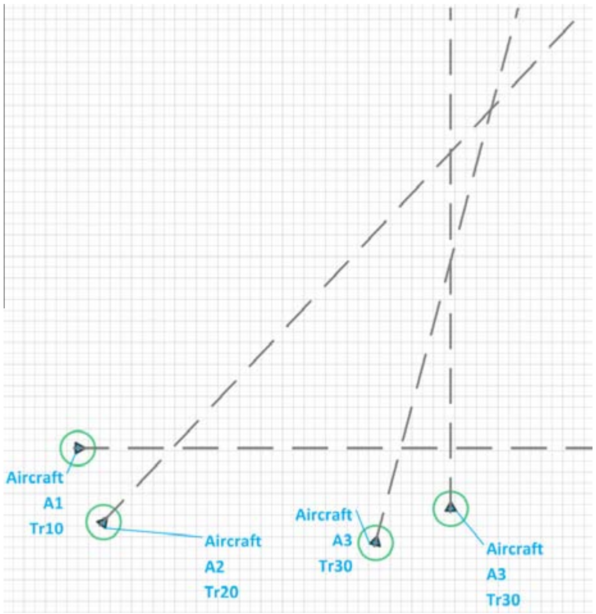

Fig. 3. Aircraft scenario of four aircraft.

interactions, it is necessary to identify, for each proximate event, the involved aircraft and their time windows. In Fig. 4, the six areas of proximate events are indicated in either black or gray, depending upon whether or not the involved trajectories generate a time window overlap, respectively. When shown in gray, therefore, there is a clearance between time windows.

Table 1 summarizes the scenario information. In this table, each pair of rows describes the proximate events for pairs of trajectories. A proximate event is described by the information of aircraft *i* and aircraft *j* and their time windows, defined by two time stamps, start (*Ts*) and finish (*Te*), in min (starting from 0:00 h).

For instance, the proximate event identified by the number 1 in Fig. 4 involves trajectories *Tr10* and *Tr20* associated with aircraft A1 and A2. The time window usage of aircraft A1 starts at *Ts* = 451 and ends at *Te* = 453. In the case of the proximate event identified by number 4, the involved trajectories are *Tr10* of aircraft A1, with a time window from *Ts* = 526 to *Te* = 530, and *Tr40* of aircraft A4, with a time window from *Ts* = 531 to *Te* = 535.

In order to avoid the overlap in time windows in proximate event $n = 1$, an adjustment of 3 min may be applied to the original trajectory of aircraft A1 (*Tr10*), creating a new trajectory *Tr11* with exactly the same 3D information, or waypoints, as *Tr10* (i.e., untimed *Tr11* = untimed *Tr10*) but with different time-stamps. Similarly, proximate event $n = 2$ may be avoided by applying an adjustment of 5 min to the original trajectory of aircraft A1 (*Tr10*), leading to a new trajectory *Tr12* with exactly the same 3D information as *Tr10* (i.e., untimed *Tr12* = untimed *Tr10*) but again with different time-stamps. In Table 2, the new information for proximate events is listed, considering the new time stamps obtained for trajectories *Tr11* and *Tr12*.

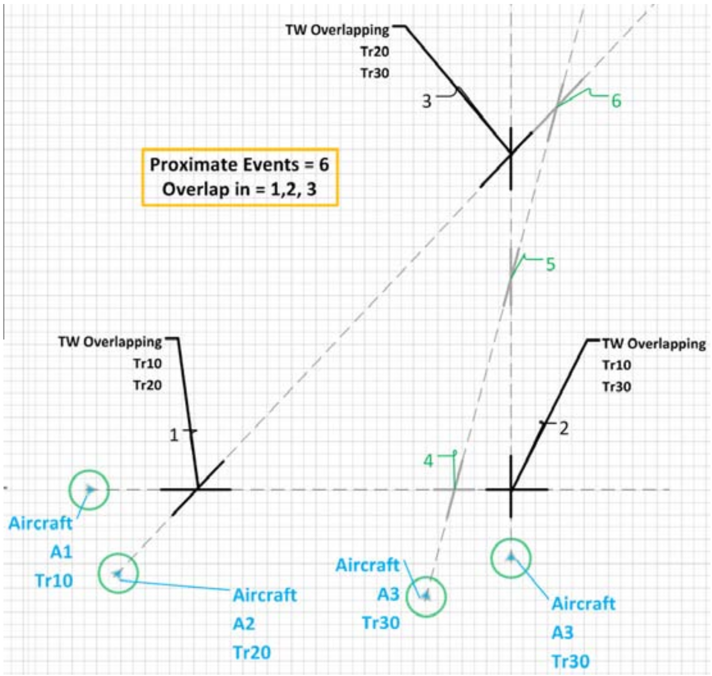

Fig. 4. Proximate events.

Table 1
Initial data for the proximate events between nominal trajectories.

proximate event	Aircraft ⟨*i*⟩	Time window		Trajectory number (*Tr*__)
		Ts	*Te*	
1	1	451	453	10
	2	451	453	20
2	1	538	542	10
	3	538	542	30
3	2	625	630	20
	3	625	630	30
4	1	526	530	10
	4	531	535	40
5	3	582	586	30
	4	577	581	40
6	2	663	667	20
	4	657	660	40

Table 2
Additional data for proximate events for *Tr11* and *Tr12*.

Proximate event	Aircraft ⟨*i*⟩	Time window		Trajectory number (*Tr*__)
		Ts	*Te*	
1	1	454	456	11
	2	451	453	20
2	1	541	545	11
	3	538	542	30
4	1	529	533	11
	4	531	535	40
1	1	456	458	12
	2	451	453	20
2	1	543	547	12
	3	538	542	30
4	1	531	535	12
	4	531	535	40

Thus, the complete scenario is described by the combined 18 time windows.

Fig. 5 illustrates the state of the system where aircraft A1 executes trajectory *Tr11*. As observed by checking the time windows from Tables 1 and 2, trajectory *Tr11* avoids a time window overlap in proximate event $n = 1$ but not in proximate event $n = 2$, where an overlap occurs with trajectory *Tr30*. As a network effect, an overlap in time windows is induced in proximate event $n = 4$.

Alternatively, it is possible to implement trajectory *Tr12* as shown in Fig. 6, in which time window overlaps in proximate events 1 and 2 are avoided, but an overlap in proximate event $n = 4$ ensues.

Based on the time windows for the remaining proximate events between aircraft A2, A3 and A4 and on the application of the same approach (fine tuning nominal trajectories to avoid time overlaps), the amount of interdependencies to be analyzed (i.e., time windows) increases because each new trajectory uses the same areas with different time stamps *Ts* and *Te*.

The total number of possible combinations of trajectories to select from for this basic scenario, and therefore the total amount of final states of the system that should be evaluated is $k_1 \times k_2 \times \cdots \times k_m$, where k_i is the number of potential trajectories for aircraft i, $i = 1, 2, \ldots, m$. Thus, the construction of supported combinations of paths is a problem that grows in an exponential way particularly as the number of aircraft increases.

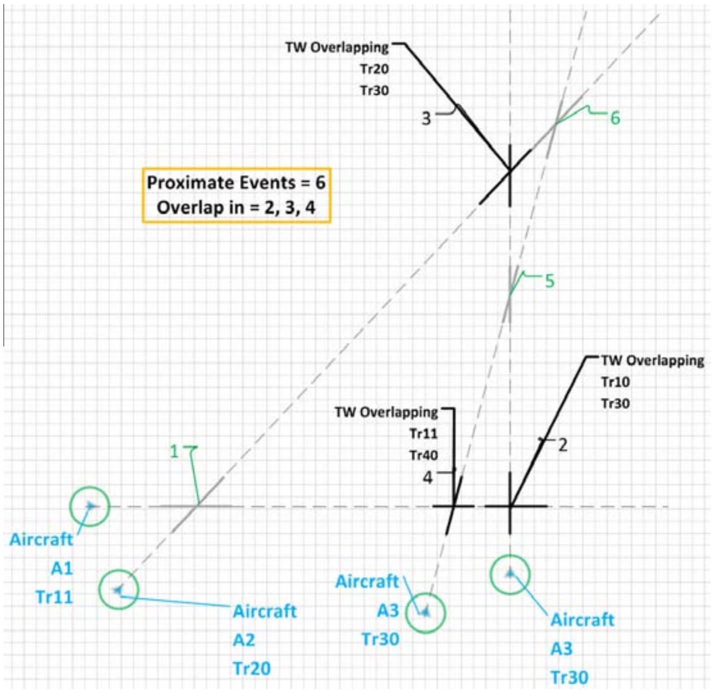

Fig. 5. Proximate events with *Tr11*.

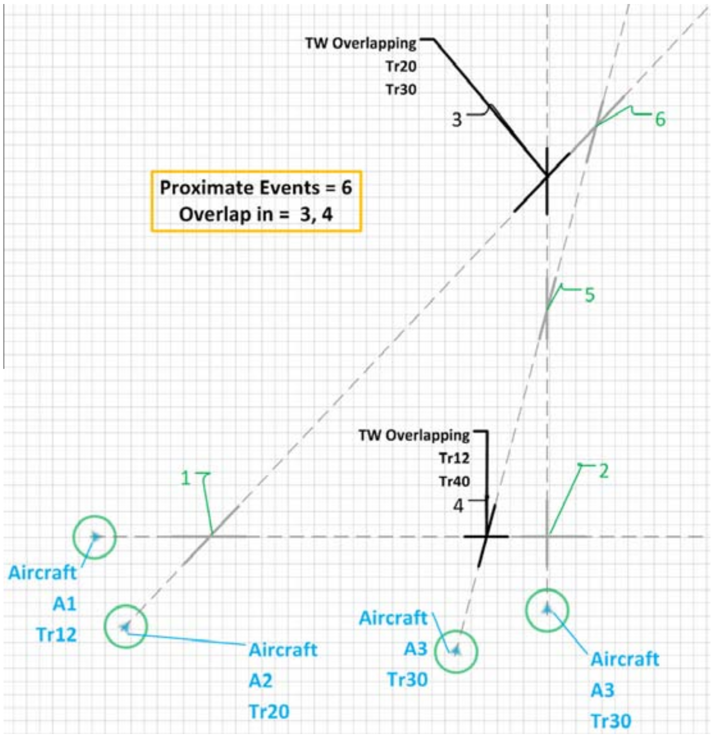

Fig. 6. Proximate events with *Tr12.*

3. Discrete event modelling framework based on CPN formalism

The CPN approach is a high level modelling formalism for complex systems that has been widely used to model and verify *discrete event dynamic systems* (DEDS), allowing the cause-effect representation of not only the system dynamics and static behavior but also of the information flow. In the current work, CPN formalism is used to specify all the events that lead to a system state change together with all the preconditions that should be satisfied in order that an event could occur.

CPN models can be simulated to explore a particular set of decisions, and they can also be used to analyse the state space of the system, containing the different states that can be reached from a certain initial condition, together with the sequence of events that can drive the system to a set of goal states. Jensen (Jensen, 1996) provides a comprehensive discussion of the basic concepts, methods and use of CPN. Narciso et al. (2010) provide a fairly informative summary of the main CPN components which are used to address modelling requirements.

Over the last decade Petri nets and its extensions have been applied in the solution of transport problems, including road safety to regulate movement of transit vehicles and pedestrians crossing, modelling urban transportation, describing multi-agent systems for traffic control, modelling of advanced driving-assistance systems, as well as traffic control of marine vessels (Ng et al., 2013).

Some analyses and resolution of air traffic problems have been addressed with the use of CPN. Examples include a description and analysis of missed runway approaches using a CPN model (Everdij et al., 1997 and the implementation of a CPN tool that simulates the arrival process in ATC and generates potential solutions to the sequence planning problem (Oberheid and Söffker, 2008). The development of a mathematical model of *airborne collision avoidance system* (ACAS) operations, based upon an extension of the CPN formalism, is presented by Netjasov et al. (2013) and more recently by Tang et al. (2014). Control actions at a *terminal manoeuvring area* (TMA) are modelled by Zúñiga et al. (2013), using CPN formalism, in order to coordinate TMA traffic during busy periods. A strategic network and collaborative conflict resolution method based on discrete event modelling to assign one conflict-free trajectory in the presence of a large number of 4D trajectories per aircraft is presented by Ruiz et al. (2014).

4. CPN model for simulation and validation

In this section, we present the CPN model as developed and evaluated. The model presented in Fig. 7 has been implemented using *CPNTools 4.0.0* (CPNTools, 2015). *CPNTools* is a mathematical tool for editing, simulating, and analyzing CPNs. This tool includes a simulator for untimed and timed nets, and it allows the construction of partial or full state spaces diagrams.

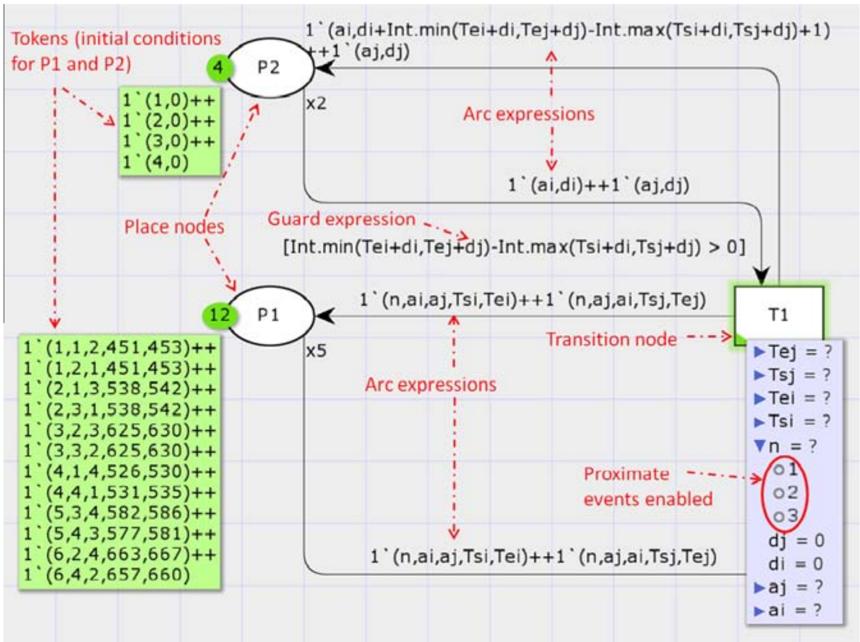

Fig. 7. Discrete Event Solver in CPN.

The model is based on the logic of cause-effect between the following events:

- Calculation of the overlap time between trajectories in the proximate events.
- Assignment of adjustments to provide clearance time for proximate events with overlapping time windows.

The colors, places and transitions of the CPN model are summarized in Tables 3–5, respectively. The initial conditions (the proximate events presented in Table 1) are placed in *P1*, and the departure time adjustments (initially equal to 0 for each aircraft) are placed in *P2*.

The initialized model is presented in Fig. 7. In the rectangle associated with *P1*, for instance, the first element on the left corresponds to the proximate event $n = 1$ (first color), between aircraft $a_i = 1$ and $a_j = 2$ (second and third colors), with aircraft $a_i = 1$ having the time window from $Ts_i = 451$ (fourth color) to $Te_i = 453$ (fifth color).

In Fig. 8, M_k is a marker signifying the state that has been reached, with k being the number of transitions to reach the state M_k. Hence, M_0 refers to the initial state as depicted in Fig. 4. We note that under the initial conditions at M_0, at least one overlap has been detected (as previously noted, there are initially three proximate events $n = 1$, 2 and 3); accordingly, transition *T1* is enabled.

The proximate event $n = 1$ (with a time window overlap of 2 min) may be addressed by applying a fine tuning of 3 min to aircraft A1. After each decision (i.e., firing the transition *T1*), the state of the system is updated (with value modifications for

Table 3
Colors in the CPN model.

Colors	Definition	
	Domain	Description
a_i, a_j	*Int* 1 … *N*	Aircraft identification
d_i, d_j	*Int* 1 … *N*	Shifts accumulated for a_i and a_j
Ts_i, Ts_j	*Int* 1 … *N*	Start time for the proximate event for a_i and a_j
Te_i, Te_j	*Int* 1 … *N*	End time for the proximate event for a_i and a_j
N	*Int* 1 … *N*	Number identification for the proximate event between a_i and a_j

Table 4
Places in the CPN model.

Places	Description	
	Token colors	Operation
P1	1‘(n, a_i, a_j, Ts_i, Te_i)	The tokens stored here represent the list of proximate events in the scenario
P2	1‘(a_i, d_i)	The tokens stored here correspond to the shifts calculated and assigned to each aircraft to avoid overlaps

Table 5
Transitions in the CPN model.

Transitions	Explanation
T1	Simulates the discrete events of calculation of the overlap or clearance in each proximate event, and simulates the assignment of shifts for aircraft if necessary to avoid time overlaps

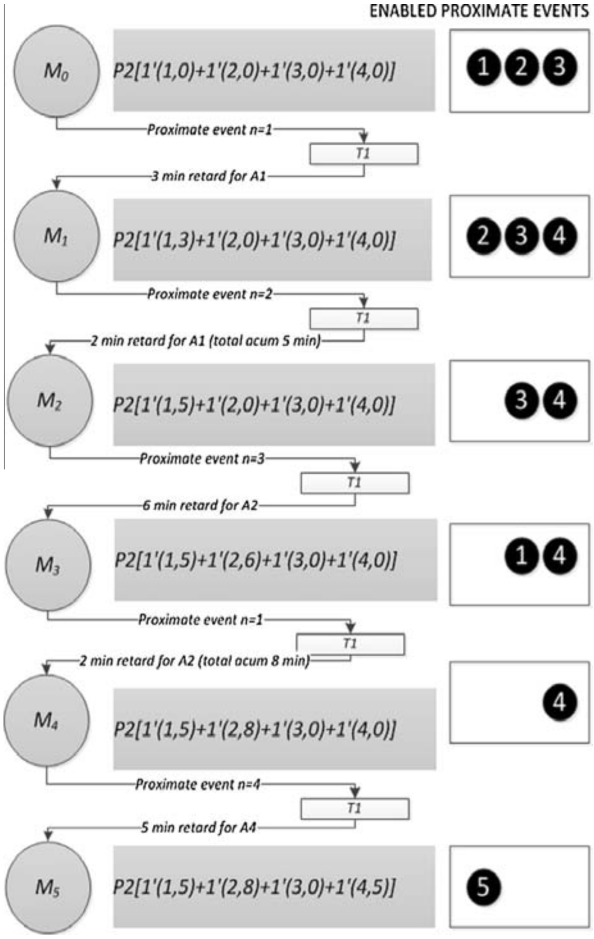

Fig. 8. Simulation of the state space exploration of the system.

color d_i in the tokens of *P2*). The state of the system after fine tuning A1 is indicated in Fig. 8 by the tokens and color values in *P2* at M_1.

After each decision, the model computes clearances and overlaps for the proximate events. In the updated state M_1 (as also previously depicted in Fig. 5), proximate event $n = 4$ has been enabled (as a synergy effect) while proximate events $n = 2$ and $n = 3$ are still enabled.

The overlap for the proximate event $n = 2$ is subsequently resolved by applying an additional shift of 2 min to aircraft A1 (hence, a total fine tuning of 5 min for A1). The new state after this decision is indicated at M_2 in Fig. 8.

By assigning 5 min of fine tuning to aircraft A1, overlaps in proximate events $n = 1$ and 2 are avoided, but overlaps in proximate events $n = 3$ and 4 still need to be solved. Next, a fine tuning of 6 min is applied to aircraft A2 (which addresses the overlap in proximate event $n = 3$). The resulting state of the system is indicated at M_3 in Fig. 8.

As a consequence of applying a 6-min fine tuning to aircraft A2, proximate event $n = 1$ again becomes enabled (a time window overlap is induced), resulting in proximate events $n = 1$ and 4 requiring resolution. By applying 2 additional minutes of shift in aircraft A2 (thus, a total fine tuning of 8 min for A2) the overlap in proximate event $n = 1$ is avoided and the new state of the system is presented at M_4 in Fig. 8.

By applying a 5-min fine tuning to aircraft A1 and an 8-min fine tuning to aircraft A2, the overlaps in proximate events $n = 1$, 2 and 3 are avoided, but proximate event $n = 4$ is still enabled. This can then be solved by applying a fine tuning of 5 min to aircraft A4 The updated state of the system is reported at M_5 in Fig. 8. This leads to a new proximate event $n = 5$ being enabled. As necessary, other decisions must subsequently be implemented until a complete solution, involving no overlaps in time windows, is obtained and transition *T1* is finally disabled).

By simulation in *CPNTools*, it is possible to explore the state space and find different solutions by way of a '*reachability tree*'. In Fig. 9, the reachability tree's final states, denoted by M_x, M_y and M_z, which constitute the set of feasible solutions for the proposed scenario, are presented. For instance, a feasible solution M_x has been obtained by applying a fine tuning of 10 min to aircraft *A1* and of 5 min to aircraft *A2*, as is observed in the state variables described by the tokens and colors in *P1* and *P2*. In each of these feasible solutions, all time window overlaps in proximate events are avoided.

5. Optimization models for analyzing and solving airspace demand–capacity imbalances

The CPN model that we developed appears to be effective in simulating the network effects, the decision making process, and the search for feasible solutions for the conceptual scenario. This DEDS approach makes it possible to formalize the representation and the analysis of events occurring within a dynamic system – in this case, the spatial and temporal interactions and their effects, as well as their logical sequence of occurrence (Ruiz et al., 2014).

Various simulation–optimization methodologies and approaches have been developed to combine the capability of simulation models to be highly descriptive of systems being simulated with the benefits of analytical optimization techniques (Zuñiga et al., 2011; Narciso et al., 2012). Because of the extreme complexity associated with solving time adjustment allocation problems and the difficulty in finding solutions to large-scale problems within a reasonable computational time, the DEDS approach is implemented using *constraint programming* (CP). CP is a technology for solving combinatorial optimization problems (Rossi et al., 2006; Milano, 2012). Mathematical programming is based upon a *model and run* paradigm, relying on a simple vocabulary and standard formats to model problems (Wolsey and Nemhauser, 1999). CP, on the other hand, features a *model and search* paradigm, requiring rich modelling languages with combinatorial objects and having "a distinctive flavor of programming" (Michel, 2012). A major generic challenge facing CP is scalability (Perron et al., 2004), with problems to which it is usually applied being NP-hard.

Assessment in modelling constraints is understandably a critical issue for CP. An excess of constraints may lead to failure to reach a solution, while a lack of constraints will increase the scenarios to be computed. The use of redundant constraints, on the other hand, will not contribute in any real way. One of the primary methods for building and quantifying confidence in the constraints is *verification and validation* (V&V) and the sensitivity analysis of computational simulations. In the simulation community, verification can be seen as the assessment of the accuracy of the solution to a computational model by comparison with known solutions, while validation may be viewed as the assessment of the accuracy of a computational simulation by comparison with experimental data. However, in the CP area, the validation of the constraint model should check the state space of the problem solution. Since CP is usually embedded in declarative programming, the user need not write an algorithm to solve the problem but need only model the problem to be solved. Therefore, once the model has been generated and validated (in the current case, the CPN model and simulation results), CP can be used even without requiring the constant intervention of an expert to steer the optimization process. This methodology has been successfully applied to model and optimize flexible manufacturing systems (Riera et al., 2002). It must be noted that a full understanding of the constraint effects on the search space together with a formal state space analysis are the key aspects in facing the scalability issue when applying the model to much larger scenarios.

Let $C = [Int.min(Te_i + d_i, Te_j + d_j) - Int.max(Ts_i + d_i, Ts_j + d_j)]$, where d_i and d_j represent the fine tuning for aircraft a_i and a_j, respectively; $Int.min(\cdot)$ is a function which outputs the smaller of two exit time stamps; and $Int.max(\cdot)$ is a function which outputs the larger of two start time stamps.

C is defined to enable fine tuning for those proximate events with an overlap in time windows. On the one hand, when $C > 0$, an overlap clearly occurs; on the other hand, there is no overlap when $C \leqslant 0$. We accordingly establish a set of constraints (one for each pair of proximate events) of the form:

$$C \leqslant S \tag{1}$$

where $S \leqslant 0$, with its magnitude $|S|$ being the required time separation or minimum clearance. In the CPN model presented in Section 4, the guard expression for the transition *T1* takes the form $C > 0$, specifically in order to detect the overlaps. In the

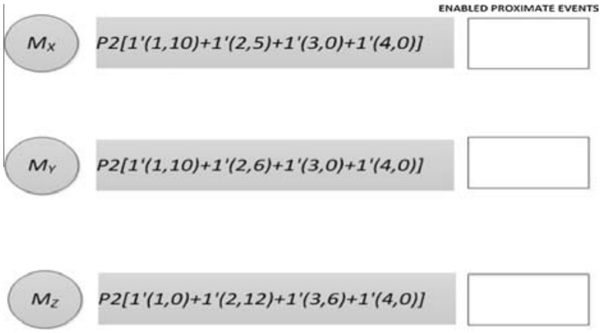

Fig. 9. Final states arrived at by exploration of reachability tree.

case of an overlap, fine tuning of d_i and d_j may then be applied in line with (1) to provide the specified minimum clearance S. The CP problem formulation is given below.

Parameters:
A $\equiv$ the set of all air craft
$Te \equiv$ the set of start time window stamps
$Ts \equiv$ the set of end time window stamps
$TD \equiv$ the set of all take off time deviations (in min)
$Tr \equiv$ the set of all aircraft without proximate events or all aircraft already on the en route phase
$P \equiv$ the set of all proximate events
$C_P \equiv$ the set of clearance or overlap value for each proximate event
$S \equiv$ the required clearance time (in s)

Variables:
d = the set of fine tuning values applied for each aircraft (in min)
minimize S

Constraints:

$$[Int.min(Te_i + 60 * (d_i + TD_i), Te_j + 60 * (d_j + TD_j)) - Int.max(Ts_i + 60 * (d_i + TD_i), TS_j + 60 * (d_j + TD_j))] \leqslant S \tag{2}$$

$$C_c \leqslant S \quad \forall c \in P \tag{3}$$

$$0 \leqslant d_a \leqslant 15 \quad \forall a \in A \tag{4}$$

$$d_a = 0 \quad \forall a \in Tr \tag{5}$$

$$0 \leqslant TD_a \leqslant 180 \quad \forall a \in A \tag{6}$$

Constraints (2) and (3) ensure that for each proximate event the minimum clearance time is obtained. By inserting TD_i and TD_j (CTOT deviations or adjustments) in (2), it is possible update each proximate event and iterate to solve under the new conditions. Constraint (4) ensures that all fine tuning adjustments are not more than 15 min. Constraint (5) ensures that fine tuning is not applied if an aircraft is already in the en route phase or is not interacting with other aircraft, while constraint (6) admits deviations less than or equal to 180 min.

Thus, to show the performance of the proposed approach and the implemented model in IBM ILOG CPLEX Optimization Studio, a case study scenario composed of a set of 4010 realistic 4D trajectories in the European airspace was evaluated. This scenario was designed by using data for the day with the highest peak traffic throughout the entire year, according to the real air traffic demand data as reported in the STREAM project (STREAM Eurocontrol WP-E project, 2015), a research undertaking sponsored by Eurocontrol SESAR WP-E. In order to stress the scenario, all the flights are allocated in the same flight level over a time frame of 2 h. All the experiments were performed using an Intel 5-Core computer in a 64-bit architecture with 4 GB RAM.

The demand across the European airspace for this scenario and its distribution, based on the analysis of the untimed en route positions of the trajectories obtained after applying a bi-dimensional (i.e. latitude and longitude positions) D-transform (Menon and Shon, 2006) are represented in Fig. 10. The spatial demand range from 0 to 45 trajectories for the same spatial region is shown. Highly demanded spots pertain to regions with demand consisting of two or more trajectories.

After analyzing the highly demanded spots information, the total number of proximate events is detected using the macro and micro detection algorithms described in Nosedal et al. (2014). However, for the bounded adjustment process, only the proximate events with $C \geqslant -15$ min are considered. Also, only the tightest event is considered per pair of aircraft. Fig. 11 presents the frequency distribution for the more than 37,000 proximate events with C within the interval $[-900, 74]$ s (where the lower limit pertains to the longest clearance of 15 min, while the upper limit is the size of the largest overlap of 74 s actually observed in the scenario).

The proximate events with overlapped time windows represent the interferences or potential conflicts to fulfill the AU's preferences (adherence to en route reference BTs) and to allow the measurement of the airspace demand–capacity balance or imbalance for the nominal scenario (that is, when all trajectories are performing according to the original 4D trajectories). By noting the proximate events on the extreme right side of the histogram (where $C > 0$) in Fig. 11, it is possible to observe an apparent demand–capacity imbalance in this scenario.

A solution to this demand–capacity imbalance may be obtained by applying time departure fine tuning, implemented by using the CP model to finding a feasible combination of reduced shifts (or bounded adjustments), while the maximum attainable clearance is used for the tightest events, without the elimination of trajectories. The 'bounded adjustment model' is specified by treating S as an objective function to be minimized, while the set of constraints maintains the demand–capacity balance (with the constraints representing the spatio-temporal interdependencies between trajectories).

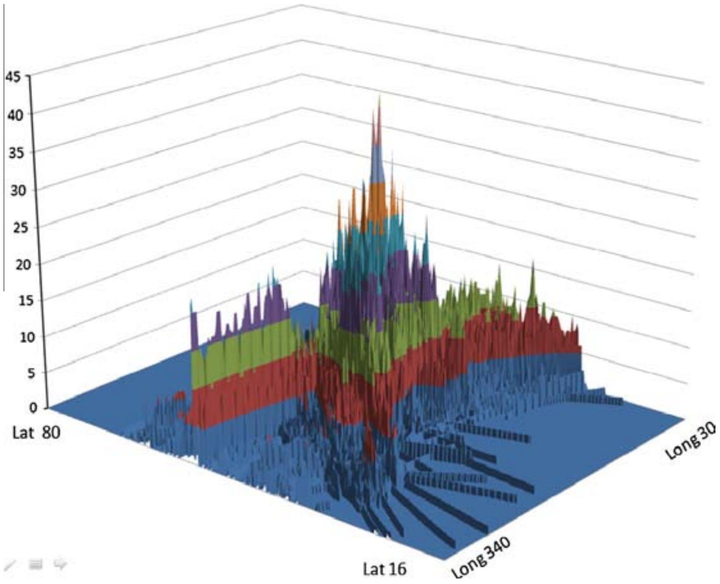

Fig. 10. Highly demanded spots distribution over Europe.

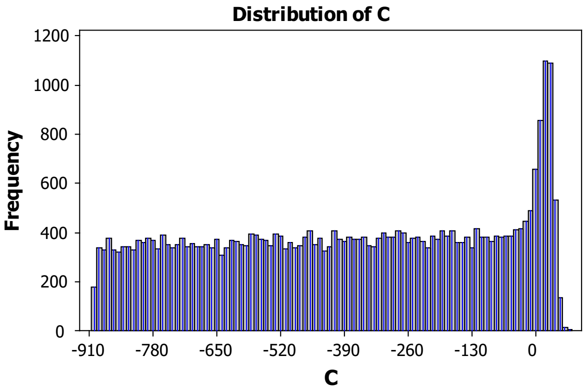

Fig. 11. Frequency distribution of clearances and overlaps in the 37,252 proximate events.

Experiments were conducted with different allowable shift values – i.e., upper limits d_{max} of the interval $[0, d_{max}]$ for CTOT time adjustment. Applying this alternative approach to the case study scenario, the computed required clearance time had a minimum magnitude of 47 s ($S = -47$) corresponding to $d_{max} = 15$ min. In Table 6, the allowable shift values tested in twelve experiments (starting from 15 min, and being reduced by 1 min at a time) and the corresponding minimum clearance times are summarized.

In Fig. 12, each of the reference values of S (ranging between 0 and −47 s) from the first twelve experiments is plotted against the associated upper limit d_{max} of shift times. The resulting simple regression line is $S = 13.70 - 4.126 \times d_{max}$. The coefficient of determination R^2 and p-value for the slope (as reported in Fig. 12) suggest a highly significant linear relationship between the upper limit for allowable CTOT time adjustments (d_{max}) and the required minimum clearance time (the magnitude of S), with 99.1% of the variation in S explained by the variation in d_{max}.

In Fig. 13, the frequency distributions of CTOT time adjustments (in min) are presented for twelve different d_{max} values. Fig. 14 presents the resulting distribution profiles of the variable C (as previously defined) for each corresponding d_{max}, pertaining to experiments 1–12, respectively (left to right and up to down).

In general, from Figs. 13 and 14, it is possible to observe that the system absorbs the overlapping *without* “tightening” effects for the global scenario (wherein a disturbingly high concentration on the extreme right side of the distribution histogram occurs). The solutions appear to provide a more robust traffic network, increasing the clearances between proximate events, after the bounded adjustments.

For instance, in the first experiment, as shown in Figs. 13 and 14, CTOT time adjustment values d_i are computed within the allowable shift interval [0, 15] min, and the demand–capacity imbalance is solved by adjusting 57% of the departures ($d_i = 0$ for 1739, or 43%, of the 4010 trajectories). The attained clearance for the tightest events is 47 s, and the interval for C in this scenario is $[-47, -1680]$ s.

Table 6
CTOT time adjustment results.

Experiment	No. of aircraft	N (proximate events)	Adjustment interval (min)	Sum of $K_a = 0$ (aircraft)	Sum of $K_a = 1$ (aircraft)	S (s)	Sum of d_a (min)	Run time (s)
1[a]	4010	37,252	[0, 15]	–	–	−47	12,609	169.8
2[a]	4010	37,252	[0, 14]	–	–	−42	11,770	49.8
3[a]	4010	37,252	[0, 13]	–	–	−40	10,902	43.2
4[a]	4010	37,252	[0, 12]	–	–	−36	9760	66
5[a]	4010	37,252	[0, 11]	–	–	−33	9048	46.8
6[a]	4010	37,252	[0, 10]	–	–	−29	8087	37.8
7[a]	4010	37,252	[0, 9]	–	–	−25	7309	37.2
8[a]	4010	37,252	[0, 8]	–	–	−20	6379	39
9[a]	4010	37,252	[0, 7]	–	–	−16	5697	34.2
10[a]	4010	37,252	[0, 6]	–	–	−12	5415	52.8
11[a]	4010	37,252	[0, 5]	–	–	−6	4110	64.6
12[a]	4010	37,252	[0, 4]	–	–	0	3281	69
13	4010	37,252	[0, 15]	2123	1887	−120	0	10.89
14	1887	16,339	[0, 15]	879	1008	−120	0	9.57
15	1008	15,116	[0, 15]	10	998	−120	0	9.14
16	998	14,195	[0, 15]	8	990	−120	0	8.22
17[a]	1008	15,116	[0, 15]	–	–	−65	7583	15.02
18[a]	998	14,195	[0, 15]	–	–	−68	7532	96.86

[a] Solutions obtained by applying the first model (i.e., only fine tuning).

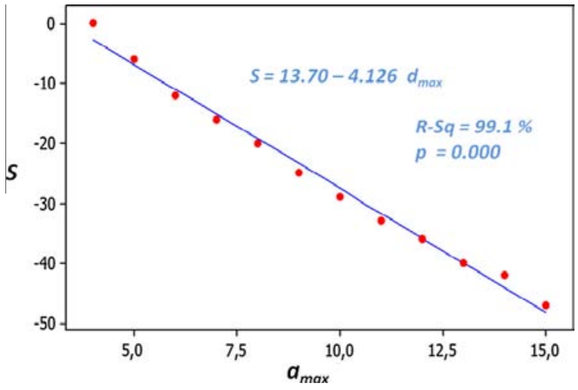

Fig. 12. Fitted line plot between S and the maximum CTOT time adjustment (d_{max}) allowed in the solution.

In the last experiment (C12), as shown in Figs. 13 and 14, the d_i values are computed within the interval [0, 4] min, and the demand–capacity imbalance is solved by adjusting just under 41% of the departures ($d_i = 0$ for 2369, or roughly 59%, of the trajectories). The resulting clearances are in the interval [0, −1050] s, with the tightest proximate events having "*0*" second of overlap between time windows.

From Figs. 11 and 14, the shifting process on the distribution of C is observable, moving toward the left side away from a concentration of proximate events on the right side. Also observable is an apparent reduction in the volume of tight proximate events on the extreme right side after the bounded adjustment; in other words, we observe, global robustness without local tightening effects for all the experiments.

By using CTOT time adjustments within [0, 15] min, the complete set of trajectories is handled with the same airspace distribution, but without time window overlaps ($S = -47$ s), while all the AUs' preferences (slots and agreed upon reference BTs) are satisfied. Thus, by means of the bounded adjustment model, a global solution with positive effects in terms of airspace demand–capacity balance is provided, but this solution does not achieve the separation minima (i.e. $S = -105$ s) to absorb longitudinal deviations due to the wind.

To estimate the amount of aircraft trajectories that prohibit the AUs' demands from being satisfied without applying any regulation, the original set of constraints (time window information) is modified by introducing new variables in the constraint expressions. For each trajectory a, $a = 1, 2, \ldots, N$, a Boolean variable K_a, is introduced to enable or disable detected proximate events. $K_a = 1$ means elimination (i.e., flight level change) or blockage of trajectory j, while $K_a = 0$ indicates that the trajectory is still in the scenario (i.e., original flight level). Additionally, an objective function is defined to determine the minimum amount of delays $\sum d_i$, for $i = 1, 2, \ldots, N$, while a minimum clearance S is specified (representing an additional constraint). By way of these modifications, the model allows the computation of the maximum number of aircraft to handle without applying any other regulation, but at the same time putting in place a set of clearances for the proximate events with a minimum time separation of S. This is done while preserving the AUs' BT preferences which are possible to fulfill.

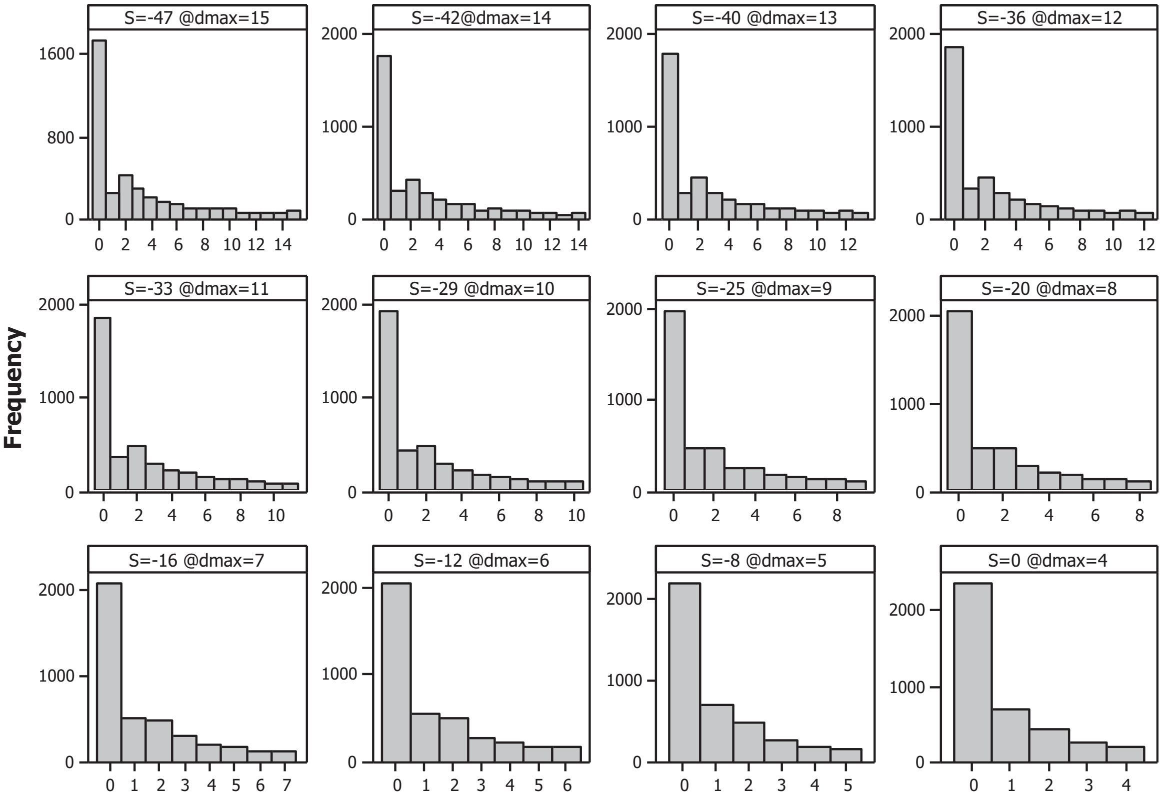

Fig. 13. Frequency distribution for the CTOT time adjustments for the 12 experiments.

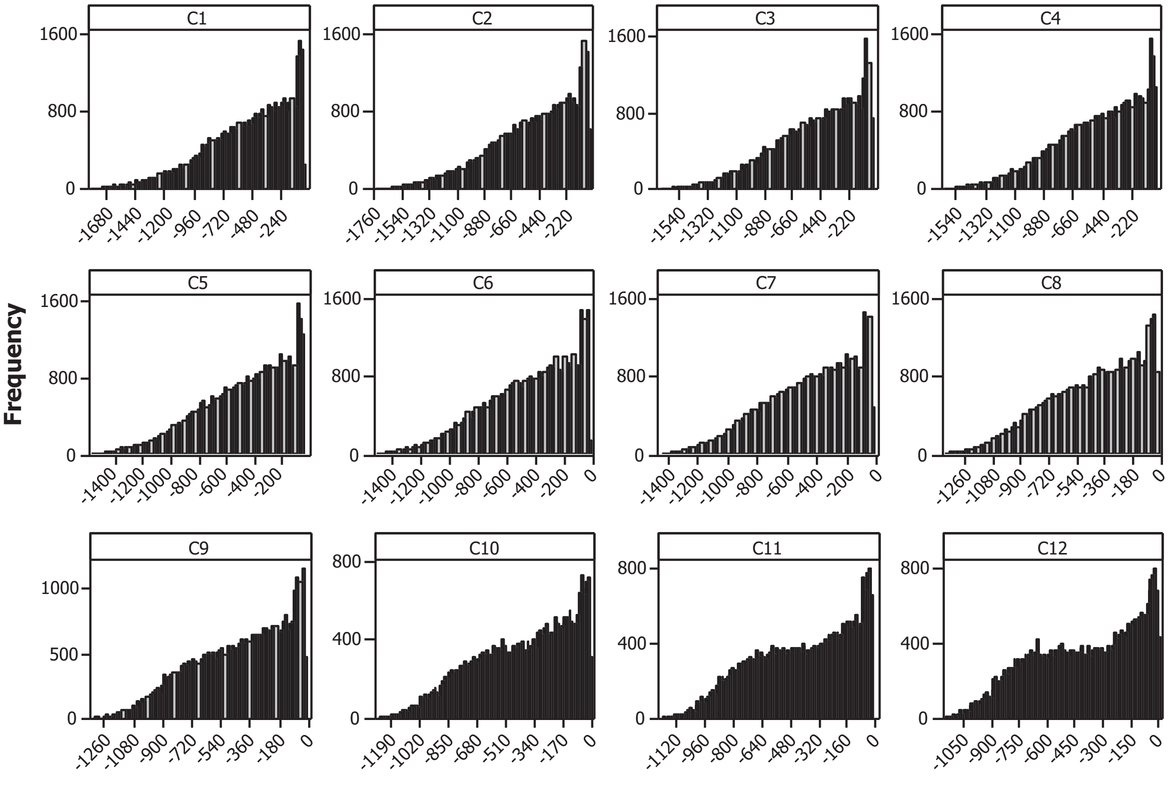

Fig. 14. Frequency distribution for the C after bounded adjustment for the 12 experiments.

Based on the above mentioned and in order to provide robust solutions ($S = -120$ s), the CP model is modified to allow these robust time separations (considering longitudinal variation because of wind variations) by adding the flight level allocation as degree of freedom complemented with the fine tuning. The modified model is presented as follows:

Parameters:
$A \equiv$ the set of all aircraft
$Te \equiv$ the set of start time window stamps
$Ts \equiv$ the set of end time window stamps
$TD \equiv$ the set of all take off time deviations (in min)
$Tr \equiv$ the set of all aircraft without proximate events or all aircraft already on the en route phase
$P \equiv$ the set of all proximate events
$C_P \equiv$ the set of clearance or overlap value for each proximate event
X = the required clearance time (in s)
$\tau \equiv 7200$ s (artificial clearance due to FL change)

Variables:
d = the set of fine tuning values applied for each aircraft (in min)

$$K_a = \begin{cases} 1 & \text{to denote that aircraft a is assigned to a different FL} \\ 0 & \text{to denote that aircraft a is kept in the FL} \end{cases}$$

$$\textit{minimize} \sum_{a=1}^{n} d_a$$

Constraints:

$$[Int.min(Te_i + 60 * (d_i + TD_i), Te_j + 60 * (d_j + TD_j)) - Int.max(Ts_i + 60 * (d_i + TD_i), Ts_j + 60 * (d_j + TD_j))] \leqslant S + \tau(K_i + K_j) \tag{7}$$

$$C_c \leqslant S \quad \forall c \in P \tag{8}$$

$$0 \leqslant d_a \leqslant 15 \quad \forall a \in A \tag{9}$$

$$d_a = 0 \quad \forall a \in Tr \tag{10}$$

$$S \leqslant X \tag{11}$$

$$0 \leqslant TD_a \leqslant 180 \quad \forall a \in A \tag{12}$$

The results after applying the modified model to solve the case study scenario are presented in Table 6, experiments 13–16. From these experiments, it may be observed that by separating around 47% of the trajectories ($\sum K_a = 1887$), a clearance of 2 min ($S = -120$ s) is obtained for the tightest proximate events for a subset of 2123 trajectories. Then for the sub-problem composed of 1887 trajectories, by separating almost 54% of the trajectories ($\sum K_a = 1008$), it is possible to attain a clearance of $S = -120$ s for a subset of 879 trajectories. These numbers of separated trajectories represent demands in excess of the available airspace capacity, considering a specified minimum required clearance between proximate events.

From results obtained in experiments 15 and 16, we are able to observe how tight and coupled these trajectories (a subset from the entire scenario) are in terms of network interdependencies. The last assumption is reinforced by the observed response of S to the number of trajectories eliminated (e.g., comparison of N and S for experiments 17 and 18) suggests that the remaining proximate event overlaps are almost uniformly distributed among the trajectories. This implies that no cluster synergies may be used to reduce the sub-problem's complexity by way of breaking it down into independent sub-problems, as in Naldi et al. (2013).

6. Conclusions and further research

In this paper, the network dynamics of an air traffic scenario have been characterized using a discrete event modelling approach and formalized with CPN to be implemented as a simulation model. The discrete event simulation reflects the dynamic and adaptive behavior of the ATM system and, in turn, provides intelligence for exploring the evolution of the global state of the system in response to induced changes (this capacity being intrinsic to Petri net models (Murata, 1989). The system is further replicated in a CP model to perform a bounded adjustment process.

The CP models developed here allow for the analysis and solution of large scenarios using different rules (e.g., minimum number of affected trajectories or maximal value of shift). After the experimental results, some measures for the air traffic scenario may be obtained. First, by using departure bounded adjustments in the interval [0, 15] min, the largest attainable minimum clearance is 47 s, while still preserving the slots allocated for departures. For this solution, less than 60% of the flight departure times require adjustment. Alternatively, the minimum allowable clearance ($S = 0$) is attained by applying departure bounded adjustments in the interval [0,4] min, in this case with adjustments for 41% of the flight departure times.

Based on the analysis of all proximate events and their associated time window stamps, the computed distribution histogram for the values of C (overlaps and clearances), is proposed as an estimator or reference measure of the airspace demand–capacity imbalances. Based on this profile distribution for the clearances and overlaps, it is possible to obtain both qualitative and quantitative descriptions of the potential capability to absorb the overlaps by application of departure time bounded adjustments. The proposed bounded adjustment model provides an extra degree of freedom to tackle congested scenarios in which some network dynamics may be induced when spatio-temporal analysis is not applied.

Despite all of the technological and management efforts developed in the SESAR and NextGen framework, 4D reference BTs are subject to different types of perturbations and uncertainties that can provoke some differences between the planned intended trajectories and the trajectories actually flown. To deliver more robust solutions, the model is extended to apply flight level allocation for those cases where the time separation is not achieved by means of the fine tuning or to provide more robust solutions. By means of applying the flight allocation level as an extra degree of freedom is possible to solve part of the scenario demand imbalance and decouple from the entire scenario smaller and independent sub-problems. Further research should be conducted to consider and include tactical mechanisms like bounded speed adjustments.

In terms of equity and fairness, by using this departure bounded adjustment in conjunction with robust slot assignment procedures (Pellegrini et al., 2012; Narciso and Piera, 2015), AUs do not incur extra costs, because the solutions proposed preserve the reference BTs, which specify the preferred slots at airport as well as the 4D trajectories. From a network perspective, the bounded adjustment approach is an effective tool to relax tight interdependencies between trajectories, preserving the original trajectories' geometric profiles (AUs' preferences).

However, it is well accepted that a major limitation of current ATM systems is the lack of effectiveness due to the limited integration between the layered planning decision support tools. For that reason truly effective application of this approach, or any other traffic management initiative, requires the integration with the surface decision support systems. Calculations reported in Brinton and Lent (2012) indicate that approximately 15 min would be an appropriate queuing buffer for a departure queue management system, which is consistent with the fine tuning model developed. By means of this integration, the proposed approach could contribute to a more efficient ATM by improving capacity management and probably shortening ATC workload supported by synergies between airside and landside (ground surface) management decisions.

Acronyms	Meaning
4D or 4DT	Trajectory described in terms of 3 spatial dimensions and time stamps 4-dimensional trajectories
ACAS	airborne collision avoidance system
AFP	airspace flow program
ATC	air traffic control
ATFM	air traffic flow management
ATM	air traffic management
AU/AUs	airspace user/users
BT	business trajectory
CDQM	collaborative departure queue management
CNS	communication, navigation and surveillance
CP	constraint programming
CPN	coloured Petri nets
CTOT	calculated take-off time
DEDS	discrete event dynamic systems
FL	flight level
FMS	Flight Management System
GDP	ground delay program
NAS	National Airspace System
NextGen	next generation air transportation system
NM	nautical miles
NP-Hard	nondeterministic polynomial time
RBT	Reference Business Trajectory
SESAR	Single European Sky ATM Research
STREAM	Strategic Trajectory de-confliction to Enable seamless Aircraft conflict Management
TBO	trajectory based operations
TMA	terminal manoeuvring area
V&V	verification and validation
WP-E	Work Package E

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Chapter 5

Research summary, conclusions and further research

5.1 Research summary

Based on the analysis of 4D trajectories an efficient algorithm for the macro and micro detection of collective regions over Europe for a realistic and overstressed scenario was presented. The proposed algorithm generates a microanalysis of interdependencies between trajectories for large scenarios, thus providing a global scope and information to improve the robustness of en route trajectories with respect to the surrounding traffic.

The CP models developed in this research allow for the analysis and solution of large scenarios using different rules (e.g., minimum number of affected trajectories or maximal value of shift).

After the experimental results, some relevant indicators for the air traffic scenario were obtained. Based on the analysis of all proximate events and their associated time window stamps, the computed distribution histogram for the values of overlaps and clearances, is proposed as an estimator or reference measure of the airspace demand and capacity imbalances. Based on this profile distribution for the clearances and overlaps, it is possible to obtain both qualitative and quantitative descriptions of the potential capability to absorb the overlaps by application of departure time bounded adjustments.

The proposed bounded adjustment model provides an extra degree of freedom to tackle congested scenarios in which negative network dynamics may be induced when spatio-temporal analysis is not considered.

In terms of equity and fairness, by using this departure bounded adjustment in conjunction with robust slot assignment procedures [51][48], it is expected that AUs do not incur extra costs, because the solutions proposed preserve the reference BTs, which specify the preferred slots at airport as well as the 4D trajectories. From a network perspective, the bounded adjustment approach is an effective tool to relax tight interdependencies between trajectories, preserving the original trajectories geometric profiles (AUs' preferences).

Finally, in this research the initial CP model is extended to apply flight level allocation for those cases where the time separation is not achieved by means of the fine tuning, or to generate more robust solution, where the same approach was applied to provide solutions increasing the minimal clearance time value between proximate events. By means of applying the flight allocation level as an extra degree of freedom it is possible to solve part of the scenario demand imbalance and decouple from the entire scenario smaller and independent sub-problems.

5.2 Conclusions

Accordingly with the research motivation and objectives initially stated, the main contributions of this thesis are the development of the models and tools that allows the detection of all the en route potential spatial interdependencies between trajectories and the analysis of these interdependencies considering the global traffic network under ideal conditions (i.e. weather perturbations to the RBT are not considered).

For the analysis of these interdependencies was developed and introduced a causal model that allows the simulation of cooperative combination of the time stamp component of the RBT agreed by the AU's. Then by extending this approach, the analysis and solution of congested scenarios is obtained by means of CP models, where the obtained solutions allow the maximization of the clearance time between potential proximate events.

For the proposed solutions in the congested scenarios new indicators were introduced (i.e. hotspots quantifications, airspace hotspots distributions, overlap or clearance time for potential proximate events, amount of interdependencies per trajectory).

Based on the models developed and results obtained this research provides a framework that could enable:
a. Integration by linking the land side with the air side considering the global interdependencies.
b. Horizontal connectivity by linking the AUs business models (i.e. RBT) with the ATFCM under a sustainable competitive services with the creation of an easily extendable and adaptable robust cooperative DST dealing with feasible time stamp agreements considering the TBO interdependencies under a network scope.

Besides this research promotes an incremental transformative approach to consolidate loose knowledge exploring the feasibility of a new process that could be deployed as a TBO service, considering the importance of trajectory adherence and the different disturbances and uncertainties that affect RBT's.

5.3 Further research

By linking the land side with the air side to empower TBO as a flexible synchronization mechanism several challenges arise and new research opportunities emerge, such as:

- Implementation of a state space analysis tool in which any significant time stamp change of a 4DT can be traced upstream and downstream to compute its impact to the rest of RBT's, providing the feasible variables domain values in which the agreed trajectories will not require an ATC intervention.
- Development of DST using a trajectory predictor to evaluate the speed changes combinations to improve clearance robustness at identified TBO interdependencies as a fine tuning algorithm to tackle uncertainty.
- Analysis and computation of the environmental impact of the TBO synchronization approach (i.e. emission and fuel consumption)
- Analysis and identification of clustering trajectories (i.e. critical trajectories that tighten the network due to their interdependencies).
- Integration with the surface decision support systems for validation and assessment experiments (e.g. shadow mode trials).

Appendices

Appendix A

Paper III

In this paper, based on field data from two years of operations at a European Airport, empirical evidence of the influence of arrival variability on departure delay flight for short scheduled ground times (i.e., up to 60 minutes) is revisited, including three types of arrival situations, on time, early and late. Based on the results obtained, in this paper we provide evidence and quantification of the impact of early and late arrivals on airport operations, with direct effect on gate assignment scheduling and the turnaround process. Early arrivals are shown to generate higher airport operational disruptions compared with late arrivals that allow better reaction capacity to compensate for the disturbances.

TITLE: “*Revisiting the impact of flights’ arrival variability on departure punctuality: a causal analysis of earliness landing*” (1)

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Abstract

In this paper, based on field data from two years of operations at a European Airport, empirical evidence of the influence of arrival variability on departure delay flight for short scheduled ground times (i.e., up to 60 minutes) is revisited, including three types of arrival situations, "on time", "early" and "late". For early and late arrivals, variability is measured together with the extension of the Scheduled Ground Time (i.e., Actual Ground Time), and the number of departure delay minutes recorded for the next departure (i.e., average departure delay) are considered. The paper includes analysis, for a specific ground handler, of the compensation capacity of the turnaround process when "late" arrival occurs. Based on the results obtained, in this paper we provide evidence and quantification of the impact of early and late arrivals on airport operations, with direct effect on gate assignment scheduling and the turnaround process. Early arrivals are shown to generate higher airport operational disruptions compared with late arrivals that allow better reaction capacity to compensate for the disturbances.

Keywords: air transportation, punctuality, variability, earliness impact, operational disruptions.

I. Introduction

Airport operational performance depends upon a number of factors as well as hidden interdependencies between them, all of which affect runway capacity to some degree. In addition to physical constraints, such as airport layout and infrastructure resources, several tactical factors have an important impact at that operational level that can increase the airline dwell time at the airport and introduce disturbances in aircraft departure sequence and the sustainability of throughput.

Several indicators [1] and procedures [14] have been recently developed to mitigate the effects of lack of integration of strategic, tactical and operational decision making tasks [9][25][28][29]. A well accepted indicator for the operational performance of airlines and airports is "punctuality". Air transport punctuality is usually calculated as the rate of flights delayed by more than 15 minutes compared to airline scheduled departure and arrival times. Thus, two key values are usually measured [13] to evaluate punctuality:

> **Departure punctuality**: the difference between the actual off block time and the scheduled off block time.
>
> **Arrival punctuality**: the difference between the actual on block time and the scheduled on block time.

In an air traffic context characterized by a high amount of tightly scheduled aircraft operating in a highly dynamic environment, it is not uncommon for flights to experience delays [21]. These delays lead to considerable losses for both the airlines in particular and society as a whole, which was estimated to be a staggering $41 billion annually in [30].

Flight delays' economic impact spreads upstream and downstream on the value chain of the airline market [6]:

- On the demand side, passengers may factor in predicted delay times when choosing among carriers. Increased delays add to the cost of travel and therefore, act to reduce passenger demand.

- On the supply side, increased delays force carriers to expand anticipated flight (block) times, decrease aircraft utilization, and increase flight crew costs. These higher costs lead to increased airfares.

Whereas in ground transportation the concept of reliability has been extensively studied, literature in air transportation is scarce [19]. Punctuality is a valid indicator from a passenger viewpoint. However, punctuality alone is not an appropriate indicator to measure and to improve operational air transport reliability. It is better to focus on the variability of operations and its consequences. [13]

The operational reliability of an airline network is the outcome of the interaction between fixed schedules and the unpredictable stochastic dynamics [2] that affects flight at the operational level. Airline schedules are designed and usually optimised to achieve the maximum possible profits. A trade-off situation exists, wherein an airline tries to utilise/optimise its resources (fleet and crew) while considering the flexibility/reliability of scheduled operations. [36]

Most scientific literature focuses on the impact of "late" arrivals on the airport operation (gate scheduling [12] and the scheduled ground time, including the turnaround process) and its multiplicative factor, contributing to the generation of extra departure delays (i.e., analysis of delay propagation [3]). In a traditional production planning approach [8], the main focus is tackling tardiness because jobs that are not completed before their due date are the main cause of revenue reduction, followed by a loss of reputation due to bad service quality factors and worse the loss of a customer segment. [10]

More recently, the importance of earliness penalties have emerged in several industrial planning policies such as those scheduling on a just-in-time (JIT) policy, enhancing the idea that early as well as late delivery must be discouraged [32] due to the economic costs that can be incurred in peak periods. The awareness of earliness has increased because jobs completed early in an industrial context results in costly inventories, warehouse costs due to space utilization and material handling operations and potential profit losses due to environmental degradation of product quality [35].

In air transportation, early arrivals can put additional pressure on airport, airline, ATC and handler resources: the local ATC has to cope with an unexpected demand profile both on the airside during the descending operations and on the landside with a proper scheduling of runways, taxiways and gates that are usually occupied longer than planned, and additional resources that are needed to cope with the workload peak pressure (e.g., baggage handling).

Furthermore, early arrivals may have no gate available and may disrupt the ramp operations by a re-scheduling of handling operations to remote positions [18]. More importantly, a combination of late arrivals in the preceding period and of early arrivals in the following period can lead to excess demand during a particular period [13] for all of the landside and airside resources. This negative synergy is illustrated in Figure 1: the resource capacity (on the left side) is exceeded by the cumulative effects of late arrivals during the previous period plus early arrivals over the expected workload in the current period (right side).

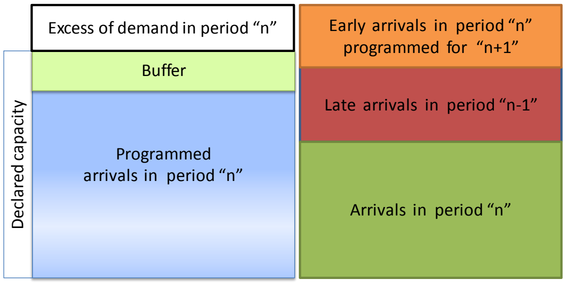

Figure 1. Imbalance between demand and capacity for resource "X" at period "n"

In this work, based on field data from two years of operations at a European Airport, a case study is presented to provide empirical evidence of the influence of arrival variability on departure delays for flights with short scheduled ground times. The variability analysis includes three types of arrival situations as follows: "on time", "early" and "late". By analysing the delays observed between the three types of arrivals and modelling their impact in departure punctuality, some indicators are identified, exposing results that challenge generalized assumptions regarding the impact of earliness when landing.

The remaining sections of this paper are organized as follows: Section II includes the literature review. Next, Section III focuses on the case study data description and the variability analysis results. Finally, Section IV presents the discussion of the results and our conclusions.

II. Literature review

The build-up of aircraft delay for landing aircraft at airports was first studied theoretically by Bowen and Pearcey [5]. However, delays not only occur at runways and their respective holding areas but also occur at any bottleneck (point of congestion) in an airport's process chain [7] and can expand easily through the different airport sub-processes [38] due to the tight interdependencies between actors (i.e., airline, handling companies, airport) and shared resources (i.e., runway, apron, passenger terminal facilities, and freight facilities among others).

Most delay analysis focuses on arrival delays rather than the departure delays because arrival delays are more closely related to ultimate passenger satisfaction. On the other hand, when trying to understand the source of arrival delays and airspace congestion in general, study of departure delays becomes quite relevant [20][33]. In terms of frequency of occurrence, as shown in [30], almost 60 percent of flights experienced delays that occurred at the gate.

In [24] and [37], the penalties for stochastic flight delays (such as early or late arrivals and late departures) that often occur at most airports and impact the gate availability to complete the programmed turnaround operations are analysed. Daily disturbances reduce the effectiveness of the already planned gate assignments, resulting in oversaturation at some gates coexisting with idle gates elsewhere. Parking positions cannot be easily reassigned at the last moment due to the complications of moving passengers through the terminal and increasing the workload for remote operations.

Arrival delay is recognized as one major factor influencing features in the turnaround time process duration and variance [4].

Incoming delay has an important influence on the individual sub-process duration and process interaction times (buffers) [27]. The results reported in [39] suggest that delays and buffers represent important cost drivers in airlines' cost models. In [11], the costs of earliness and building extra buffers into scheduled block times are analysed, and their results show the hidden flight lateness costs are less than the early arrival costs for a large percentage of flights.

In aggregated statistics (Figure 2), the relevance and effect of "short" variations (i.e., arrivals and departures with delays in [-5, 5] minutes are considered on time) have been neglected. The impact of the "early" arrivals is not often mentioned, so it is not measured and it is not analysed.

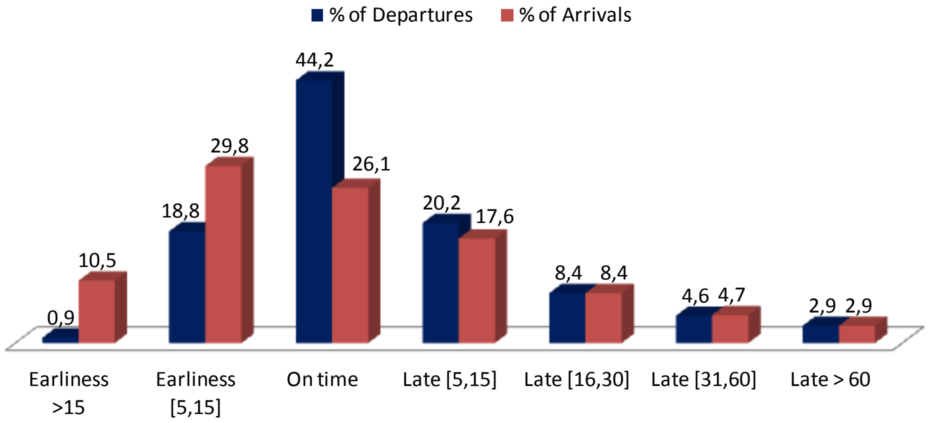

Figure 2. Aggregated statistics of departure and arrival punctuality in Europe for 2013 (adapted from [15])

Long delays and disruptions [16] can be tackled by reassignment algorithms upon the pre-established assignment in real-time operations. However, short delays cannot be tackled by reassignments due to operational constraints, among which are the penalties derived from passenger movements to another gate [24]. This holds true particularly for hub airports because the high gate utilization makes early arrivals highly disruptive. [19]

The economic impact of flight delays due to large-scale disrupting events, e.g., airport closure due to storms, is estimated to account for 40% of total annual delay costs in the National Air Space in the US, whilst the remaining 60% of costs are due to small-scale delays. [31]

For airline scheduling, airport flow management and also benchmarking purposes, punctuality is expressed in percentage of flights delayed less than 15 minutes [7]. The results reported in [11] indicate that the on-time arrival probability depends significantly on the definition used. If a flight is determined to be late when the arrival time is later than its scheduled arrival time (including the portion of departure delay attributed to an aircraft arriving late from its earlier flight), the overall on-time arrival percentage for the airline industry drops to 56.5%. This value is significantly lower than the 82% on-time arrival percentage for the year 2007 based on the U.S. Department of Transportation's definition (the U.S. Bureau of Transportation Statistics reports a flight to be late only if it arrives 15 minutes or more after its scheduled arrival time).

Similarly for Europe, by applying the above definition for late arrivals, the percentage of delayed flights in 2013 constitutes 54.7% of the flights, as represented in Figure 3, the Rome Fiumicino (identified by the ICAO code LIRF), or at 51.4% for Zurich airport (ICAO code LSZH).

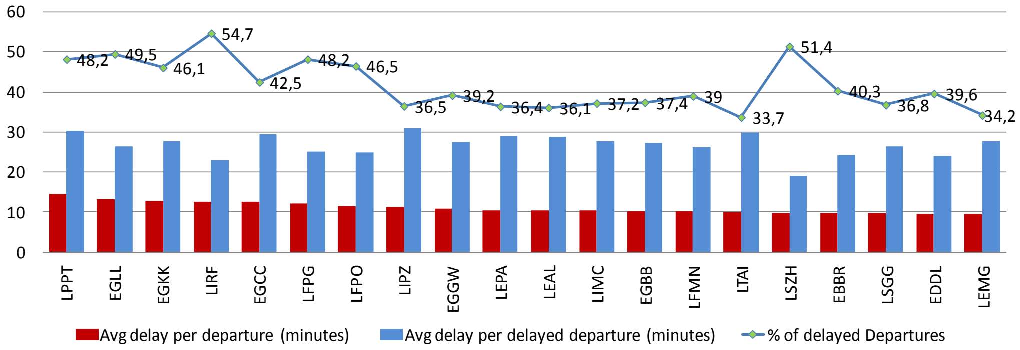

Figure 3. Top 20 affected departure airports 2013 in Europe (adapted from [15])

In [22] are presented records for all USA domestic flights on major airlines from 1995 to 2010, from two different perspectives, one focused on the departures and the other on the arrivals. From this study, the empirical cumulative distribution function for arrival delays in 2010 was obtained, showing that earliness arrival disturbances are more frequent than lateness disturbances. From this empirical cumulative distribution function, it is possible to estimate for a specific value or interval of delay the corresponding probability of occurrence. For example, for the interval [-20, 20] minutes, this probability of occurrence rises to 70%, and for the interval [-5, 5] is approximately 20%.

Similar results can be observed by the empirical cumulative distribution of arrival delays obtained for two specific airports, Haneda and Heathrow, as reported in [7].

III. Case study, data processing and results

The present work relies on the exploratory data analysis (EDA) [23] of real data gathered from 2 consecutive years of operation with departure delays registered at Brussels Airport for 3626 flights considering only A320 aircraft with SGT (Scheduled Ground Time) of up to 60 minutes. Table 1 presents a summary of the data.

EDA introduces a variety of techniques and advocates exploring data for patterns and relationships without requiring prior hypotheses. Exploratory analyses can incorporate methods of statistical inference, but use them more as indicators of the strength of a relationship or the fit of a model than as confirmation of a hypothesis when data have been transformed to agree better with basic assumptions [34].

Table 1. Field data obtained for 2 years for A320 departure delayed flights in the same airport.

Year	Early arrivals	Percentage	Late Arrivals	Percentage	On time Arrivals*	Percentage	Flights
2012	758	44.8 %	876	51.8 %	58	3.4 %	1692
2013	728	37.6 %	1137	58.8 %	69	3.6 %	1934
Total	1486	41%	2013	55.5%	127	3.5%	3626

* Sharply on-time with respect to their STA.

Figure 4 summarises the main data processing tasks for the analysis of the field data obtained.

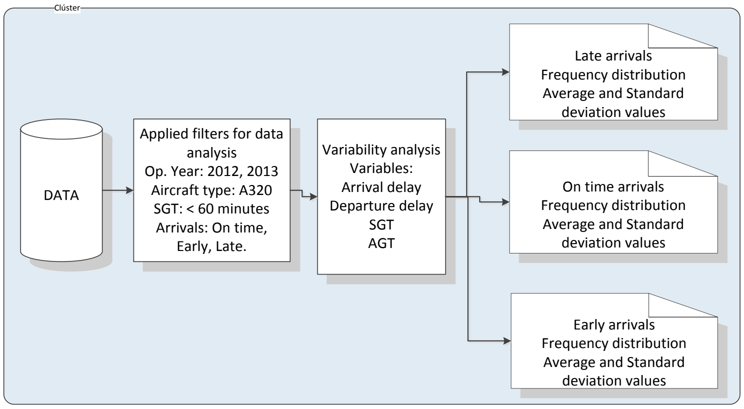

Figure 4. Data processing for EDA

In accordance with the previously described process, in Table 2 (overall arrivals), Table 3 (early arrivals), Table 4 (late arrivals) and Table 5 (on time arrivals), each table contains the calculated average and standard deviation values. In each case, the year and the variable under analysis are indicated.

Table 2. Variability analysis for the overall values

Year	Average SGT (min)	Std Dev	Average AGT* (min)	Std Dev	Average Arrival Delay (min)	Std Dev	Average Departure Delay (min)	Std Dev
2012	46.458	9.866	62.459	27.705	5.262	31.345	21.172	31.366
2013	45.277	9.231	58.552	22.944	8.332	31.43	21.608	35.973

*AGT (Actual ground time) = Off blocks time stamp – On blocks time stamp.

From Table 2, overall perspective, the variability of the SGT and AGT has been reduced from 2012 to 2013 and the departure delay has increased less than 0.5 minutes in 2013, but the average arrival delay is 3 minutes longer, an increase of almost 58 % more than the observed value in 2012.

Table 3. Variability analysis for early arrivals

Year	Average AGT (min)	Std Dev	Average Arrival Delay (min)	Std Dev	Average Departure Delay (min)	Std Dev
2012	73.253	31.906	-11.478	21.144	12.871	18.967
2013	66.982	24.685	-8.714	7.124	11.413	20.723

As shown in Table 3, the separated analysis of the early arrivals reveals that the average arrival delay decreased in 2013 (i.e., less anticipation), and more striking is the reduction in the standard deviation in 2013, which is one third of the observed for 2012.

Table 4. Variability analysis for late arrivals

Year	Average AGT (min)	Std Dev	Average Arrival Delay (min)	Std Dev	Average Departure Delay (min)	Std Dev
2012	53.599	20.215	20.095	32.36	29.162	38.12
2013	53.42	20.491	19.752	36.435	28.743	42.373

As shown in Table 4, the behaviour seems to have very small variations from 2012 to 2013, with the exception of the variability of the departure delays because their standard deviation is 4 minutes greater in 2013.

Table 5. Variability analysis for on time arrivals

Year	Average AGT (min)	Std Dev	Average Departure Delay (min)	StdDev
2012	55.19	12.984	8.9828	7.364
2013	54.188	14.655	11.58	11.538

Noteworthy in Table 5 is the variation in departure delay for the on time arrivals, which increases an average of 2.6 minutes and presents more variability in 2013, and its standard deviation is 4 minutes higher.

From the data summarized in Tables 3, 4 and 5, the impact of arrival variability is analysed (i.e., early or late operations) in terms of average delay minutes for departures, and then we compare the differences, with the results are presented in Table 6.

Table 6. Average delay minutes for departures per type of arrival

Value	2012 Late Arrivals	2012 Early Arrivals	2013 Late Arrivals	2013 Early Arrivals

Average departure delay (min)	29.162	12.871	28.743	11.413
Average arrival delay (min)	20.095	-11.478	19.752	-8.7143
Adjusted departure delay* (min)	9.067	NA	8.991	NA

*Adjusted departure delay= Avg. departure delay – Avg. arrival delay, only apply for late arrivals.

Based on the values presented in Table 6, the average delay for early arrivals can be computed as 26.9 % greater than the average adjusted departure delay observed for late arrivals.

From the perspective of the impact measured in terms of the AGT and extra ground time, in Table 7, the values for AGT are summarized.

Table 7. Average values for AGT per type of arrival

Value	**2012 Late Arrivals**	**2012 Early Arrivals**	**2012 On time Arrivals**	**2013 Late Arrivals**	**2013 Early Arrivals**	**2013 On time Arrivals**
Average AGT (min)	53.599	73.253	55.19	53.42	66.982	54.188
Accumulated Extra ground time (min)	7943	18456	521	10223	14653	799
Percentage of Extra AGT	29.50%	68.56%	1.94%	39.81%	57.07%	3.12%

Considering the 2012 values in Table 7, it is estimated that the average AGT for early arrivals is 36.6% larger that the observed AGT for late flights, whereas for 2013, this value is 25.4%.

In contrast to the percentage distribution by arrival type of late, early, and on time, as presented in Table 1, where the greatest number of the delayed departures correspond to late arrivals, the distribution is quite different (Table 7) in terms of extra AGT. The greatest amount of extra AGT corresponds to early arrivals.

To have a better understanding of the impact of early and late arrivals and to provide a more accurate measure of its magnitude, an analysis by time intervals is presented, as seen Table 8 and Figure 5 and Figure 6. We propose a new metric, **the multiplier factor (MF), to recognize the effects of arrival delays into departure delays, and it is computed by Eq. 1 and Eq.2 for late and early arrivals, respectively:**

(Eq.1)

$$MF = abs\left[\frac{Avg.Adjusted\ Departure\ Delay}{Avg.Arrival\ Delay}\right]$$

Where:

Avg. Adjusted Departure Delay is equivalent to the Avg. Extra GT.

Avg. Arrival Delay corresponds the average time in advance with respect to the SBT.

For the early arrivals the MF is computed as:

(Eq.2) $$MF = abs\left[\frac{Avg.\ Departure\ Delay}{Avg.Arrival\ Delay}\right]$$

Table 8. Impact analysis for early and late arrivals in 2012 and 2013

Arrival interval	MF for Early arrivals 2012	MF for Early arrivals 2013	MF for Late arrivals 2012	MF for Late arrivals 2013
[8:00,8:59]	0,8589	1,2424	0,4039	0,2218
[9:00,9:59]	1,0581	2,1198	0,8300	0,4021
[10:00,10:59]	1,4221	1,5827	0,4844	0,4180
[11:00,11:59]	1,1596	1,3376	0,7397	0,6862
[12:00,12:59]	0,8354	0,9340	0,3584	0,5561
[13:00,13:59]	0,6769	1,2176	0,4516	0,6218
[14:00,14:59]	1,4138	1,4100	0,4647	0,4280
[15:00,15:59]	1,0604	0,9308	0,5391	0,4537
[16:00,16:59]	0,7186	1,5329	0,5197	0,4420
[17:00,17:59]	0,8178	0,8901	0,5764	1,1992
[18:00,18:59]	0,9587	1,1988	0,3823	0,3211
[19:00,19:59]	1,5462	1,1834	0,3963	0,4476
[20:00,20:59]	1,4567	1,2217	0,2818	0,4189

The column “Arrival interval” is used to group the recorded data considering their STA.

In figure 5 and figure 6 the arrival delay values from early arrivals are multiplied by -1 to have the positive value for the graphical representation and comparison of MF with the late arrivals.

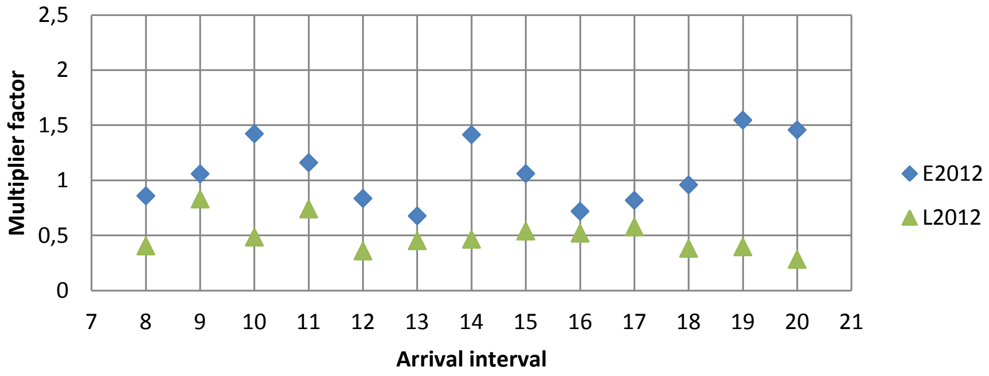

Figure 5. Multiplier factor for early and late arrival flights in 2012

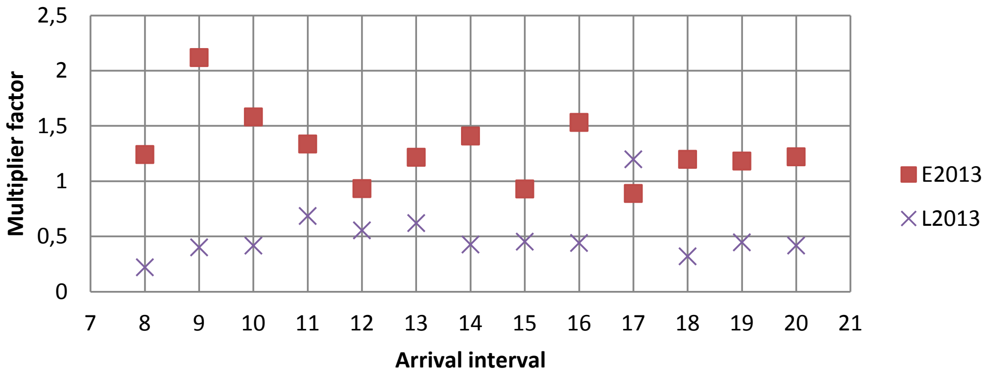

Figure 6. Multiplier factor observed for early and late arrival flights in 2013

The observed curves (Figures 5 to 6) confirm that the impact of late arrivals is lower in terms of inducing extra ground time and departure delay in comparison with the early arrivals, this pattern is observed in both 2012 and 2013. Beside these comparisons reveal different performance throughout the day.

IV. Discussion and conclusions

By means of the variability analysis for early and late arrivals, the impact in terms of extra time for the next departure for flights has been measured. Based on the above comparisons, it has been defined and measured the "multiplier factor", for early and late arrivals, as an indicator of disturbances in the departure performance. By means of the EDA, some light is shed on some incorrect assumptions that early flight arrivals do not affect the apron operations as much as late flight arrivals.

As it can be observed, depending on the arrival interval, for late arrivals MF can take values lower than 1, the meaning of this is a compensation capacity to absorb part of the disruption (i.e., arrival delay time) and reduce their impact (i.e. departure delay time). Based on the analysed data from 2013 (i.e., 1934 flights), from almost 15% of the late arrivals with departure delay, a total amount of 784 minutes of delay were reclaimed during the turnaround. A direct financial saving of 23520 dollars can be estimated considering a cost of approximately 30 dollars per ground minute [26], and additional savings could be obtained if new robust turnaround procedures are designed to better react in front of earliness arrivals.

As a result of the empirical evidence that early arrivals are more disruptive than late arrivals, a new challenge is open to adapt present operational airport decision support tools to avoid the impact of early arrivals by designing a buffer mechanism that can be activated in a flexible, efficient and reactive context. In fact handling operators are used to monitor the ETA to react in front of delayed arrivals, usually by shifting or re-scheduling the programmed operations, however, there is a lack of indicators to predict if a flight will arrive earlier than the ETA. Thus, new indicators should be elaborated together with new robust procedures to tackle earliness problems, avoiding an increment of the operational cost (i.e., adding more resources to tackle the same workload). In [25], an algorithm is presented to sequence the departure aircrafts (Departure Manager) considering their impact on the ATC workload, and the same causal approach could be used to design an algorithm to sequence the arrival aircraft (Arrival Manager) in the Terminal Manoeuvring Area (TMA) to mitigate the impact of earliness (i.e. departure disturbances).

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Appendix B

Paper IV

In this paper, it is presented a causal analysis of the airport turnaround processes, which is a key factor to enhance the Air Traffic Management reliability. Cause effect relationship analysis demands for a knowledge representation technique that considers the stochastic, dynamic and synchronous nature of the turnaround process, and allows representing both the structure and the different ways in which the subprocesses can be influenced. In this work an exhaustive timed evaluation of the different perturbations that can affect the turnaround time due to precedence task interdependencies is presented. This examination is used to illustrate the complexity of the turnaround process at operational level (e.g., dynamic critical paths) and to provide a comprehensive turnaround behavior analysis by taking advantage of causal methods and simulation models as a useful tool to improve turnaround reliability by a better understanding of the impact of delays on the full turnaround process.

Causal analysis of aircraft turnaround time for process reliability evaluation and disruptions identification

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Causal analysis of aircraft turnaround time for process reliability evaluation and disruptions identification

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Causal analysis of aircraft turnaround time for process reliability evaluation and disruptions identification

In this paper, it is presented a causal analysis of the airport turnaround processes, which is a key factor to enhance the Air Traffic Management reliability. Cause-effect relationship analysis demands for a knowledge representation technique that considers the stochastic, dynamic and synchronous nature of the turnaround process, and allows representing both the structure and the different ways in which the sub-processes can be influenced. In this work an exhaustive timed evaluation of the different perturbations that can affect the turnaround time due to precedence task interdependencies is presented. This examination is used to illustrate the complexity of the turnaround process at operational level (e.g., dynamic critical paths) and to provide a comprehensive turnaround behaviour analysis by taking advantage of causal methods and simulation models as a useful tool to improve turnaround reliability by a better understanding of the impact of delays on the full turnaround process.

Keywords: turnaround; reliability; causal analysis; airport.

1. Introduction

Now a day, aviation provides a worldwide transportation network, to satisfy present industrial demand, supporting the movement of passengers and cargo, playing a vital role in facilitating economic growth (Baker 2015).

It is well accepted by the industrial community, that supply chain performance is highly dependent on the rapid and reliable movement of goods, which is well supported by the air transportation system by providing fast and reliable delivery of high-value low-weight products. Airports and en route airspace together with the aircraft are the key components that define the capacity of the overall air transport system. Airports consist of several subsystems (Piera 2009), such as runways (where aircraft land or take-off), taxiways (that aircraft use for reaching and leaving runways), apron stands (where aircraft stop), and terminals (buildings where passengers transfer between ground transportation and airport facilities), each with its own capacity limitations. En route airspace has also a limited capacity, and consist of several sectors each one under the control of an Air Traffic Controller (ATC), which must preserve a safety distance between the aircraft flying in the sector.

The demand of both land side and air side capacity resources is characterized by the flight plan issued by the different Airspace Users (AU's), which specify the departure and arrival locations, flight duration, alternative airports in case of bad weather, and information about the aircraft, among others. Unfortunately, despite the flyable airspace could allocate all the aircrafts, the demand of trajectories are not well distributed through the full airspace, instead, airlines propose flight plans based on several factors (winds, weather conditions, fuel usage, passenger preferences, etc) which results in a spatial concentration of flight in certain sectors during some time windows while some other sectors are practically empty.

At strategic level, in Europe, the Central Flow Management Unit of EUROCONTROL (CFMU) verifies in advance all the flight plans considering the airspace structure, and in case that the amount of flight in a certain sector exceeds the declared capacity, some flight plans are rejected and the airline must propose a less efficient trajectory. At tactical level, ATC's issue directives (e.g., headings, flight level change, speed change) to aircrafts in order to preserve the safety distance of those aircraft flying in the sector (Zúñiga et.al. 2013). Unfortunately, at operational level, there are several uncertainties (e.g., weather and wind conditions) and perturbations (i.e., poor adherence to the proposed trajectory) which propagate through the full aeronautic processes, which can provoke non-added-value and capacity-wasting operations such as ground delays (Nosedal 2014 and 2015) and holding trajectories (Ruiz 2013) which affect to a constant increasing amount of agreed slots (slot is the permission given to an airline to use the full range of airport infrastructure necessary to operate on a specific date and time for landing or taking-off) degenerating into an unstable air traffic management (ATM) system due to unbalanced demand/capacity problems. In (Piera 2014) it is presented a causal approach to obtain a better understanding of emergent dynamics in the ATM system that arise as a result of tight interdependencies between ATM system actors (i.e., people, procedures, equipment) working together or impacting each other, leading to higher levels of complexity.

To improve ATM reliability, by detecting and designing mitigation mechanisms to avoid the free propagation of perturbation between the airside and landside resources with a direct impact on airport operational capacity (Narciso 2015) that affects the tactical capacity of ATC's and even propagates to strategic decision making tasks affecting the CFMU level, in Europe and in the USA two important research programs SESAR (Single European Sky ATM Research) and NextGen (Brooker 2008) has been enhanced to design new ATM concepts with the aims of improving fuel efficiency, cost efficiency, safety, and airspace capacity. As a results of the development of new technology and working methods, it is envisaged that future operations will require new trade-offs between safety, efficiency, and capacity enhancing reliability concepts in ATM.

In this paper, it is presented the causal analysis of the airport turnaround processes, which is a key factor in for the ATM system, since delays generated during a turnaround may affect the landside capacity and propagate to the airside capacity by negotiating new slots and in consequence can affect the reliability of the full ATM system.

The causal analysis has been developed as part of the FP7 project Interaction leaded by main European aeronautic stakeholders (http://www.interaction-aero.eu/) and contributes to procedural features to avoid, detect and repair turnaround faults. Thus, the analysis of the turnaround interdependencies, contribute to detect a failure in the programmed target of block time (TOBT) which is the main airport source of airside delays, and if possible, provides mitigation mechanisms to correct the problem and isolating the delay at airport level.

Turnaround complexity arises due to the effects of interdependencies between different actors that are able to generate an event that could block, freeze, delay, or disable/ enable other activities programmed in the same or in another sub-process (Wu 2008 and Abd 2014).

Specification requirements in terms of cause-effect relationship between sub-processes (e.g., ground operations) demands for a knowledge representation technique that considers the stochastic, dynamic and synchronous nature of the turnaround process, and allows representing both the structure and the different ways in which the sub-processes can be influenced (e.g., dynamic critical paths). The proper representation, analysis and assessment of all the event-relationships (i.e., disruptions identification and reliability evaluation) that determine the comprehensive turnaround behaviour are essential in dealing with innovative robust improvements.

The remaining sections of this paper are organized as follows, Section 2 includes the turnaround description and the case study data are described. Section 3 illustrates the main turnaround reliability results obtained from the real data analysis (e.g., simultaneous equations, central tendency measures, discrete event simulation and variability comparisons). Finally, Section 4 presents the conclusions.

2. The turnaround process description and case study data

The Turnaround process includes a set of operations performed in the aircraft while it is parked in the airport, between the arrival and the next departure, those operations must be executed in parallel or in a sequential way. Thus, all the operations must be coordinated to optimize the process without incurring changes in the TOBT (the time that an aircraft operator (AO) or ground handler (GH) estimates that an aircraft will be ready, all doors closed, boarding bridge removed, push back vehicle available and ready to start up /push back immediately upon reception of clearance from the tower).

Several actors of different organizations are involved in the turnaround process, each one working for a particular goal and with a lack of information sharing mechanisms, making it a complex operation due to the tight interdependencies between tasks. The main actors involved in the turnaround process are: AOs, GH, air navigation service provider (ANSP) and airport operator. The typical tasks involved in the turnaround may be grouped in four process categories: passenger, baggage, freight and ground services. The ground services comprise the set of operations required from the moment the aircraft arrives at its stand (actual in block time) until the time it leaves it (actual off block time).

The turnaround process can be specified by an activity network, in which the process data concerning the tasks to be completed are specified, how long each task takes and the constraints on the order in which the previous tasks must be finalized (precedence, resources availability, space constraints, legal restrictions, etc.).

As an example, Figure 1 and Table 1 illustrate the ramp layout considered for the turnaround process.

The present work relies on the analysis of real data gathered from 106 turnarounds for A320 aircrafts, the sample of flights were recorded from a European international airport during one week in June 2015. In Table 2, the turnaround activities (grouped per operation), together with the precedence constraints (third column) are described, based on the airline procedures.

3. Analysis and results

This section illustrates the application of various methods of analysis and the main turnaround reliability results obtained from the available real data for the case study under evaluation.

3.1 Aggregate analysis of individual operation duration and its contribution on the global turnaround duration or actual ground time (AGT)

The analysis of the observed individual turnaround task durations (i.e. without defining nor separating by on time and delayed or extended operations) together with their influence in the turnaround as a whole, provides the baseline to formalize a model to measure the impact on the AGT expected duration. The analysis is performed by proposing one simultaneous equation model (SEM) in the next form:

$$\sum C_{Sn} T_{Sn} \leq (100 + ME) * AGT \qquad (1)$$

$$\sum C_{Sn} T_{Sn} \geq (100 - ME) * AGT \qquad (2)$$

Where:
$T \equiv corresponds\ to\ each\ operation\ indidual\ duration$
$C \equiv corresponds\ to\ each\ operation\ contribution\ to\ predict$
$the\ total\ AGT\ duration$
$S \in \{A, B, C, D, E, F, J, H, I, J, K, L, M\}$
$n \in \{1, 2, \ldots, 106\}$

$ME \equiv represents\ the\ maximum\ error\ or\ deviation\ in\ the\ prediction\ of\ the$
$AGT\ based\ when\ Cs\ are\ applied.$

Due to the size of the equation system (in this case 312 equations) we solve this system by using Mixed Integer Linear Programming (MILP) and specifying ME as the objective function to be minimized. The coefficients C_S , with C_S >=0, correspond to the variables to be computed (i.e. the solution searched). The optimal solution reached using CPLEX ILOG is quantified below for each operation with a maximum bias of 23% (i.e., *ME* = 23).

$C_{Refueling} = 22; C_{Cleaning} = 116; C_{Boarding} = 87; C_{Catering} = 42; C_{Deboarding} = 48; C_{Start\_deboarding} = 0; C_{Ready\_for\_OB} = 99; C_{Bulk\_unloading} = 23; C_{Bulk\_loading} = 16; C_{Pot\_wat\_serv} = 0; C_{Toilet\_serv} = 0; C_{PRM\_arrival} = 49; C_{PRM\_dep} = 18;$

Based on the previous results (i.e., considering a maximum bias of 23%) the contribution function to compute the AGT total duration in minutes is expressed as:

$$AGT=(22*T_{Refueling}+116*T_{Cleaning}+87*T_{Boarding}+42*T_{Catering}+48*T_{Deboarding}+ 99*T_{Ready\_for\_OB}+23*T_{Bulk\_unloading}+16*T_{Bulk\_loading}+49*T_{PRM\_arrival}+18*T_{PRM\_dep}) / 100$$

Accordingly to the values for C_S it is possible to determine the sensitivity of the AGT duration for time execution variations in each individual operation It should be noted that the impact will depend directly (i.e., it is proportional) to C_S and the operation time extension T_S.

Thus, the above function provides evidence of correlation between individual operation time extension and the total turnaround duration. However, does not provide evidence of the causality between delays for individual disruptions in the turnaround.

3.2 Standard values definition

Before the analysis of causality for delays in the individual task and turnaround disruptions, establishment of standard or reference values is needed. These standard values will allow further classification of the individual operations and turnaround duration in two main categories: ‘on time’ and ‘delayed’. The causal analysis will rely on well accepted hypothesis:

a. The airline policy accepts 50 minutes as the maximum duration for an “on time” turnaround process (complete turnaround on A320 aircraft).
b. It is assumed a normal distribution or near to normal for the turnaround time duration.
c. It will be assumed also a normal distribution for all the individual operations time durations.

In Figure 2 the distribution for the data sample is illustrated and the percentage of ‘on time’ and ‘delayed’ operations. In Figure 3, the distribution of the recorded data for cleaning operations is presented.

Based on the above, these operation times can be described by means of the average and the standard deviation parameters. In Table 3, all the values obtained from the distributions analysis, for all the operations included in the turnaround are summarized. In Table 3 (seventh column), it is also indicated the observed percentage of occurrence for delays per each operation together with the maximum delay extension in minutes (eighth column).

3.3. Simulation of the turnaround process considering explicit sequence interdependencies

The turnaround process described in previous section introduces several explicit interdependencies (i.e., sequence and preconditions), which are specified in this section using the Coloured Petri Net formalism (Narciso 2012) for a causal analysis. The implemented model is presented in Figure 4 and formalizes the explicit interdependencies between operations and the individual time duration previously defined for ‘on time’ and ‘delayed’ (i.e., standard values).

This model will be used to analyse quantitatively the effects produced by individual delays (Table 4), and the effects produced by the combination of several operation delays occurring for one turnaround (Table 5). The simulation data analysed supports the identification of the combinations of delays that cause a time disruption in the turnaround duration (i.e., extension over 50 minutes).

It should be noted that CPN model reproduce only the effect of the explicit interdependencies (i.e., sequence or precedence restrictions), implicit interdependencies introduce additional dynamics in the system (i.e., spatial restrictions, human resources availability, etc.). A comparative analysis of the standard values with the sample data confirms the presence and effects of these dynamics.

3.4 Causal analysis

Based on the defined standard values, the individual operation times and the complete turnaround durations are classified and compared in terms of their variability, in order to check if there is a systematic effect between the specific operation duration and the observed turnaround time extension (i.e., recorded AGT).

To identify the causal relationships it is performed a variability analysis between the ‘on time’ and ‘delayed’ individual operations and the turnaround duration.

In Figure 5, comparison of the variability by means of box plots diagrams is summarized for all the individual operations. In the first box plot, the comparison for ‘on time’ and ‘delayed’ turnarounds (i.e., AGTs) is provided.

It can be noted in figure 5, that for some cases the specific operation was not performed, then in the box plot graph appears a third box (left hand side), which corresponds to the AGT duration mean and variability in absence of this specific operation. The above condition applies for Catering, Potable water servicing, Toilet servicing or PRM servicing operations.

Based on the former results and with the aim to identify threshold delay values to improve the reliability of the turnaround process, it has been analysed the critical delay values to determine when an operation individual delay may become a disruption for the turnaround time duration, together with their frequency of occurrence. Thus, it has been performed the comparison of the cumulative probability plot for the observed values from each operation classified when were executed in a turnaround determined as ‘delayed’ or determined as ‘on time’. Figure 6, includes all the comparisons. In the first graph, the comparison for 'delayed' vs 'on time' cumulative probability plots is provided, followed by those for each individual operation.

3.5 Results

One clear example of the effect of the referred implicit interdependencies between operations is the result obtained for Deboarding operations. Considering the result from SEM, the $C_{Deboarding} = 48$, suggest a medium/low impact of the Deboarding duration on the total turnaround time and by considering the results from the CPN model (based on the explicit interdependencies), an individual or isolated delay on the Deboarding operations will not have effect on the extension of the turnaround process.

However, from the results obtained by means of causal analysis of the recorded data, the average turnaround duration observed for 'delayed' Deboarding operations is 55 minutes (i.e., turnaround 'delayed') and for 'on time' Deboarding is 48 minutes (i.e., turnaround 'on time'). The effects of the variability of the Deboarding duration are confirmed through the cumulative probability plot comparison.

It can be observed that Deboarding operations of 15 minutes or larger disrupt the turnaround duration (i.e. durations bigger that 50 minutes), meanwhile for all the 'on time' turnarounds, the Deboarding operations were performed below 15 minutes, and these pattern occurred for 30 % of the 'delayed' turnarounds on the sample.

The complete analysis for each operation is summarized in Table 6. Negative values (third column) suggest an examination of the current sequence of tasks in order to modify the execution procedures, due to the implicit interdependencies (e.g., availability of human resources or spatial blockage). Note, that by delaying these identified operations a better performance of the turnaround process is observed (interferences are avoided or better coordination between resources or activities is allowed).

4. Conclusions

This paper focuses on the advantages of using causal methods and simulation models as a useful tool to improve turnaround reliability by a better understanding of the impact of delays on the turnaround process. Aiming to assess the time reliability and disruption analysis for design policies and strategies that could mitigate the propagation of delays through the turnaround and avoid any impact in the airport KPIs, an exhaustive timed evaluation of the different perturbations that can affect the turnaround time due to precedence task interdependencies has been performed.

This examination is used to illustrate the complexity of the turnaround process at operational level (e.g., dynamic critical paths), including the implicit interdependencies as source of emergent dynamics that affect the performance of the overall turnaround operation.

The causal analysis of the different perturbations has been measured in order to provide insights for better design of policies and strategies for a robust and efficient turnaround that could mitigates undesirable dynamics or at least detect them in advance and enhance the robustness of the turnaround and their related processes and actors performance (e.g., airlines, airports, ground handlers, etc.) with direct and indirect impact on ATM system reliability.

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Table 1. Ramp layout and equipment for ground services.

No.	Area / Equipment
1	Tow tractor area
2	Air start unit area
3	Ground power unit area
4	Stairs area
5	Catering vehicle area A
6	Air conditioning unit area
7	Lower deck cargo loader area A
8	ULD train area A
9	Catering vehicle area B
10	Fuel area
11	Conveyor belt area
12	Bulk train area
13	Lower deck cargo loader area B
14	ULD train area B
15	Cleaning truck area
16	Potable water vehicle & catering vehicle area
17	Lavatory vehicle area

Table 2. Ground services by operations.

No.	Activity	Precedence	Operation
1	Chocks On		Start deboarding
2	External Power	1	Start deboarding
3	Placing the PBB/stairs	1,2	Start deboarding
4	Aircraft doors open	3	Start deboarding
5	Deboarding at L1	4	Deboarding
6	End of Deboarding	5	Deboarding
7	Aircraft inspection	3	Deboarding
8	PRM servicing ARRIVAL	5	PRM arrival servicing
9	End off PRM servicing ARRIVAL	8	PRM arrival servicing
10	Placing the catering vehicle at R1	3	Catering
11	Catering at R1	4,8,9	Catering
12	Moving out the catering vehicle at R1	11	Catering
13	Placing the catering vehicle at R2	12	Catering
14	Catering at R2	13	Catering
15	Moving out the catering vehicle at R2	14	Catering
16	Placing cleaning vehicle	3	Cleaning
17	Cleaning	4,8,9	Cleaning
18	Moving out the cleaning vehicle	17	Cleaning
19	PRM vehicle placement Departure	17,3	PRM departure servicing
20	Prm Servicing departure	19	PRM departure servicing
21	Boarding at L1	17,2	Boarding
22	End off Boarding	21	Boarding
23	Placement conveyor belt	3	Bulk unloading
24	Bulk unload front holds	23	Bulk unloading
25	Bulk unload back holds	23	Bulk unloading

26	Bulk load front holds	24	Bulk loading
27	Bulk load back holds	25	Bulk loading
28	Moving out conveyor belt	26,27	Bulk loading
29	Placing FUEL HYDRANT DISPENSER or TANKER	2	Refueling
30	Start Refueling	9	Refueling
31	End off Refueling	30	Refueling
32	Moving out FUEL HYDRANT DISPENSER or TANKER	31	Refueling
33	Placing Potable Water vehicle	2	Potable water servicing
34	Potable water servicing	33	Potable water servicing
35	Moving out Potable Water vehicle	34	Potable water servicing
36	Placing Lavatory vehicle	2	Toilet servicing
37	Toilet servicing	36	Toilet servicing
38	Moving out Lavatory vehicle	37	Toilet servicing
39	Document delivery/lmc	22	Bulk loading
40	Moving out stairs	39	Ready for OB
41	Hand bags	39	Bulk loading
42	Cargo Holds close	28	Bulk loading
43	Moving out the PBB/Stairs / aircraft door close	39	Ready for OB
44	Ramp check	43,42,40,38,35,32	Ready for OB
45	Off Blocks	44	Ready for OB

Table 3. Individual duration standards for “on time” and “delayed” operations.

ID	Individual Operations	On time		Delayed		% of delayed operations[1]	Max individual delay duration (min)[1]
		Avg. time (min)[1]	Std. deviation (min)	Avg. time (min)[1]	Std. deviation (min)		
J	Refueling	9	4	17	4	35.8	12
E	Cleaning	13	4	17	3	41.5	7
G	Boarding	17	4	21	3	36.8	7
D	Catering	13	4	16	2	49.1	5
B	Deboarding	11	5	16	5	30.2	10
A	Start deboarding	2	1	3	1	32.1	2
M	Ready for OB	2	1	4	1	33.0	3
H	Bulk unloading	9	7	16	4	40.6	11
I	Bulk loading	19	11	30	7	43.4	18
K	Potable water servicing	3	1	4	1	22.6	2
L	Toilet servicing	3	4	7	6	21.7	10
C	PRM arrival servicing	4	3	8	4	6.60	8
F	PRM departure servicing	4	3	7	2	10.4	5

[1] based on the time performance and variability observed in the sample (recorded operations).

Table 4. Simulations result summary for individual delays

ID	Operations	Simulation	
		AGT variation[2]	Influence on the AGT
J	Refueling	0	N
E	Cleaning	+6	H
G	Boarding	+7	H
D	Catering	0	N
B	Deboarding	0	N
A	Start deboarding	+2	M
M	Ready for OB	+2	M
H	Bulk unloading	+5	H
I	Bulk loading	+12	H
K	Pot Water Serv	0	N
L	Toilet serv	0	N
C	PRM arrival	+8	H
F	PRM dep	0	N

[2] These values are determined considering the minimum AGT time obtained by simulating absence of delays in the whole process and the event of maximum delay for a specific operation.

Where:H = High, M= Moderate, L= Low, N= Null

Table 5. Simulation of different combinations for individual delayed operations

Number of Delayed Ops	Turnaround individual operations with delay													AGT variation[3]	Impact on the AGT
	A	B	C	D	E	F	G	H	I	J	K	L	M		
4	X							X	X				X	+27	H
5	X							X	X	X			X	+27	H
6	X							X	X	X		X	X	+27	H
9	X			X	X	X	X	X		X		X	X	+27	H
9	X	X	X		X	X	X	X	X				X	+27	H
3	X							X	X					+25	H
7	X	X	X					X	X	X	X			+25	H
9	X		X	X	X	X	X	X			X		X	+25	H
10	X	X	X			X	X	X	X	X	X	X		+25	H
5				X	X			X	X		X			+23	H
8		X	X		X		X		X	X	X		X	+23	H
8		X	X	X		X	X	X		X			X	+17	M
7			X	X	X	X		X		X			X	+16	M
5						X	X		X	X			X	+14	M
9		X	X	X	X	X			X	X	X	X		+14	M
5	X					X		X				X	X	+9	L
6				X		X	X	X		X			X	+9	L
2			X					X						+8	L
2				X	X									+6	L
2		X								X				+5	L
2											X	X		0	N

[3] These values are determined considering the minimum AGT time obtained by simulating absence of delays in the whole process operations.

Where: H = High, M= Moderate, L= Low, N= Null

Table 6. Causal analysis results for individual delayed operations

ID	Delayed Operation	AGT variation (min)[4]	Threshold (min)[5]	Occurrence (%)[6]
J	Refueling	+1	17.5	5
E	Cleaning	+5	20	2.5
G	Boarding	+3	23	2.5
D	Catering	+2	20	2.5
B	Deboarding	+7	15	15
A	Start deboarding	-3	-	-
M	Ready for OB	0	-	-
H	Bulk unloading	+0.5	22.5	2.5
I	Bulk loading	+3	32.5	10
K	Pot Water Serv	-3	-	-
L	Toilet serv	-4	-	-
C	PRM arrival	+2	5	15
F	PRM dep	-3	-	-

[4] These variation is calculated respect the expected turnaround duration values when that operation is completed "on time", these values correspond to difference between medians for turnaround duration for "on time" vs "delayed" operation.

[5] The referred threshold should be interpreted as the lowest value to detect or predict that an individual delay became a disruption in the turnaround duration.

[6] The value reported as the percentage of occurrence for each operation, means the percentage of observed turnarounds with individual operation duration values in the threshold or bigger, and it is computed as:

(% of delayed turnarounds in the sample) * (% of individual operations time equal or larger from the delayed turnarounds)

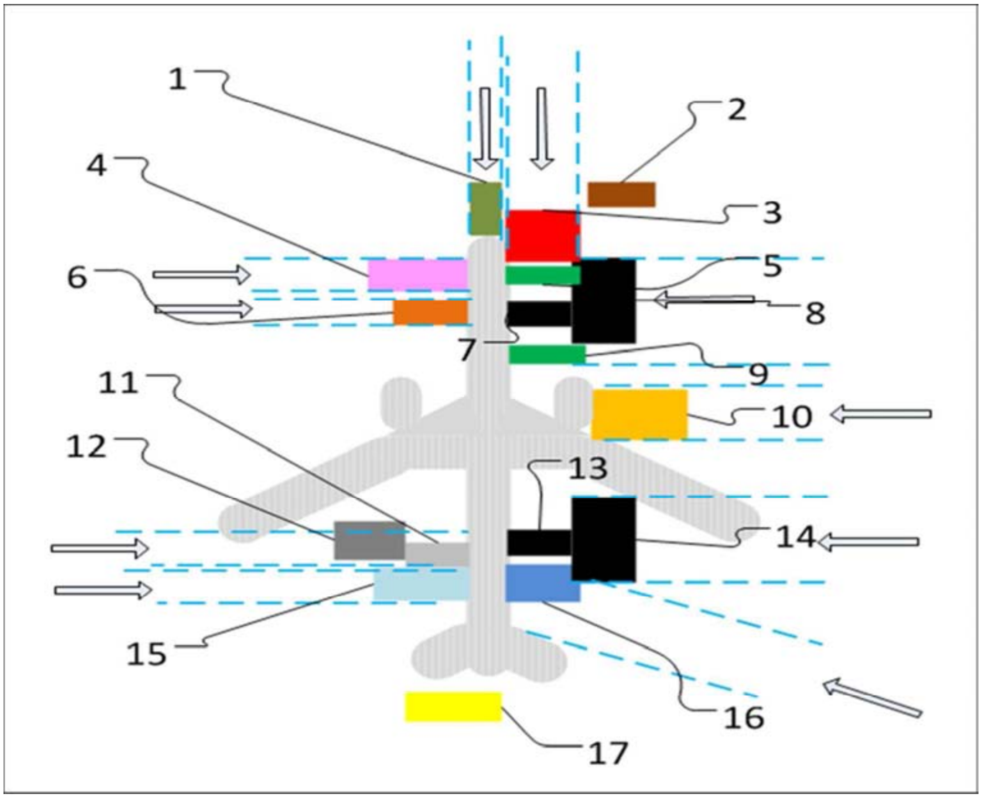

Figure 1. Turnaround process, equipment and ramp layout.
158x128mm (150 x 150 DPI)

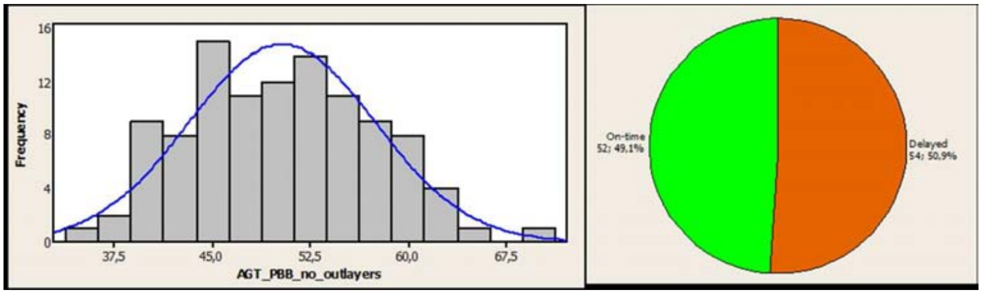

Figure 2. Distribution for 106 records of AGT in PBB (without out-layers) and percentage of delayed and on time operations in PBB for recorded AGT.
158x46mm (150 x 150 DPI)

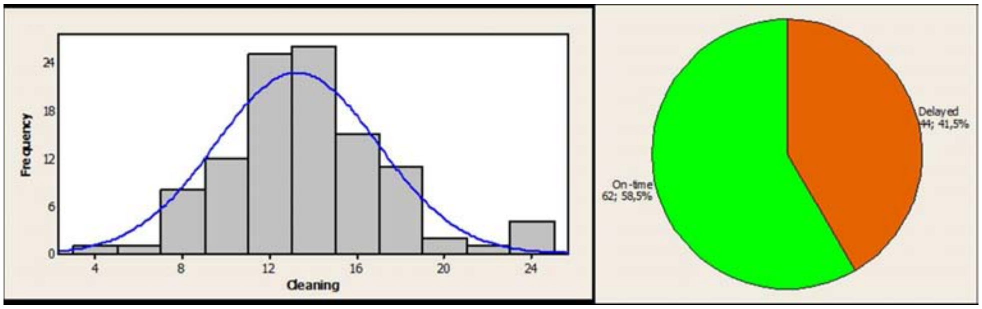

Figure 3. Cleaning times distribution for the sample and percentage of delayed and on time cleaning operations.
158x48mm (150 x 150 DPI)

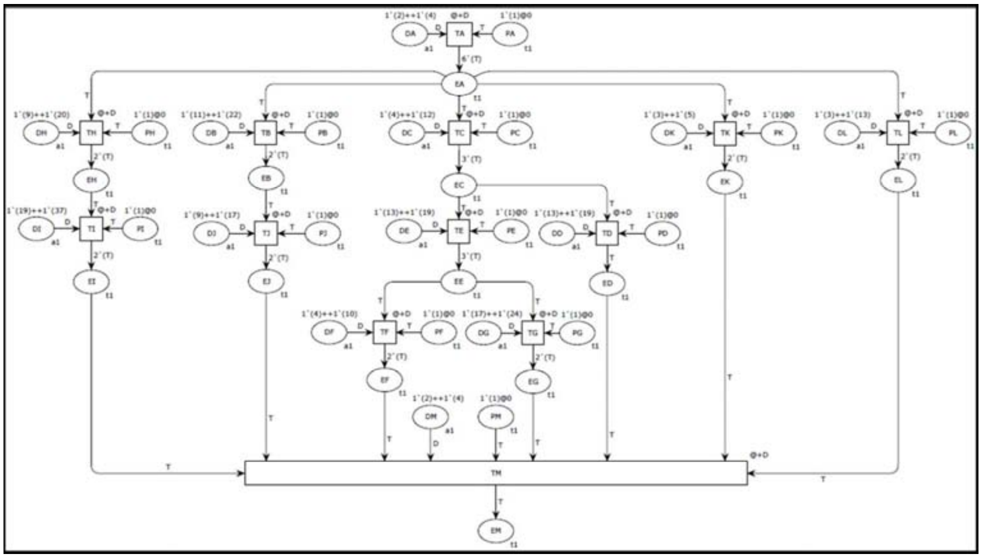

Figure 4. CPN model to simulate the complete turnaround process.
235x161mm (148 x 122 DPI)

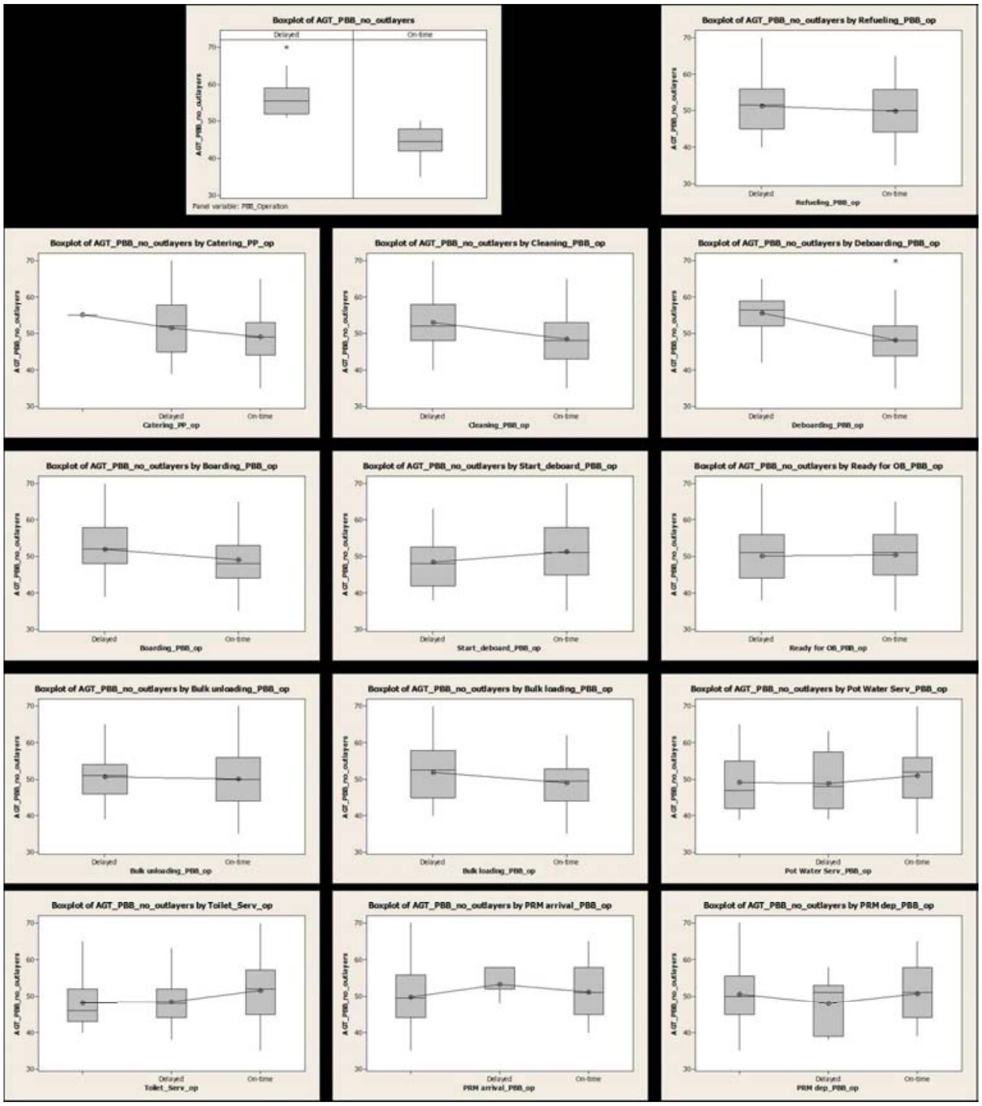

Figure 5. Variability analysis delayed vs on time operations (comparison of median values for turnaround duration).
332x374mm (150 x 150 DPI)

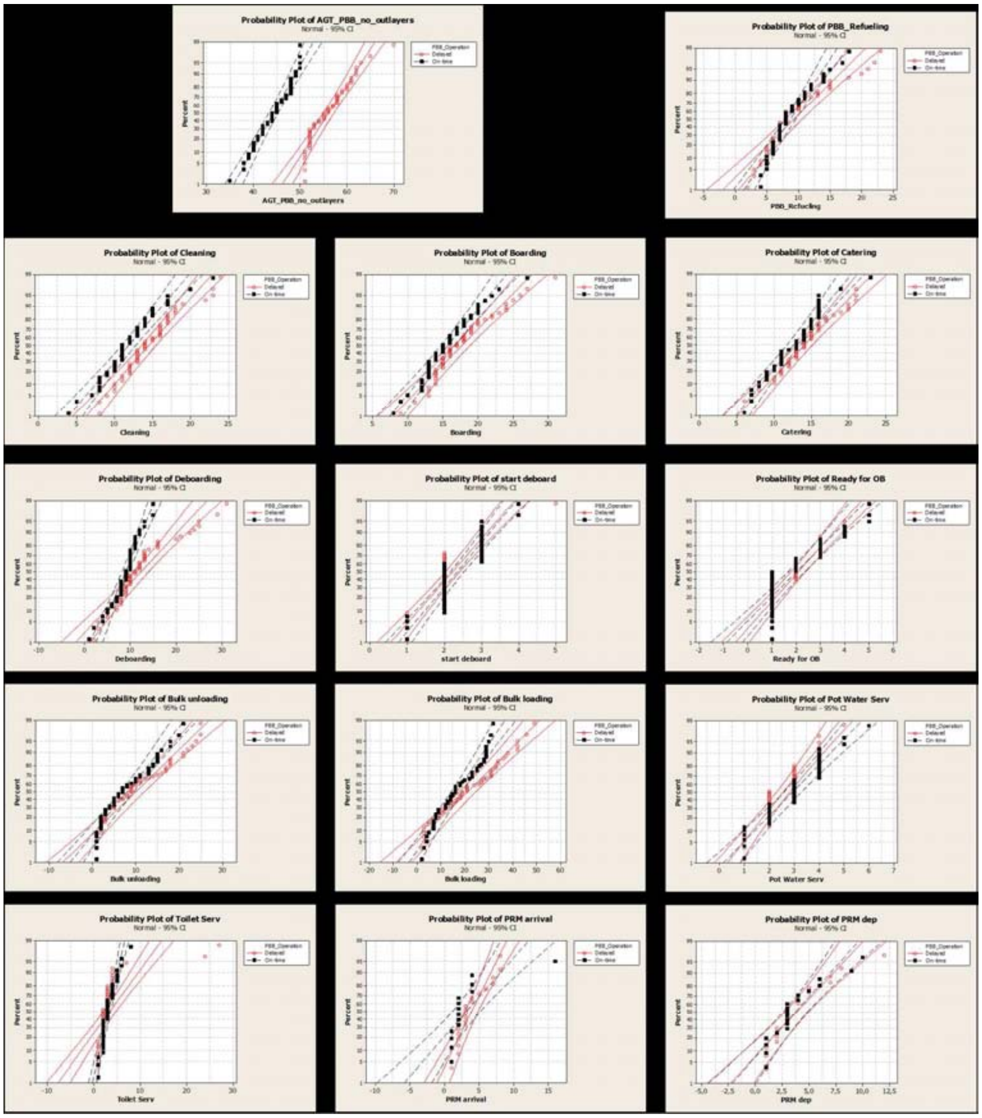

Figure 6. Empirical cumulative distribution plots.
336x382mm (150 x 150 DPI)

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