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Managing turnaround performance through Collaborative Decision Making

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A B S T R A C T

The purpose of this paper is to explore turnaround performance as a resultant from both Collaborative Decision Making (CDM) processes and collaborative measures. This paper presents how CDM operates in the Turnaround Process (TAP) to propose a new method for managing the collaborative turnaround performance of all actors by predicting the most critical indicators. To achieve this, data from a CDM airport is used. Sample data of 6500 observations, taken from turnaround movements handled in 2014 at Madrid-Barajas Airport, were obtained from three separate databases and analyzed separately (in three databases). To predict turnaround performance, this paper also introduces a predictor dependent variable called "*star values*" as a measure of minimal delay conditions in order to predict time performance. The analysis shows that the proposed method unveils a new approach in determining how collaborative performance can be measured in the TAP and the predicted key performance indicators, which shows variations in the predicted CDM indicators. Results challenge managers and policymakers to find which improvements can be enacted for better usage of airport infrastructures and resources for optimum use as well as enhanced TAP. In terms of theory use and extension, the study reveals how CDM is an essential element in the literature on air traffic management.

1. Introduction

Collaborative Decision Making (CDM) is an airport operations' standard that has an impact on the Turnaround Process (TAP) at airports. CDM aims to improve air traffic flow and capacity management by reducing taxi times, turnaround times which translates into, for instance, economic benefits and environmental friendly conditions. However, due to its diverse composition of actors, the assessment of turnaround performance relies on a CDM system that includes, inter alia, ground handlers, airlines, the airport management, and air navigation service providers.

The introduction of CDM at airports relies on the accepted fact that air traffic is rapidly increasing globally, and this trend is predicted to continue. In Europe, for example, the monthly monitoring of the European skies, as shown by Eurocontrol (2015b), indicates continuous growth in traffic from month to month. In other areas, studies in airport business show how the commercialization of the airport sector has facilitated air travel with the rise of low cost carriers (Graham, 2013), and how mergers and acquisitions are facilitating growth in aviation markets (Merkert and Morrell, 2012). As a result, flight demand is anticipated to reach 14.4 million movements in the next two decades (Krstić Simić and Babić, 2015; SESAR, 2014).

This increase in air travel signals positive economic benefits (Profillidis and Botzoris, 2015). However, it also exerts constraints, such as congestion in the skies, delays at airports, and bottlenecks in operations, to the whole network. Moreover, there are negative effects on the environment, notably noise and air pollution (Martini et al., 2013). Increased capacity, safety, efficiency, and the environment are the main goals for the EU. This creates an important supply and demand for runways that is being felt across major airports in Europe.

To address the anticipated needs for future air traffic management and the development of air traffic (Madas and Zografos, 2008;

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Forsyth, 2007; Wu and Caves, 2002), new technologies, concepts, and policies are emerging in order to optimize air traffic management (ATM) infrastructure to facilitate the collaborative management of the ATM network via Next Generation (NextGen) in the USA, and Single European Sky Air Traffic Research (SESAR) in Europe. For example, at the network level, the long-term strategic development of the entire air traffic infrastructure in the EU (SESAR, 2015) involves many programs such as moving from airspace to 4D[1] trajectory management and traffic synchronization. At the airport level, Airport Collaborative Decision Making (ACDM) is one of the optimization standards for airport services under the Single European Sky (SES) initiative, and was introduced in Europe almost a decade ago (Eurocontrol, 2006). Aside from its unique implementation requirements (Corrigan et al., 2015), an implication for CDM post implementation at airports, has been that turnaround performance from all actors can be measured to explicitly show both operational and financial benefits to a diversity of actors, such as ground handlers, airlines, airport management, and air navigation service providers.

In Europe, CDM is a standard for interoperability and a requirement for all airports (ETSI, 2010). At the airport level, CDM is required of all airport actors. However, the completion of CDM implementation does not necessarily mean that the expected outcomes are realized (Eurocontrol, 2006). After CDM implementation at an airport, continuous improvement becomes a daily activity in order to maintain optimal on-time performance. This paper argues that there is a lack of strategic alignment on how actors manage their operations in the TAP by using collaborative measures that are part of CDM. When CDM is viewed as a single-loop performance system, turnaround operations are difficult to manage, not only because of the diversity of airport actors, but also because there is poor alignment of both horizontal and vertical collaborative measures. The CDM performance indicators are not connected to airport actors to support operational improvements. This misalignment highlights the need of appropriate key performance indicators (KPIs) within CDM as a feedback mechanism to push for continuous improvement.

One driving force for CDM implementation has been the anticipation of its benefits to all actors involved at the airport level (Eurocontrol, 2006). However, there is still no recognized cross-organizational approach to how collaborative measures can be used by airport actors as a reference for cost benefit analysis. Because the CDM system is adjustable and there are variations in measures, the relationship between output from CDM operations and actions taken by diverse actors, such as ground handlers, airlines, air traffic controllers, and airport management, need to be examined. This may create a driving element that transforms the CDM system for airports, seen earlier as an ATM system, to a Performance Management System (PMS) (Bititci et al., 2015), defined as “the cultural and behavior routines that determine how measures are used to manage the performance of an organization” (Bititci, 2015a).

Using collaborative measures as a feedback mechanism for all airport actors (Van Bakel et al., 2015) can enables the alignment of the output from different CDM users as well as their push to change the behavior for their input. Moreover, by being able to measure turnaround performance within the CDM framework, this will contribute to the future functioning and continued improvement of ACDM (Eurocontrol, 2015b). In addition, turnaround performance is important because when showing how CDM indicators are critical, the system will be comprehensive of all operations. Ultimately, understanding the measures from local turnaround performance contributes to the airport performance benchmarking system-wide (Oum and Yu, 2004; Lupo, 2015). Overall, understanding the implications of these measures would maintain the credibility of CDM at airports and long-term visions of using the CDM framework.

As such, this paper argues that despite many studies on CDM functioning, there has not been enough research to explore how turnaround performance measures can be managed and aligned between CDM users and their collaborative output. We propose a new method that determines collaborative turnaround performance, in a way that enables tracked measures to be used as a performance management system. The paper does so by answering the following research question: How is TAP performance within CDM managed through collaborative measures? To answer this question, it is important to understand how CDM operates and what operational benefits it brings to the turnaround (see Appendix).

The research adapted insights from Performance Measurement Management (PMM) literature that show how integrated PMM with many actors can be achieved. It also adapted the use of the Classification and Regression Tree (CART) method, using the QUEST algorithm. A classification tree is a non-parametric statistical method that, by using a predictor variable, which is the (*star values*[2] in this case), can classify recursive partitioning to analyze and predict objects. The proposed framework consists of several stages: data mining, data processing, and data analysis and result validation. The results show that this method identifies turnaround performance by predicting the most critical KPIs that affect CDM operations, which then are linked back to the airport actors to manage delay reductions in the turnaround and, hence, both strategically and operationally drive collaborative performance.

The rest of this paper is structured as follows. In Section 2, we present a background on CDM as part of ATM literature as well as insights from PMM literature. In Section 3, we present the overall methodology and predictor *star values*. In Section 4, the analysis of the results is presented, while, in Section 5, the validity of our calculations that warrant consideration from other researchers is examined. Section 6 opens with a discussion of the results and, finally, Section 7 discusses the conclusions and implications for future research.

2. Collaborative Decision Making in air traffic management

Part of the ATM literature deals with airport performance in understanding collaborative approaches to airport operations (Castelli and Pellegrini, 2011; Auerbach and Koch, 2007), including collaborative approaches in airport business (Nucciarelli and Gastaldi, 2009). Collaborative systems in aviation are also evident in other areas such as the collaborative Safety Performance System (Ulfvengren and Corrigan, 2014). This makes ATM an important area of study with an emphasis on terminal airspace and airport operations (de Neufville and Odoni (2013); Koeners and Rademaker, 2012; Krstić Simić and Babić, 2015). However, there is not enough extant literature on how CDM is integrated. To this end, most ATM systems in Europe adopted operating systems to be able to use advanced satellite technologies, and for local airport operations to advance collaborative thinking to reduce congestion and cost.

As indicated, ATM has to increase its role in airport operations, since mastering the ATM fundamentals promises to decrease traffic

[1] 4D is a new concept being investigated by SESAR and Eurocontrol as a way to connect aircraft and ground systems to optimize aircraft trajectory in three dimensions over time.

[2] This term is introduced by the authors in this paper to represent delay conditions, which are the dependent variables used in the calculations in Section 3.

overloads, excessive congestion, and extra costs caused by delays in scheduling. For example, one of the most technological changes in ATM systems (SESAR, 2015) was the introduction of CDM (Eurocontrol, 2006). The evolution in air traffic technologies and new roles of logistics in air traffic has made airport performance more diverse (Petruf et al., 2015), and more types of standards are continuously being included in NextGen and SESAR technologies.

According to the monthly report from Eurocontrol (2015a), network performance can be traced to the role of airports in implementing CDM locally, where a significant predictability was seen with the central network manager. Hence, airport management appears directly dependent on the ATM systems for sharing data and integration management, which implies that any change in airport operations will have an impact on airport CDM. The overall airport performance is now based on collaborative thinking from different actors (Groppe and Bui, 2007; Corrigan et al., 2015), which is quite difficult to quantify and define. In the CDM era, operations presupposes both the quality of shared data (Martin, 1998), and a shift in engineering geared toward system integration (Chang et al., 2001).

To fit the complex demands of modern air traffic users, CDM airports need to adopt more innovative ATM systems that are capable of accommodating CDM as a cross-organizational management tool in order to impact user behavior with the characteristics of various interests. The emphasis on CDM indicators from collaborative airport operations, as well as the general role of airports in the network, has the objective of combining the diversity of actors with intricate, automated computerized systems, which evolve at the pace of rapid technological changes, and increase air traffic capacity and other functions through the understanding of collaborative measures (de Neufville and Odoni, 2003).

As part of ATM, local airport performance and measurement have always considered ground-handling services to reflect performance in airport logistics; however, because of new automation in current ATM operations, collaborative challenges are still present with a multi-actor approach, which makes performance and management a big challenge (Liu et al., 2014). Despite this challenge, the new trends in air traffic infrastructure present new research areas (Ginieis et al., 2012). Several optimization models require unique understanding and PMSs for their sustainability.

2.1. Performance measurement & management for Collaborative Decision Making at airports

Performance Measurement and Management (PMM) literature (Bititci, 2015b; Chenhall and Langfield-Smith, 2007; Franco-Santos et al., 2012; Humphreys and Francis, 2002; Brudan, 2010) provides several insights on how measures are used to manage operations. The theory shows that measures support the implementation of companies strategy, they improve management's control, measure provide improvements for future profitability. PMM literature also separates the notion of managing the science from the art of organization. Accordingly, it shows how measures can be managed as a social system, such as with airport CDM. This leads to the need for the design of an integrated PMS. Furthermore, the separation of managing collaborative measures, on the science side, and creating feedback mechanisms, for managing the art side, is evident in CDM operations. While there are several studies on CDM operations, such as by Corrigan et al. (2015) on CDM implementation, as well as others on the regional differences in this concept (Brinton et al., 2011; Okwir and Correas, 2014), other studies focus more on the operation and optimization of CDM (Groppe and Bui, 2007; Auerbach and Koch, 2007; Pick and Rawlik, 2011; Schaper et al., 2011; Koeners and Rademaker, 2012; Kim et al., 2013; Tobaruela et al., 2014; Petruf et al., 2015). However, there are not enough studies devoted to output performance as an inter-organizational practice within the collaborative thinking of the CDM framework.

2.2. Model to evaluate Performance measurement management at airports using Collaborative Decision Making

This section proposes a model to evaluate CDM turnaround performance. As part of the large ATM system, theory on CDM implementation has four major network benefits—*capacity, efficiency, environment,* and *safety*. For each benefit, a set of major indicators has been recommended for consideration by an airport using CDM. Among these performance indicators, there exist both network and actor benefits (Eurocontrol, 2006). For CDM network performance, the main objectives for CDM outcomes according to Eurocontrol include: 1) to protect air traffic services, 2) to enable aircraft operations with minimum penalty, and 3) to allow the best use of airport resources.

Following studies on methodology development in ATM, such as by Tobaruela et al. (2014), this paper explores the key role of CDM indicators in the airport (i.e., managing turnaround performance). The paper fills this gap by considering a non-parametric data-mining technique to validate airport operations from collaborative CDM measures.

Fig. 1 suggests a model derived from CDM theory (Eurocontrol, 2006, 2012), which combines CDM inputs and outputs to obtain performance at airports. For inputs, it considers CDM operational standards, such as trust, information sharing, and collaboration between the actors involved, the resources used at airports, and airport infrastructure (Eurocontrol, 2012).

This model takes into account airport operators, aircraft operators, ground handlers, and air navigation service providers as airport partners, and their activities as input to the system. As for outputs, this model considers all areas that impact airport activity, such as efficiency, environment, capacity, and safety, as the main, sustainable air-transport system parameters for the future, and they are in line with those of the Advisory Council for Aviation Research. However, this paper will be limited to local airport CDM or airport performance, and not network performance, because the former is the main purpose of our paper.

3. Method

3.1. Research approach

The research approach follows the assessment model presented in Fig. 1. We used operational data from Madrid-Barajas Airport, sampled from the CDM database that corresponds to airport actor KPIs. The CART method was applied for the three databases, and all datasets were analyzed separately. The following is a stepwise description of the method we used.

In general, the CART method—a non-parametric statistical tool that helps segment, rank, and predict membership of items in the classes of a dependent variable—has been applied to other areas in various studies (Chang, 2012; Harper and Winslett, 2006; Zhang and Bonney, 2000; Prakash et al., 2012). Moreover, it uses an interpretation of the results utilizing a nodal split to form a classification tree. Each node shows a particular class of indicators, and saturation is always reached when the classification node terminates. The CART algorithm begins with all observations in a single dataset to form a tree with a particular split fall. For every split, there is a particular threshold reached, and the observations are then split into two groups. The split is made on the basis of the independent variable to reduce the total variation in the categorical dependent variable. Following the data after the split, the algorithm then selects the best-fit node for continuous split to reduce the total

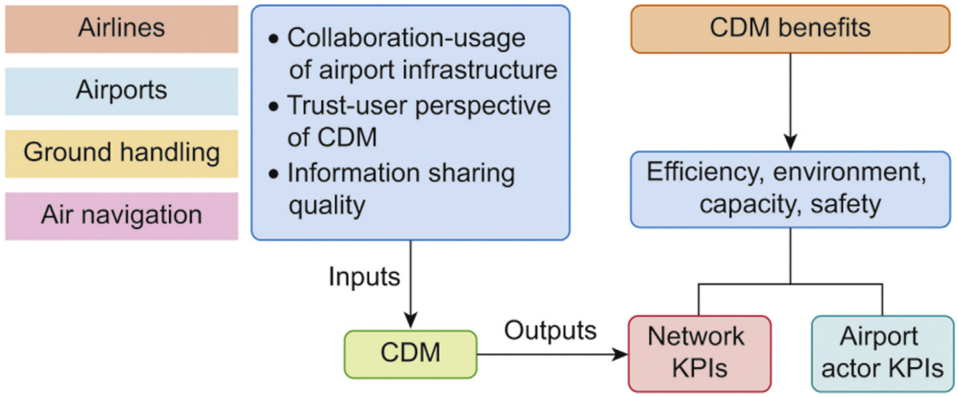

Fig. 1. A model to evaluate CDM measures.

variation in the categorical dependent variable. Further, we find that the CART method warrants the classification of several performance indicators with a better meaning and robust statistical approach using the steps presented below.

The dataset which forms the group (N), its total variance is calculated. In this case, dependent variables (explained in Table 2) is calculated in the group as $[\sum x]$, and the total value is squared as $[\sum x]^2$. The independent values are then sorted in increasing order to the dependent variables. As such, the best split is produced with minimum variance as follows:

$$= \frac{\sum_{Total\ groups}\left[\sum x^2 - \frac{(\sum x)^2}{N}\right]}{Total\ observations}$$

A new type of data is then classified and simulation is repeated with the above steps until saturation is reached.

In order to apply the CART method to our data, as a first step, we were able to examine our sample data with three algorithms in order to select the most suitable for the calculation. The algorithms tested prior to full calculation were QUEST, CRT, and CHAID. From the pilot results, our results show that from all of the three algorithms tested on our sample, QUEST had a higher prediction accuracy compared to the rest of the results. Secondly, QUEST was able to classify measures with high accuracy and less computational time; in other words, QUEST met all prerequisites for our data. As such, the rest of the analysis was performed using QUEST.

3.2. Data and sample design

Table 1 shows the sample data taken from the Madrid-Barajas Airport database, as previously mentioned; the CDM database is maintained by Aeropuertos Españoles y Navegacion Aérea (AENA) as part of an on-going CDM project. Moreover, AENA operations use a large integrated database called SCENA. Our sample is drawn from flights operated for the year 2014 along with observations. For every month, we selected a single day to represent the average number of flights for that month. This had the advantage of allowing for the capture of actual flights conducted. Had monthly or aggregated data been employed, specific flight data would not have been available for analysis because then we could not decipher how flights follow each other during turnaround. Therefore, following a daytime selection of the sequence of flights was vital, and allowed for sequential analysis of flight scheduling to be examined by KPIs. The extraction of turnaround-time data included all data from CDM actors. Flight variables included all estimated and actual times for every event, as described by CDM operational indicators. Further, the CDM turnaround data also included variables for every flight, such as type of aircraft, taxi runway, name of airline, stand or gate, and all CDM indicators (independent variables). Three databases were then developed, each of which was analyzed independently with SPSS analytics software. Table 1 shows the way in which the data from 12 months was distributed in the three databases.

Fig. 2 shows a record of live performance of CDM operations and how the indicators are recorded. The system database records actual times and estimated time. According to Eurocontrol, delay is the time difference in minutes between Scheduled Times (ST) and Actual Times (AT) of any activity that is being recoded in the milestone. This difference is measured at all phases of flight, inbound, turnaround and outbound. These times are the independent variables presented in Table 2. To attain on-time performance with perfect conditions, the difference between AT and ST should be delay $= 0$ min. Hence, for the dependent variables, new variables are proposed and named *star values*. We call them so because they are the minimal delay conditions that can optimize the system to no delay (see Fig. 3, Fig. 4, Fig. 5).

For example, if the scheduled *time* for takeoff for flight X was set at 10.30, but because of the nature of operations in the TAP, takeoff occured at 10.37 as actual time. In this instance, the difference between Actual and Scheduled is 7 min, which will be the delay time for flight x at takeoff. The other possible event of the delay would be that if flight x takes off at a time 7 min earlier than scheduled, so the delay in this case could be -7 min. The two possibilities are delay conditions which cause disruptions which may have far-reaching consequences in the whole network. The delay condition is then calculated as:

$$Delay = (AT - ST)\ minutes$$

Table 1
Sample data selected.

Databases	Selected months	Total observations for each database
Database one	January, February, March, April	2100
Database two	May, June, July, August	2168
Database three	September, October, November December	2232

Table 2
Dependent variables (star values).

Definition	Star values in minutes (Nominal)
ON TIME (T)	*For T = all delays from -0.5 and above*
OVER TIME (OT)	*For OT = all delays from -0.5 and below*

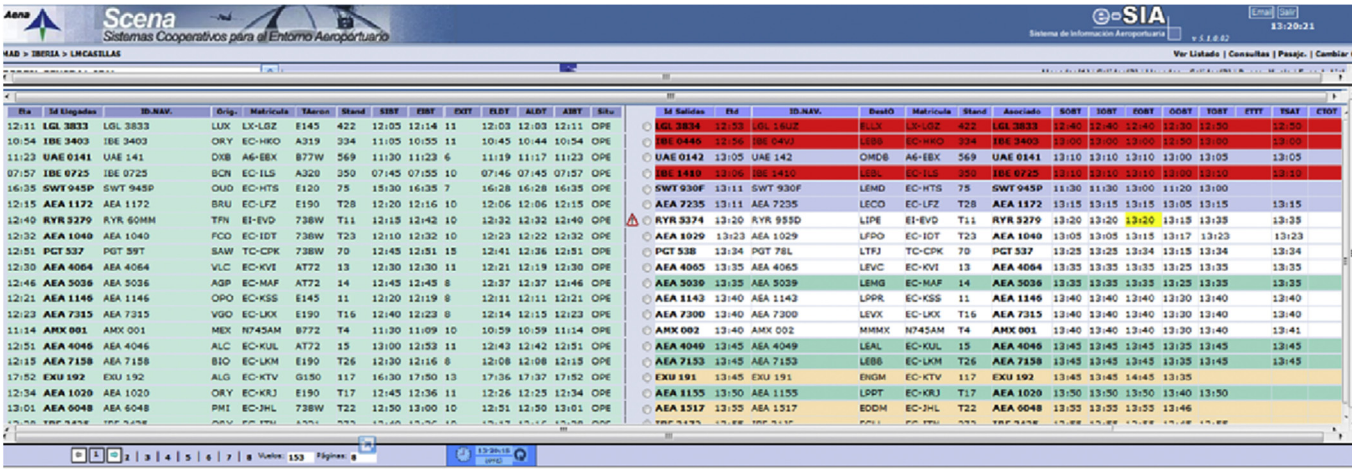

Fig. 2. A screenshot from a CDM management tool.

Table 2 presents dependent variables used. The dependent values are named *star values* because they define the delay conditions in the turnaround as the most perfect and objective system with no delays. It is important to show the level of delays in the current CDM operations by comparing them to the perfect system of proposed *star values*. Therefore, for the dependent variables, we composed a set of *star values* with three delay conditions. The delay condition is the difference between actual and scheduled time, which ultimately gives three alternatives: early arrival, on time arrival and late arrival. In order to have *star values* cater for all the three alternatives of the delay conditions, the dependent variables were allocated to two classes selecting −0.5 as mid point. First, all delays recorded in the range from - 0.5 min and above are marked as On Time (T); second, all the delays in the range from −0.5 min and below are marked as Over Time (OT). The two classes then formed a set of dependent variables that was used in the calculation as predictor variables for the independent variables recorded as a difference between scheduled and actual times from major CDM KPIs during operations.

The proposed *star values* are the key performance target for all actors when the system is considered to be a perfect system with, in other words, no delays. All actors involved should work towards narrowing all CDM Key Performance Indicator times to 0 min for better benefits. This is the very reason the dependent variables were set with such precise and minimal delay conditions.

Table 3 presents 11 independent variables. The independent variables are the major CDM Key Performance Indicators extracted from the year 2014 airport database. The independent variables are difference times between the actual and estimated for all the operations recoded, which represents the current CDM performance of all operations. Below are the indicators used as independent variables, which are delays as a result of estimated and actual times in the milestone approach.

4. Analysis of results

The study explored how TAP performance within CDM is managed through collaborative measures. In examining it, the analysis covered several steps, starting with data mining, data processing, and analysis. This section presents the steps taken to reach the results.

4.1. Data reduction

In analyzing the correlation matrix between variables, high correlations were observed, thus indicating redundancy in the data. In this case, a multivariate analysis was performed in all sets to reduce the number of independent variables. By applying principal component analysis as an extraction method and varimax with Kaiser Normalization as a rotation method, four sets of variables in the group of independent variables were produced, as shown in Table 4, and arranged according to how significant each variable was. This is also considered a suitable technique because it is a synthesis technique for reduction of variables by maintaining as much information possible for each observation. Just a few components account for much of the total variability. Thus, the table below shows the four components obtained in the data reduction process (see Table 5).

4.2. Technical analysis and post data reduction

After reducing the independent variables, a classification tree technique was then performed with the QUEST algorithm; this resulted in three classification charts where all independent variables were examined on how they are affected by the dependent variables. In order to predict which of the CDM KPIs are those that can be considered more important, a closer analysis on nodes of the tree were studied, as any change in them can significantly impact the value of the dependent variable.

From the initial split at Node 0, the dependent variable is branched into two nodes (1 and 2) belonging to Component 2. This shows that these indicators from CDM turnaround performance are the most important for this sample. Secondly, by observing the values of the dependent variable on Nodes 1 and 2, the category of the dependent variable, shaded gray, is then predicted; in this case Node 1 predicts values in the category value OT = 56.6%, while Node 2 predicts the values corresponding to the category OT = 87%, after which each of the two nodes branch off, thereby giving rise to new nodes.

From Node 1, we see that the next split branches at Nodes 3 and 4, whose most influential variables belong to Component 3 (TOBT_SOBT, AOBT_SOBT). This means that this set of variables will be the second most important within the group of independent variables studied. It also shows that Node 3 emphasizes the category of the dependent variable T, which is the objective role of the CDM system and assigns a prognostic value of 74.3% to the category T, as well as assigns 25.7% to the category OT. On the other hand, with Node 4 the same category emphasizes OT with 94.7% and only 5.3% assigned in category T, causing this node not to branch any further.

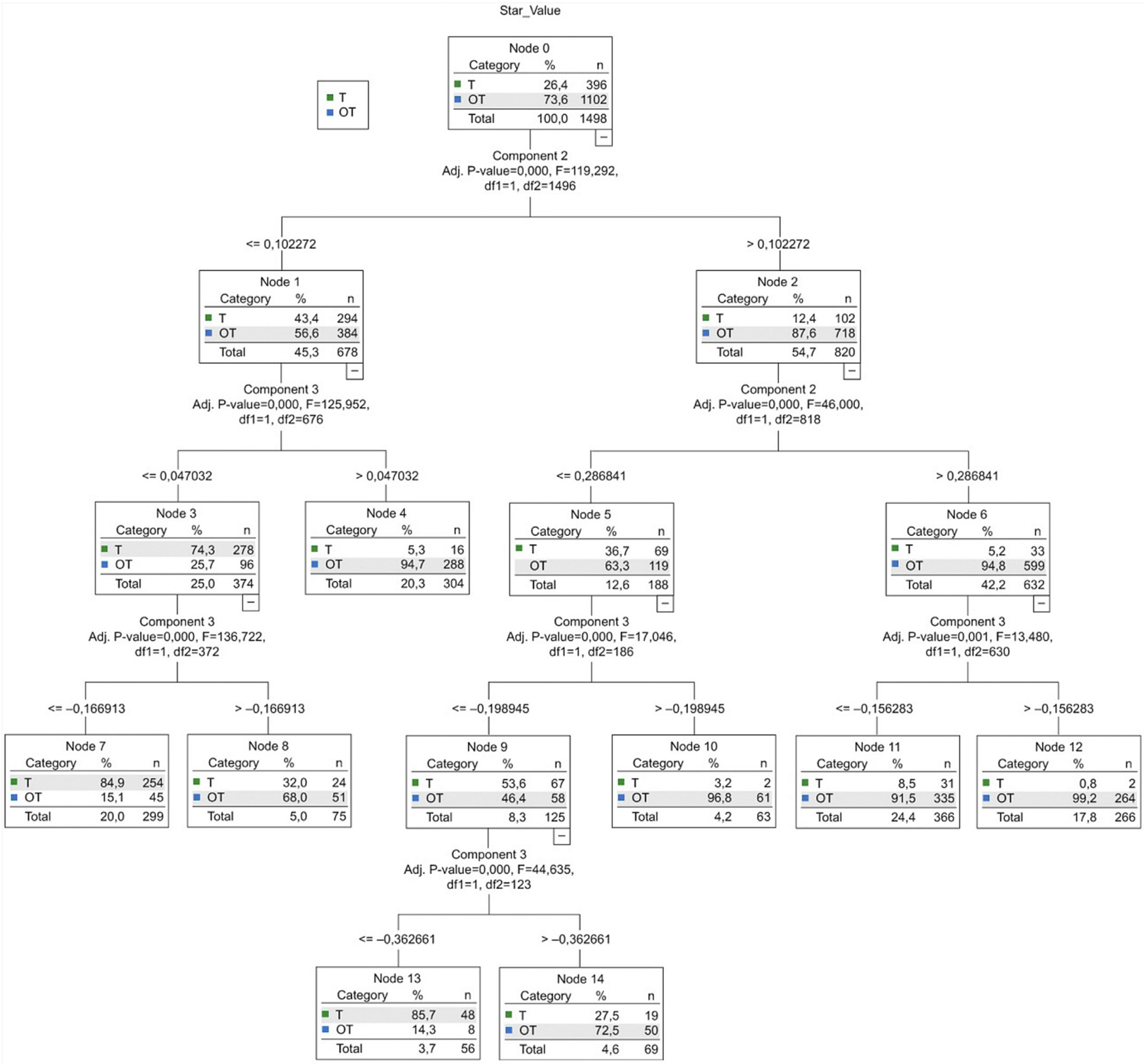

Fig. 3. Classification tree plot for Database one.

Node 2 branches at Nodes 5 and 6, having an influencing variable as Component 2, which shows that Component 2 is a very important variable in measuring turnaround performance. It is then observed that Node 5 emphasizes the category of the dependent variable OT, assigned a prognostic value of 63.3%, and category T that is assigned 36.7%. As for Node 6, the same category emphasizes OT with 94.8%, and only 5.2% is assigned to category T.

To further analyze the classification tree, take Node 3 together with Nodes 5 and 6. We see a final split, which branches into Nodes 7 and 8 with an influence on Component 3 (TOBT_SOBT, AOBT_SOBT). This means that these are a set of variables that influences this new prediction. However, Node 9 is subdivided as having influence over variable Component 3, and is split into Nodes 13 and 14, where it is observed that at Node 13, the largest predicted value of category T obtained is 85.7%.

In summary, from the analysis of the first database, the set of indicators that best predict the behavior of the CDM system are Component 2 *(AOBT_TOBT, ASRT_TOBT, TSAT_TOBT)* as most important, and Component 3 *(TOBT_SOBT, AOBT_SOBT)* as second most important.

For the second database, starting at Node 0, it is noted that the dependent variable is branched into two nodes (1 and 2) that belong to Component 2 (TOBT_SOBT, AOBT_SOBT). This shows that these are the most important CDM indicators. In other words, Component 2 is the indicator or set of indicators that best determine, predict or measure whether the collective processes in the turnaround are on time from all actors.

To continue monitoring Node 1, we see that it branches at Nodes 3 and 4, whose most influential variable is Component 3 (AOBT_TOBT, ASRT_TOBT, ASAT_ASRT*)*, which means that this set of

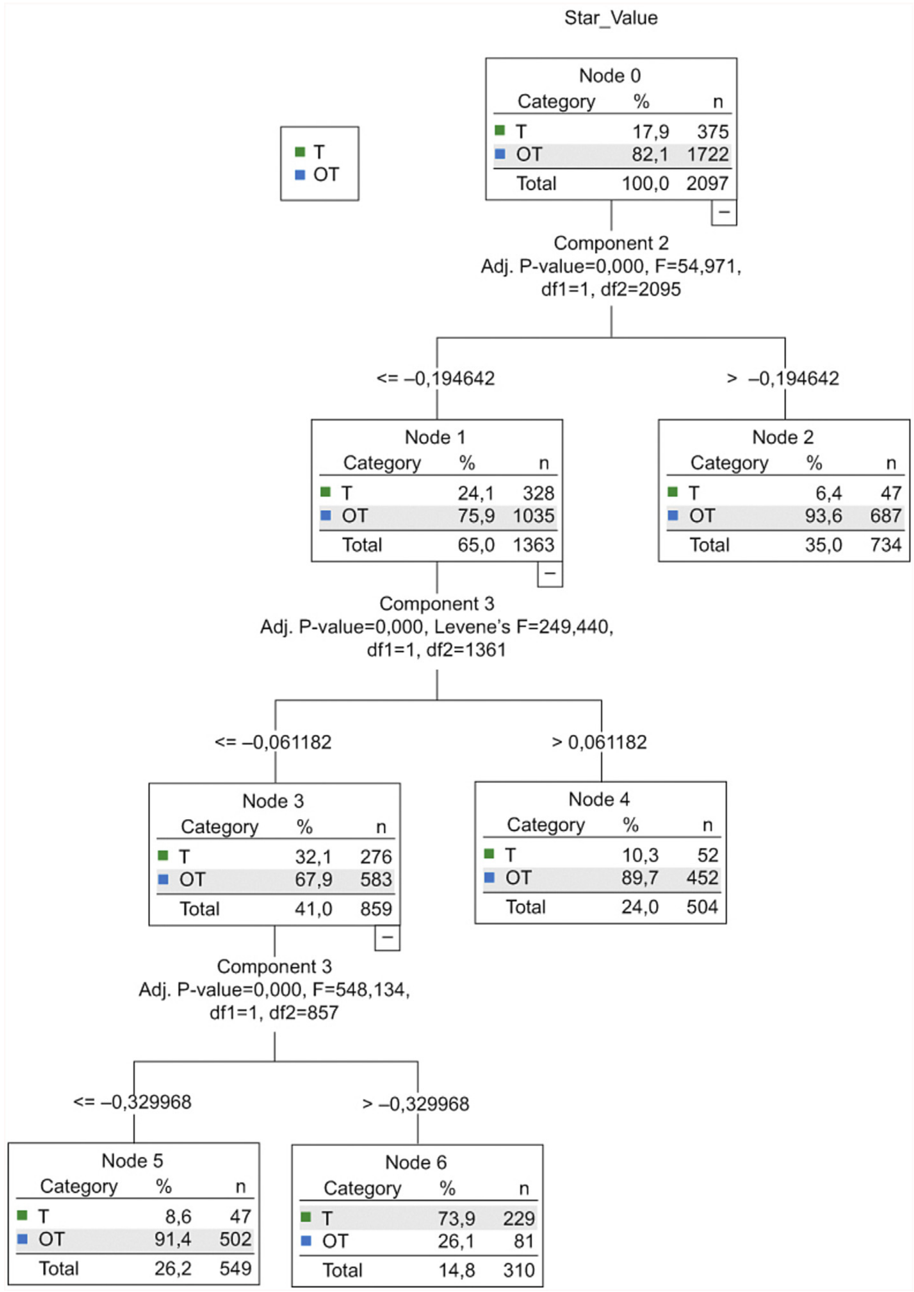

Fig. 4. Classification tree plot Database two.

indicators will be the second most important within the group of independent variables studied. It also shows that Node 3 emphasizes the category of the dependent variable OT, and is assigned a value of 67.9% with T at 32.1%. In the same category, Node 4 emphasizes OT with 89.7%, but with very low observations compared to the initial 2167 observations that were considered from the beginning.

Following the analysis of the resulting tree, it can be seen that Node 3 continues subdividing into Nodes 5 and 6, with the variable corresponding to Component 3 (AOBT_TOBT, ASRT_TOBT, ASAT_ASRT).

In summary, the set of indicators that best predict the behavior of a CDM system along with the delay conditions of *star values*, are those matching Component 2, followed by those in Component 3.

From the third calculation which corresponds to the third database. Starting at Node 0, the dependent variable branches into two nodes (1 and 2) belonging to Component 4 (AOBT_SOBT), showing that this is the most important set of CDM indicators, and that Component 4 is the indicator that best determines, predicts or measures whether the processes of the airport's turnaround for this particular sample are on time or delayed. By observing the values of the dependent variable at Nodes 1 and 2, Node 1, in this case, predicts values in the category value OT as Node 2.

To continue monitoring Node 1, we see that other branches at Nodes 3 and 4 whose most influential variable is Component 4 (AOBT_SOBT). This means that this variable will be the second most important in the group of independent variables studied. It also shows that Node 3 emphasizes the category of the dependent variable OT, and is assigned a prognostic value of 88.3% to category T. Regarding the calculation at Node 4, the same emphasis in the

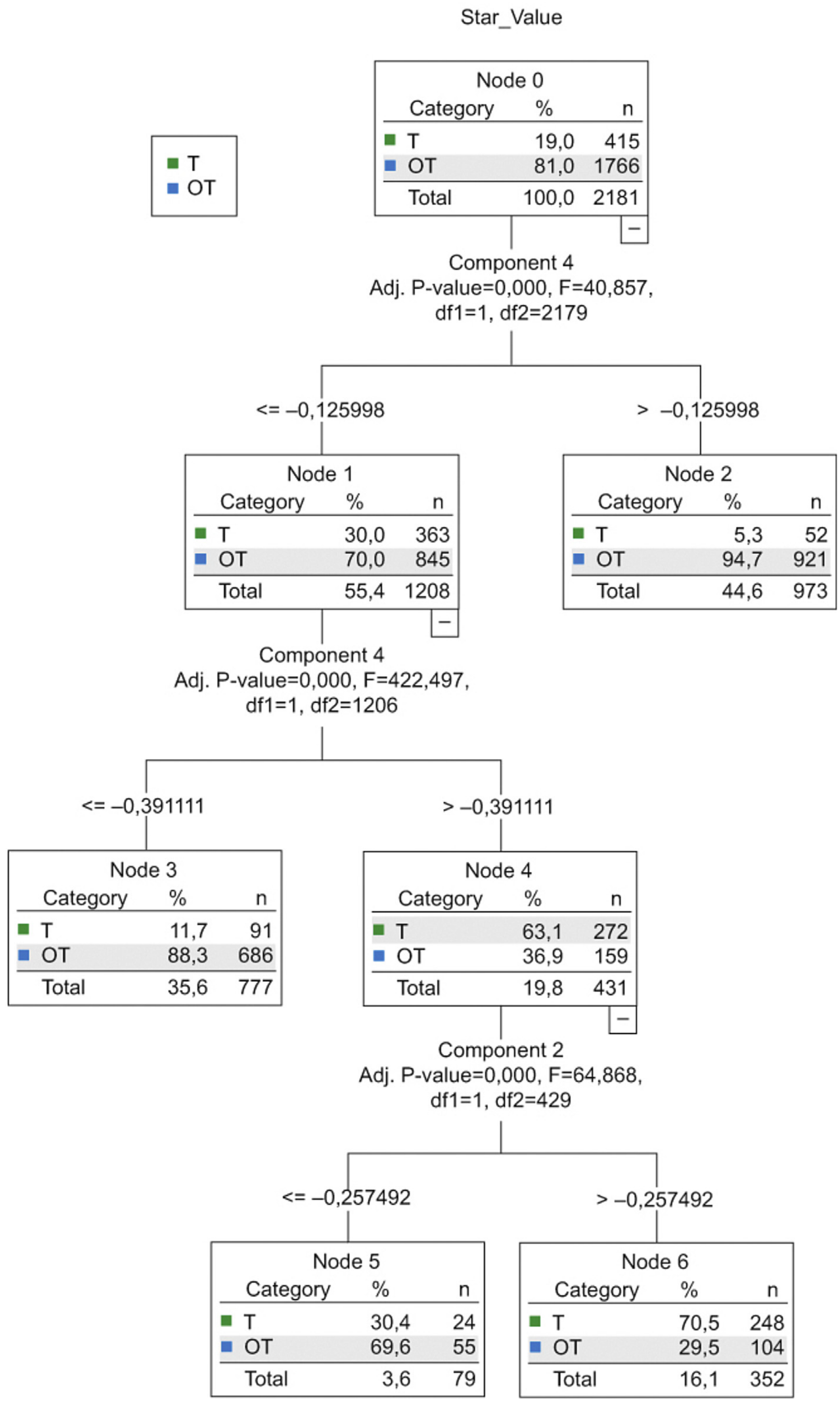

Fig. 5. Classification tree plot for Database three.

category T with 63.1% resulting classification. Additionally, it can be seen that Node 4 branches off into Nodes 5 and 6, with Component 2 *(ASRT_TSAT, ASAT_TSAT, ASAT_ASRT)*.

In summary, the set of CDM indicators that best predict the behavior of the *star value* are those matching Component 4; of second importance are those that correspond to Component 4, and reassigned to third place was the set of indicators corresponding to Component 2.

5. Validity of calculation and results

In analyzing the validity of our results, we first determined the

Table 3
Independent variables [31].

Delay codes: Difference between (Actual - Estimated) Times	Description of KPIs according to CDM framework
AOBT-SOBT	*Actual off-block time - Scheduled off-block time*
AOBT-TOBT	*Actual off-block time - Target off-block time*
AXOT-EXOT	*Actual taxi-out time - Estimated taxi-out time*
ASAT-TSAT	*Actual start-up approval time - Target start-up approval time*
ASAT-ASRT	*Actual start-up approval time - Actual start-up request time*
TSAT-TOBT	*Target start-up approval time- Target off-block time*
AOBT-ASAT	*Actual off-block time- Actual start-up approval time*
TOBT-SOBT	*Target off-block time - Scheduled off-block time*
ASRT-TSAT	*Actual start-up request time- Target start-up approval time*
AXIT- EXIT	*Actual taxi-in time - Estimated taxi-out time*
ASRT-TOBT	*Actual start-up request time - Target off-block time*

Table 4
Set of components extracted from independent variables.

Selection of components in Database 1	
Component	Set of KPIs
Component 1	*ASRT_TSAT, ASAT_TSAT, ASAT_ASRT),*
Component 2	*AOBT_TOBT, ASRT_TOBT, TSAT_TOBT),*
Component 3	*TOBT_SOBT, AOBT_SOBT*
Component 4	*AOBT-ASAT*
Selection of components in Database 2	
Component	Set of KPIs
Component 1	*ASRT-TSAT, ASAT-TSAT, TSAT-TOBT)*
Component 2	*TOBT-SOBT, AOBT-SOBT*
Component 3	*AOBT_TOBT, ASRT-TOBT, ASAT-ASRT*
Component 4	*AOBT-ASAT, AXOT_EXOT*
Selection of components in Database 3	
Component	Set of KPIs
Component 1	*AOBT-TOBT, ASRT-TOBT, TOBT-SOBT*
Component 2	*ASRT-TSAT, ASAT_TSAT, ASAT_ASRT*
Component 3	*AOBT-ASAT, AXOT-EXOT*
Component 4	*AOBT-SOBT*

Table 5
Predicted CDM indicators from turnaround.

Data set	Predicted indicators as most critical
Database One	*AOBT_TOBT, ASRT_TOBT, TSAT_TOBT*
Database Two	*TOBT_SOBT, AOBT_SOBT*
Database Three	*AOBT_SOBT*

estimated risk of calculation, and then the classification table. We found that the results were consistent with the estimated risks. The risk estimates show the proportion of the data that is not predicted by the tree. For example, Table 6 shows less risk from all three databases that were utilized in the calculation. This risk is represented in percentage of the data.

Table 7 shows how much the quantity of prediction in the classification the algorithm correctly classified in all the cases. Comparing from Table 1, the number of observations in all the three databases, QUEST algorithm was able to classify to the highest. From our results, it can be seen in Table 7 that the overall percentage of declared capacity was 90.2%, and the risk was low at 9.8% in Database 1, which is considered sufficient for this type of technique. The classification was high, with less risk in the rest of the databases as well.

6. Discussion of results

The purpose of this paper was to explore turnaround performance as a result of both CDM processes and collaborative measures from different actors. The results are discussed by the need for a cross-organizational strategy and central authority. The paper has argued that since CDM operates with many stakeholders and is highly integrated, broad, and complex, there is still lack of feedback mechanisms to inform airport actors by using the performance indicators to push for improvements. As such, this study was able to propose a method on how collaborative measures can be applied for management. In order for airports to use measures for managing operations, there is a need for airports to consolidate collaborative measures not only from an ATM system to a PMS, but also to consolidate collaborative measures to collaborative strategies in the turnaround.

6.1. Variation in predicted measures

Initially, turnaround indicators have been regularly static. The easiest integrated performance indicator for airports has been on-time performance. Airport actors use delay code systems that only show the end results, but are not able to track the propagated (or reactionary) delay implications. With the advent of CDM, the results show that airport managers can track back through the milestone approach and enhance their operations with regard to the predicted indicators. The variations in the predicted indicators show that collaboration in the turnaround process has moved from static to dynamic because of different strengths in the operations as well as by different actors with different interests, who are also bonded. These results highlight an important feature for the quality of Target Off-Block Time (TOBT)[4] (see Appendix). As part of the whole network, the stability of TOBT depends on how stable the collaborative measures predicted are, and get used by management for bottleneck reduction. In brief, the selected or predicted indicators will reflect how stable TOBT will finally appear, which has a big impact with on-time performance. Moreover, the dynamic nature of the indicators conforms to the guidelines given in the CDM implementation manual to airports that state that actors involved in airport activities that correspond to such KPIs need continuous monitoring for improved delay reductions.

Given these results, several insights into CDM operations are obtained. With this feedback mechanism, CDM becomes an extendable, profitable, self-learning system, as well as having a prudent feature—ownership rights—as an implication. These CDM features are discussed in more detail below.

6.1.1. Extendable system

The results show that turnaround performance can be both extended and enhanced. Based on our sample, the dependent variables used were set to minimal delay conditions. Moreover, the prediction of the measures shows that the CDM system is still an extendable system. The findings show that its extendable because through predicted measures, the airport can predict how much more movements it can handle with such delay or even adjusting the delays. Depending on the supply and demand on the runway and with the delay conditions provided, the current calculations

[4] TOBT is an important value for all airport partners because it is used to predict the subsequent phases in the departure process and plan the pre-departure sequence.

Table 6
Risk tables.

Risk table						
Method	Database 1		Database 2		Database 3	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Resubstitution (%)	0.098	0.008	1.08	0.007	0.124	0.007

Table 7
Classification table.

Observed	PREDICTED DATABASE 1			PREDICTED DATABASE 2			PREDICTED DATABASE 3		
	T	OT	Percent correct	T	OT	Percent correct	T	OT	Percent correct
T	302	94	76.3%	229	146	61.1%	248	167	59.8%
OT	53	1049	95.2%	81	1641	95.3%	104	1662	94.1%
Overall Percentage	23.7%	76.3%	90.2%	14.8%	85.2%	89.2%	16.1%	83.9%	87.6%

Growing Method: QUEST, Dependent Variable: *Star value*.

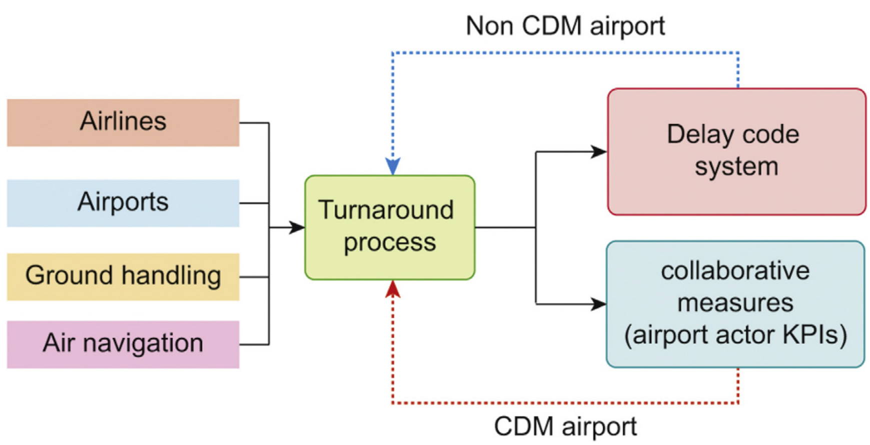

Fig. 6. CDM airport vs non-CDM Feedback Mechanism.

show even more flights can be handled when all airport resources are fully optimized by using a feedback mechanism if the amount of collaboration, information sharing could be enhanced through continuous improvement. As such, the airport can be able to predict the maximum number of movements it can handle while maintaining minimal delay conditions in operations, which could also be adjusted accordingly.

6.1.2. *Profitable system*

Since continuous improvement is the key factor to enhance the system, all actors will then benefit from the envisioned CDM benefits, as they will be able to derive tangible benefits from the feedback mechanism for continuous improvement. For example, airport actors will normalize how many additional slots can be sold and airlines will estimate how many additional rotations can be made with the same fleet. Ground handlers will normalize, using their resources adequately and service however many additional aircrafts they can with few resources, while air navigation services will handle more movements and increase runway throughput.

6.1.3. *Self-learning system*

From the predicted indicators, the significance of examining the future performance of such a system is that the use of collaborative measures creates a self-learning platform. This is because the dynamic nature of the indicators will motivate actors for continuous improvement and, through continuous improvements, the system will gradually be transformed to meet new target times for future flights, and collaboration and information sharing will continue to be improved. This is an important aspect as more target time will be refined and, hence, the quality of on-time performance can be advanced to remedy bottlenecks and redundancy in the system (see Fig. 6).

6.1.4. *Lack of ownership rights for collaborative measures*

Fig. 6 shows how collaborative CDM measures can be used as a feedback mechanism, as opposed to the previous system of using delay codes. With CDM airports and the predictions of our results, continuous improvement can be enacted with less ignorance concerning KPIs.

This paper argues that CDM indicators are collaborative and include the behavior of many actors; however, there is no feedback mechanism for how to use collaborative measures. Among all actors, important questions for management may arise: Who owns the rights to shared data, and who should be responsible for adjusting the system? Overall, we find that our results highlight the important managerial aspects in the turnaround process, like actors that use CDM requiring robust collaborative leadership that amplifies their activities beyond their individual organizational borders, as well as policy recommendations. These are also important

[3] The KPIs described in this table are standard CDM metrics for different operations being employed to track aircraft movements from landing to takeoff.

for the system during continuous improvement tasks. Further, with regard to policy recommendations, this research shows how contracts between actors in collaboration can be adapted to CDM operational requirements.

7. Conclusions and implications for future research

This paper started by presenting that it is now an accepted fact that air traffic has increased to a level of capacity that airports cannot handle, and that CDM at airports, if well implemented and managed, is meant to optimize and remedy capacity challenges and put a dent in environmental concerns. Moreover, this paper draws on CDM operational principles and real operational data to explore the role of collaborative measures in managing the turnaround process at airports. The data included turnaround times, such as Scheduled Off-Block Time (SOBT), airport slots, touchdown times, taxi-in times, on-block times, off-block times, taxi-out times, and Calculated Take-Off Time (CTOT), which is a process that includes all CDM operations before, during, and after turnaround.

Our method was able to capture the dynamic nature of CDM KPIs collectively as collaborative performance from all actors. The predicted measures then showed us how airports could use CDM measures to assess on-time performance as a result of their activities in the turnaround process. However, our method was able to predict measures that actors can use to align their strategies for CDM to benefit all parties involved. As such, the major conclusion that can be drawn from this study is that collaborative CDM measures can be used by management as a feedback mechanism to push for more enhanced decision-making and use of airport resources.

For future work, it would be worthwhile to include network benefits and performance within the framework of CDM, which can be achieved by including departure planning information as inbound and outbound indicators. In addition, this paper used a predictor variable with a minimal tolerance of delay condition. Future study should enhance the delay conditions within, say, a window of $\pm$ 5-min delays (i.e., *-5 star values 5)*, in order to explore the process of predicting the indicators. Further, more studies are called for to propose other ways that airport actors can have a cross-organizational methodology to measure turnaround performance or how collaborative measures can be used as a feedback mechanism.

With more airports being classified as capacity-critical airports (Gelhausen et al., 2013), the demand for airports to increase their capacity throughput with scarce resources is enormous. CDM is one of the innovative standards through which the future ATM system plans to fully integrate airports into a collaborative network. If well implemented and well managed, the envisioned benefits, such as the enhancement of runway throughput, proper use of resources, less taxi times, and various environmental benefits, including those at the European level as targeted by *Single European Sky ATM Research* (SESAR, 2014), will be realized. Accordingly, this study has presented a new method for further understanding of airport TAP in relation to CDM operations. In a similar manner, this new framework provides an understanding that performance as a collaborative system can be analyzed and later improved. It is through cross-organizational performance that discrepancies can be detected and linked to individual companies for optimal network benefits, that is, to better determine, predict, or measure the efficiency of the airport processes of all actors.

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Appendix

CDM operational concept

As part of the Single European Sky (SES), Airport CDM (Airport Collaborative Decision Making) is a concept for optimizing airside operations. ACDM relies heavily on *collaboration, trust and information sharing* among different airport actors such ATC, airlines, ground handling and airport operators. For ACDM to achieve its role in the TAP at airports and in the single sky network, it must coordinate the inbound, turnaround and outbound operations, reducing delays as much as possible. The following section highlights basic foundations of CDM.

Information sharing, trust, collaboration

Fig 7 shows information sharing, trust and collaboration are three general foundations for CDM at airports. For ATC, CDM information sharing replaces the "*first come, first served*" principle with the *"best planned, best served"* principle, which is supported by the pre-departure procedures. Ground handlers are to predict off-block times, receive accurate Estimated In-Block Times (EIBT) and pre-departure sequencing (Eurocontrol, 2012). Information sharing also makes it possible for the 16-milestone approach to be achieved through confirmations in the flight plan. Information exchange is also vital for the Central Flow Management Unit (CFMU) to allow space usage. For the TAP, real-time information is also important, since not every actor has full situation awareness.

Because of the strict times and the nature of the operations, trust is critical between airport actors in collaboration. In order to meet target times, all actors are expected to not only share the right information, but also accurate information even when it is not in favor of their own operations, but rather for the good of the entire network. In cases where less information is shared, this may lead to bottlenecks and stall operations. As a dependency network, CDM actors depend on each other not only for information, but also for airport space, resources and target times. Since CDM is all about information sharing, the quality of the information matters to the other actors, hence collaboration is vital. A problem may occur when actors have less information on which to base operational decisions, such as insufficient information or late information.

Main operational concepts -TOBT and TSAT

Fig 9 shows the time differences between TOBT and TSAT. In this section, we present two indicators that are affected by the quality of collaboration, information sharing and trust, which are critical to the TAP operations (i.e., TOBT and TSAT).

Target Off-Blocks Time (TOBT) represents the time when the

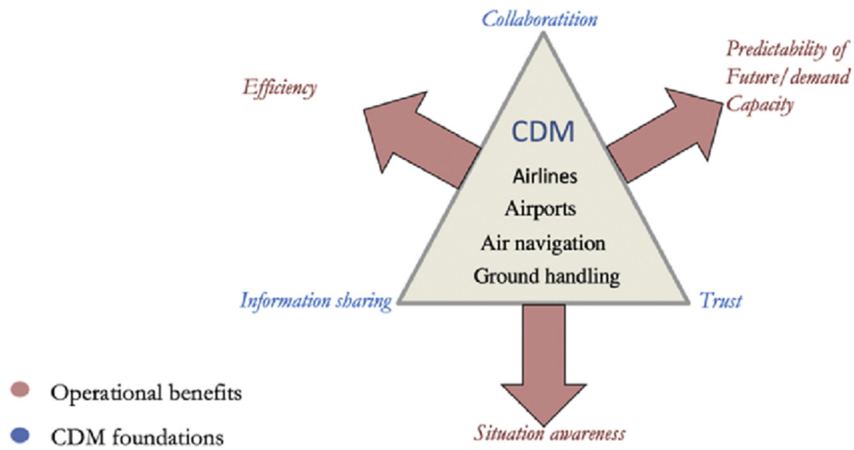

Fig. 7. CDM benefits, work foundations and airport actors involved.

turnaround coordinator estimates that an aircraft will be ready for off-block. TOBT time is communicated to all actors via CDM platform; this time means that all doors are closed, the boarding bridge removed, a pushback vehicle is available, and the plane is ready for start-up immediately with pushback within 5 min after reception of start-up clearance from ATC. This means that within a window of −5 to +5 min, the aircraft is ready to leave the stand. According to CDM operations, in case the aircraft is not ready, TOBT is lost and a new time is scheduled, and any other aircraft that is ready takes the space for taxiing. A new TOBT is then updated for the first aircraft to be ready. This kind of collaboration between actors forms the *"best planned, best served"* principle.

Target Start-Up Approval Time (TSAT) is the time issued by ATC for the aircraft to start-up while considering local constraints. TSAT is vital in reducing queuing time and creates better runway utilization. TSAT for pilots can be revised if there is a change in runway, or if there is an update in TOBT, and this can be communicated to pilots via a different channel.

Fig 8 shows how collaborative process affect the quality of TOBT. The accuracy of TOBT and TSAT at a CDM airport is an operational

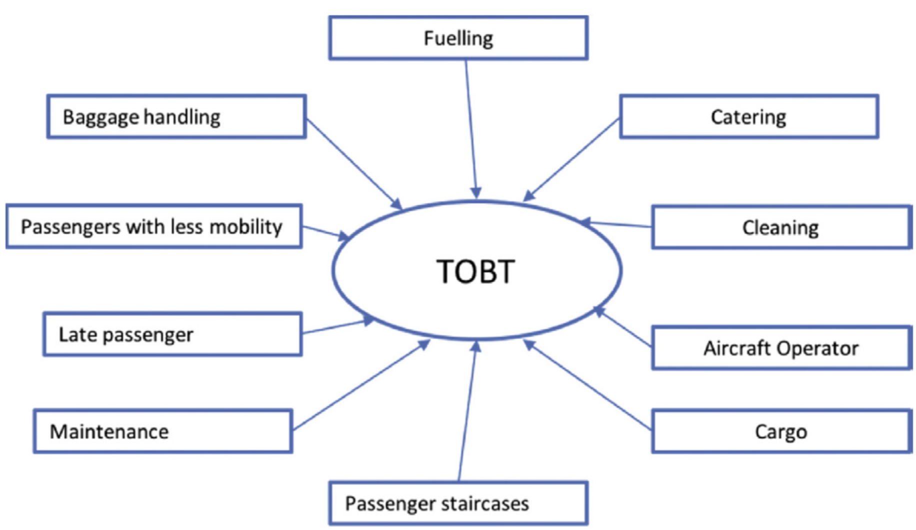

Fig. 8. Factors that affect the quality of TOBT.

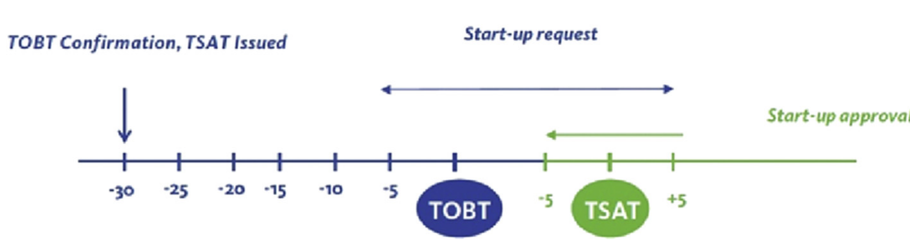

Fig. 9. TSAT and TOBT.

partnership procedure between all involved actors in the process of turnaround of an aircraft, which is to say between the Airport Operations, ATC, Aircraft Operators, and Ground Handling, including service companies such as, refueling, catering firms, cleaning companies, and then the main actor's airline and air traffic control, who are responsible for coordinating all the processes to be able to produce and maintain TOBT and TSAT quality as always scheduled.

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