Assessing the Viability of an Occupancy Count Prediction Model

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***Abstract*— This paper describes the initial validation of the approach developed by COPTRA to improve planning accuracy using an occupancy count prediction. It is based on the use of uncertainty to improve trajectory and sector occupancy estimations. The operations described in the paper take place in a Trajectory Based Operations (TBO) environment in which it is assumed an advanced Demand and Capacity Balancing (a-DCB) system is in place.**

The paper focuses on the first two validation exercises performed by COPTRA to establish the current performance model baseline and to determine the improvement achieved when applying the COPTRA occupancy prediction model.

Keywords-component; Sector Occupancy Count; Demand Prediction; Uncertainty

I. Introduction

To understand the importance of uncertainty in planning and thus understand how the integration of uncertainty into trajectory and sector occupancy estimation improves the efficiency of the planning process, we need first to understand the main notions behind TBO and a-DCB.

A. *Trajectory Based Operations*

Trajectory Based Operations (TBO) is expected to be one of the major improvements of the future ATM system. TBO will provide flexibility to airspace users and increase predictability of the ATM network. This will lead to more efficient management of ANSP's (Air Navigation Service Providers) and airport resources while applying the required safety standards.

TBO proposes a paradigm shift from radar operations (in which the current and planned a/c position are known), to Trajectory operations (in which the current and planned a/c position are known and shared). TBO is ultimately based on the ability of the cockpit automation to fly the aircraft more precisely and predictably, resulting on a reduction of the routine controller tasks through a reduction of the associated uncertainty [1]. TBO differs from "Radar Based Operations" in which the "controller" attempts to predict the flight path of the aircraft using a cognitive process that uses a combining its general intent (flight plan) and current (and recent past) sensed position from surveillance [2].

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TBO, or more specifically 4D Trajectory Management (TM) facilitates the shift from flight management through tactical intervention, towards a more strategic focus on planning and to intervention by exception [3]. The availability of precise, four-dimensional flight intent allows de-confliction of aircraft through pairwise "separation" and group de-confliction "Flow Control".

TBO provides a strategic focus on planning and intervention [3]. It binds ATM components during tactical planning and flight operations by synchronizing the view of the trajectory between different actors. It also ensures consistency between the trajectory and/or generic constraints that originate from the various ATM components and the various regions that shape this trajectory.

The trajectory monitoring with respect to its 4D target windows tolerances, is performed on the ground, preferably through automated means. Advanced DCB (a-DCB) processes will ensure that Flow and Capacity Management operations are conducted on a holistic, seamless, continuous, and fully collaborative basis. This establishes an optimised and stable Network Operations Plan (NOP), enabling all partners concerned to fine-tune the planning of their resources per the latest known information [1].

TBO enables the effective dynamic adjustment of airspace characteristics meeting predicted demand, whilst aiming to keep any distortions to the Planned Trajectories to the absolute minimum. It also provides sufficient flexibility for optimization purposes. In a nutshell, TBO creates an environment where air and ground stakeholders share a common view of the aircraft's trajectory enabling flight management to follow as closely as possible the Airspace User's (AU) ideal profile, whilst optimising the flow of air traffic. TBO acts as the glue between the ATM components by synchronizing the trajectory prediction and ensuring consistency between the trajectory and/or generic constraints that originate from the various ATM components and the various regions that shape this trajectory.

The introduction of TBO requires the development of advanced ATM tools and methods to allow the effective management of individual trajectories, both in isolation and in the context of a flow. By synchronizing the trajectory, its constraints (with tolerance levels) and its generic constraints

[9], ATM stakeholders increase their awareness enabling them to better anticipate on the events that may impact them.

TBO brings measurable improvements in ATC planning [1] that will lead to improvements in the prediction of sector occupancy counts. Ultimately, TBO enables the implementation of a-DCB to switch capacity management from the current global hour-based traffic limitations to minute-based streamlined actions at sector level.

B. Advanced DCB

DCB is carried out through a layered planning process applied at the regional level, in close cooperation both with Sub-Regional and Local levels. It starts with the long-term planning phase, several years in advance, and finishes during the flight execution phase, through the medium and short-term planning phases. It is Airspace User oriented meaning that the new process shall offer as much as required en-route capacity so that Airspace Users can meet their business objective.

SESAR proposes to enhance DCB to manage flights after departure, filling the gap between ATFCM and ATC. In addition, the User Driven Prioritization Process is triggered in case of severe capacity drop so that Airspace Users can prioritize the flights of high marginal cost.

Advanced DCB evolves the existing DCB process and concept to a distributed network management function. This function takes full advantage from the SESAR layered collaborative planning and the Trajectory Management principles, as well as the SWIM technology to improve the effectiveness of ATM resource planning and the network performance of the ATM system in Europe. SESAR 2020 addresses the development of a-DCB from three perspectives:

- Improving the local network intelligence[1] and closing the gap between DCB and ATC
- Improving the collaborative network functions and establishing a compound network intelligence
- Improving the Shared Situation Awareness and encouraging collaborative network solutions

a-DCB measures rely on improved predictability to enable ANSPs adoption and improvement of the tactical capacity management procedures to optimise traffic throughput (with the STAM -Short Term Air traffic flow and capacity Measures). These measures are supported by automated tools for hotspot detection, and for the promulgation and implementation of STAM including CDM (Collaborative Decision Making). These tools are envisaged to be at local and regional network management function level for information sharing and CDM. a-DCB measures are built on the basis of STAM deployment (hotspot, coordination tool, occupancy traffic monitoring values (OTMV)). The enhancements foreseen focus on improved predictability of operations, including iSBT/iRBT (initial Shared Business Trajectory / initial Reference Business Trajectory) supported traffic and complexity prediction, weather, airport operations (departure sequences, ground handling, gate management, runway usage, etc.), What-if function and network view capabilities.

To achieve a-DCB some aspects of Air Traffic Management (ATM) need to be improved (amongst others):

- Prediction of traffic and workload in the 1 to 4 hour range before the flight enters the airspace region of interest.
- Operator's awareness of performance impacts and trade-offs
- Efficiency of the daily operations
- Reaction to short notice traffic situations
- Exploitation of non-standard capacity opportunities
- Integration of the use of local and network datasets

COPTRA addresses the prediction of traffic and workload in the 1 to 4 hour range, with the aim to help increase the efficiency of the daily operations.

COPTRA aims to improve the information of the estimation of demand through the modelling and understanding of the uncertainty associated to it. Thus, the contribution of COPTRA will have a direct impact on the a-DCB, enabling the achievement of the new ATM paradigm focus in a more strategic phase-based.

COPTRA provides a novel approach to the estimation, based on the development and use of a toolset based on:

- Integration of trajectory uncertainty, within the trajectory description
- Estimation of sector occupancy based on the use of enhanced trajectory description and on the computation of distribution of the probabilistic occupancy counts
- Quantification of departure time uncertainty using stochastic network models.

All three toolsets combine to produce an approach geared towards the provision of better sector occupancy predictions.

STAM consists in smoothing sector workloads by reducing traffic peaks through short-term application of minor ground delays, appropriate flight level capping and exiguous rerouting to a limited number of flights. These measures can reduce the traffic complexity for ATC with minimum curtailing for the airspace users. STAM is based on high-quality data for prediction and accurate traffic analysis and will be an important contribution to dynamic DCB. Improving the occupancy count estimation, will provide better application of short term air traffic flow and capacity measures to Improve tactical capacity management.

[1] Network Intelligence refers to the “shared situational awareness” that will be obtained through the combination of common sets of values and rules, as well as the existence of highly interconnected local network management systems.

The use of uncertainty in the estimation of occupancy count is a field of research that has not been fully addressed. Amongst the research performed in this area, we can cite [4], [5] who have developed a technique for analyzing airspace demand predictions based on observed data from a prototype TFM decision support system. [6]–[8] evaluate the potential impact of improved accuracy in flight timing predictions on reducing uncertainty in traffic demand predictions, hence leading to better identification of congestion. None of the work performed so far has addressed the use of uncertainty to improve occupancy estimations.

II. THE COPTRA APPROACH

COPTRA's approach attempts to improve planning accuracy in the tactical phase. A brief description of the approach is provided to understand the validation strategy and process (please refer to [9]–[12] for a full description).

The COPTRA approach has two steps:

- Obtaining the probability that a flight is in a sector.
- Computing the distribution of the probabilistic occupancy count from the individual probabilities of a flight being in a sector.

To compute the probability that a flight is in a sector, a set of probable trajectories and a description of temporal and spatial uncertainty for each flight is provided, as shown in Fig. 1. On it, the full probabilistic setting of a flight f between departure and destination is shown. It is characterized by many probable trajectories (here r1, r2, and r3) each one of them associated with a probability, as well as their uncertainty (not shown in the figure). Different probable trajectories can cross different sectors, e.g., r1 crosses sectors 1, 2, 4, 5. Each of these probable trajectories is defined as a three-dimensional probability density (PDF), used to compute the probability that a flight is in a sector. Although two sources of uncertainty are considered, it is assumed that only time-delay uncertainty is significant for the model.

Then, the probabilistic occupancy count is calculated. The probabilistic occupancy count of a sector s at time t is represented as $\Theta_{st} : N \rightarrow [0, 1]$, which is a discrete PDF. For any number of flights, N, the PDF Θ_{st} will tell us the probability that N flights are in the sector s at time t. Using recursive methods and dynamic programming techniques, it is possible to compute the convolutions among the probabilities to obtain the probability that N flights are in the sector s at time t. The algorithm and calculation method is described in full in [11].

III. VALIDATION EXPERIMENTAL METHOD

COPTRA is at the TRL-1 maturity level and is expected to mature up to TRL-2 level. Based on this assumption, the validation performed within COPTRA will aim to provide an initial operational concept (including the algorithm description), the operational context of application, as well as an initial assessment of the potential performance benefits accrued by the application of the COPTRA algorithm. The result should be the formulation of the technology and an initial proof-of-concept of said technology. This should be completed with a description of the potential operational application of it.

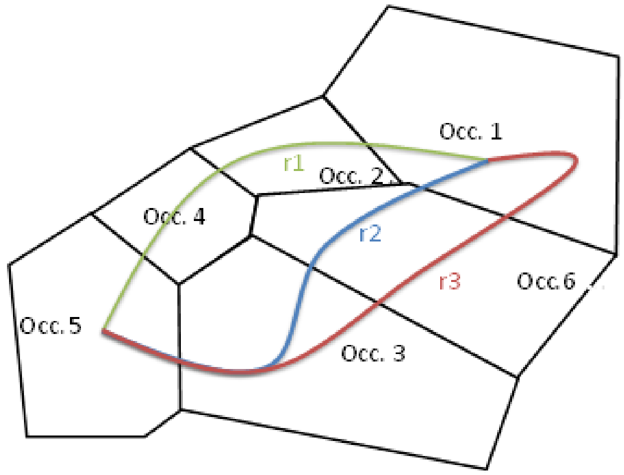

Figure 1 Full probabilistic of a flight between departure and destination

Keeping these premises in mind, COPTRA validation strategy will be based on the use of experimental work built on the analysis of historical datasets (obtained from EUROCONTROL and CRIDA / ENAIRE)[2] and the use of the COPTRA algorithm. The analysis will be based on the results obtained from five exercises as defined in the COPTRA validation plan:

- Exercise 01: Establish the quality of the current estimation process using an improved flight plan (imFPL) as the most probable trajectory given a flight plan.
- Exercise 02: Establish the initial viability of the proposed methods to estimate the occupancy in a set of sectors.
- Exercise 03: Determine the potential improvements brought by the COPTRA approach in terms of occupancy count prediction accuracy and uncertainty.
- Exercise 04: assess the possible improvements of using occupancy count distributions in predicting hotspot and linking a probability to their occurrence
- Exercise 05: Explore ways to display how uncertainty (as conveyed by occupancy count distributions) can be visualized through enhanced occupancy count graphs. These new visualizations will be presented to flow management experts and their feedback collected.

This paper focuses on the results generated in the first two exercises. For each exercise, this paper presents the dataset used to produce the results, the process followed and the validation goals.

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[2] The information is delocalized and time and date shifted to account for potential privacy issues.

A. *Exercise 01*

The first exercise compares occupancy counts obtained through flight plans (FPL) in different time horizons, with the occupancy counts obtained from the use of the improved flight plan, imFPL. The objective is to assess the quality of the predictions used currently to estimate the occupancy count of a sector and establish a baseline for further validation.

This exercise introduces the concept of the imFPL, which is a Flight Plan that has no uncertainty. The methodology to create the imFPL relies on two aspects: first, the original flight plan -which could be the initial or intermediate one- and second the radar tracks of the flown trajectories linked to the selected flight plan. The imFPL should provide the most probable trajectory between a given city pair. To do so, the historical set of radar tracks associated to a FPL is analyzed to select the most probable one. This way, each FPL is associated to its most probable trajectory, which is called imFPL. In this initial validation exercise of COPTRA, only one radar track is linked to each FPL: its flown trajectory. This simplification of the methodology allows the identification of the potential benefits expected with the use of the imFPL in order to perform a further refinement on the methodology to obtain imFPL in later studies.

The applicability of the imFPL, understood as a "sort" of probabilistic trajectory, is mainly to improve the accuracy of the predicted traffic demand, with respect of using the original flight plan, since it will allow a better calculation of the entry and occupancy counts in a sector. The idea behind this is that FPLs managed by NM and ANSPs are not always as accurate as expected, since in many occasions AUs fill their FLP in a generic way that do not match reality. The introduction of imFPL leads to a better understanding of what is expectable given a FPL, and therefore NM and ANSPs will know that although the FPL states a certain trajectory, historical data concludes that this FPL always follow a different trajectory. Since the imFPL is closer to the trajectory linked to the selected flight plan, it is expected to have an hourly entry count prediction closer to the actual value. This represents the best possible outcome of today’s non probabilistic estimation process and constitutes the baseline for the COPTRA validation process.

The dataset used in this exercise was constructed from the historical databases from EUROCONTROL and CRIDA / ENAIRE. To elaborate the dataset the following information was selected for a specific timeframe:

- FPLs at three-time horizons (3 hours, 1 hour and last filed FPL in the system. In those cases where there was only one FPL, all three FPL are assumed to be the same.
- Radar tracks obtained from the controller working position recordings, used as the imFPL.

The selection of the specific validation scenario arises from the comparison of three different criteria (calculated between April 2016 to June 2016) that give raise to three different tables:

- Ranking of days with more controller issued vectors.
- Ranking of sectors with more controller issued vectors.
- Ranking of O/D (origin/destination) with more controller issued vectors.

The number of controller issued vectors is used as the critical criteria to select the most appropriate day and sectors because it is expected that the more controller issued vectors used to shorten the planned trajectory, the higher will be the deviation from the planned trajectory, and thus the higher deviation between the planned and the real occupancy count. The cross-reference and analysis of the three tables leads to the most suitable day and sectors of study considering the limitations of data acquisition (data must be available in both the EUROCONTROL and CRIDA / ENAIRE’s databases).

The result of this analysis leads to filter the dataset for those flights traversing through the Barcelona ACC in four particular sectors: LECBLVL, LECBP1L, LECBP1U and LECBPP2 that occurred on the 12 of May of 2016.

The validation process consisted on the application of three steps (occupancy is calculated using the method included in [13]):

- Calculation of the occupancy count (OCC_{FPL}) using the FPLs estimated at the three-time horizons.
- Calculation of the occupancy count using imFPL (OCC_{imFPL}). This is taken as the best value that could have been estimated.
- Calculation of the difference between the occupancy count variables (OCC_{FPL} and OCC_{imFPL}). The difference between the control group (OCC_{imFPL}) and the dependent group (OCC_{FPL}) is calculated using the effect size [14].

In this exercise, occupancy counts predictions are made in a variable timeframe corresponding to the three look-ahead times specified (3 hour, 1 hour and 0 hour). For the case of the imFPL, as radar tracks are used, no prediction is made since they are the real occupancy counts.

The validation objective is twofold:

- Determine the current occupancy estimation results (in the best possible scenario) and establish the occupancy count error.
- Establish the baseline for further validation experiments.

B. *Exercise 02*

The second exercise compares the occupancy counts based on the imFPL as described in exercise 01, which is the real flown trajectory linked to each FPL, with the occupancy counts obtained using the COPTRA occupancy count algorithm.

The dataset used in this exercise was constructed from the historical databases located in EUROCONTROL and CRIDA. To elaborate the dataset the following information was selected for the same timeframe and geographical location as exercise 01:

- Measured actual occupancy count (directly obtained from the operational database).
- Planned occupancy count (directly obtained from the operational database).

The validation process consisted on the application of the following three steps:

- Estimation of the occupancy count using the the COPTRA algorithm: $OCC_{probabilistic}$.
- Calculation of the occupancy count using imFPL (as obtained in Exercise 01): OCC_{imFPL}.
- Calculation the difference between the occupancy counts variables. The difference is calculated using effect sizes. In this case the control group is the OCC_{imFPL}.

The validation objective is twofold:

- Improve the prediction of hotspots through the provision of probabilistic occupancy counts.
- Understand the impact of the use of probabilistic occupancy counts on the surrounding environment (contiguous sectors)

In this exercise, occupancy counts predictions obtained with the COPTRA algorithm are made in the 3 hours look-ahead time.

IV. Results and Discussion

A. Exercise 01 Results

As discussed in the Section III, the dataset elaborated to perform Exercise 01 consisted of the set of occupancy estimations performed on the selected day (at three-time periods), coupled with the actual occupancy measurements, in four Spanish air traffic control sectors. Since the data is based on the observed data, it is set in 20 min intervals. Fig. 2 shows a sample of the data obtained for sector LECBP1U. This specific sector has been chosen because there was a regulation in effect between 08:00 and 10:40. As it can be observed in the figure there is in general a difference between the estimated data and the real occupancy, even in the 3-hours-before time horizon.

As it could be expected, there is an improvement on the quality of estimations as the time of the flight approaches, with more accurate prediction in the 0 hour look ahead time than in the 3 hour look ahead time. The observations performed in Fig. 2 are corroborated by the effect size calculations shown in Table I. Since the standard deviations between the control group and the test groups differ significantly, the effect size has been calculated using Glass' Δ [14].

Table I presents the occupancy calculations at three time horizons (3 hours before flight time, 1 hour before flight and zero-hour FPL). As the FPL approaches the time of flight, the quality of the predictions improves. This is reflected by a decrease in the standard deviation (SD), the mean square error (MSE) and on the Glass' Δ. However, even in the best possible situation the error always remains significant. This is further corroborated by the value of the Δ and of the associated t-test.

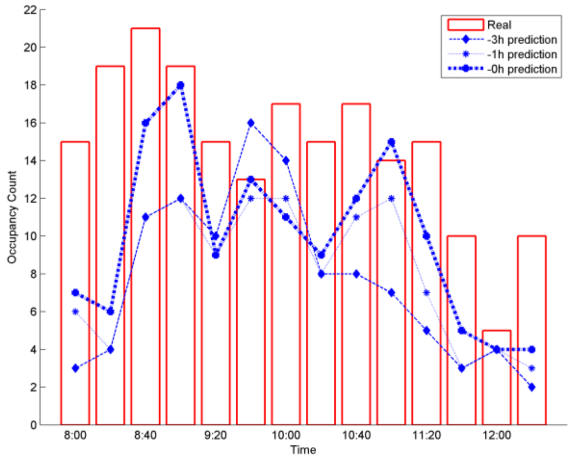

Figure 2 Comparison between estimated occupancy and measured occupancy. Period ranging from 08:00 to 12:40

TABLE I. Effect Size data for Exercise 01.

		SD	MSE	Glass' Δ	CI	t-test
LECBLVL	3h	2,7506	31,0000	1,5690	[0.5672;2.5708]	4,2689
	1h	2,5774	28,2857	1,2258	[0.3050;2.1465]	3,4353
	0h	2,4862	14,0000	0,5393	[-0.2674;1.3461]	1,5351
LECBP1L	3h	2,4099	45,4286	1,5018	[0.5169;2.4869]	4,8116
	1h	3,1483	31,3571	1,1979	[0.2831;2.1126]	3,5203
	0h	3,3553	21,1429	0,9297	[0.0671;1.7923]	2,6638
LECBP1U	3h	4,4308	68,1429	1,6671	[0.6398;2.6943]	4,2906
	1h	3,6132	54,9286	1,5480	[0.5515;2.5445]	4,3904
	0h	4,4973	34,2857	1,1227	[0.2235;2.0218]	2,8669
LECBPP2	3h	1,6723	31,9286	1,8668	[0.7851;2.9483]	5,9928
	1h	3,1796	11,1429	0,6649	[-0.1570;1.4867]	1,64186038
	0h	2,6520	6,2857	0,3069	[-0.4798;1.0936]	0,8327

Exercise 01 shows clearly that there is room for improvement in the prediction of the occupancy count for a specific set of sectors.

B. Exercise 02 Results

As discussed in Section III, the dataset elaborated to perform Exercise 02 consisted of the set of occupancy counts calculated using the COPTRA algorithms and on the real occupancy counts.

It must be pointed out that the estimation of the sector occupancy counts performed by the COPTRA model is performed in 1 minute intervals, whilst the sector occupancy counts estimations in Exercise 01 were performed in 20 minute intervals. Even though the aggregation of the data does not have any effect on the quality of the predictions, it does have an impact on the total sector occupancy counts (which are logically lower when aggregated in 1 minute intervals instead of 20). The estimations used in Exercise 01 were obtained from the operational logs (which are presented in 20 minute intervals) and cannot be changed. As for the estimations obtained through the COPTRA performance model, they were aggregated in 1-minute intervals to increase the granularity of the observations and thus obtain a more accurate representation of the evolution of the traffic.

Fig. 3 shows the comparison between the real occupancy and the occupancy using COPTRA prediction model for the same day as Exercise 01. This figure presents all the different occupancy estimations associated to their calculated probability. It must be pointed out that for the remaining of the section, all the data shown corresponds to the most likely occupancy count prediction.

Further examination of this figure shows that predictions are better adjusted than those performed currently, even though there is room for improvement. This observation is corroborated by the data shown in Table II and Table III, in which significant improvements in the calculated Glass's Δ as compared with those in Table I can be observed. For example, the Δ in Table I for sector LECBP1U at time zero is 1.12, whilst the Δ in Table III for the same sector and time is 0.93.

Fig. 4 presents the predicted occupancy using the most likely (highest probability) sector occupancy count for the 24 hour period and sector LECBP1U. The figure shows potential saturation periods at the period ranging from 08:00 to 10:00, 13:00 to 14:00 and 18:00 to 20:00. This information has the potential to be used for the identification of hotspots, but it needs to be further treated to be completely useful.

Fig. 5 zooms into the data shown in Fig. 4 for the period ranging from 08:00 to 12:40 (which includes the regulation that was actually implemented on the test day). Observation of this figure indicates that the use of uncertainty produces a "smoothing" effect that reduces the estimated peaks. In the present time, occupancy is calculated based on an all-or-nothing event – that is, the aircraft is in the sector or not- and therefore aircraft are fully counted at each sampling time. However, when using COPTRA algorithm and introducing uncertainty, the event of an aircraft being in a sector is spread in time and in fractional part, since there is a probability associated to that aircraft being in the sector at one time or another. This induces a "smoothing" effect that erodes peaks in occupancy count prediction. Given the specifications of the COPTRA algorithm this "smoothing" effect is proportional to the standard deviation of the entry and exit times. The reduction of this effect will be explored in later validation exercises.

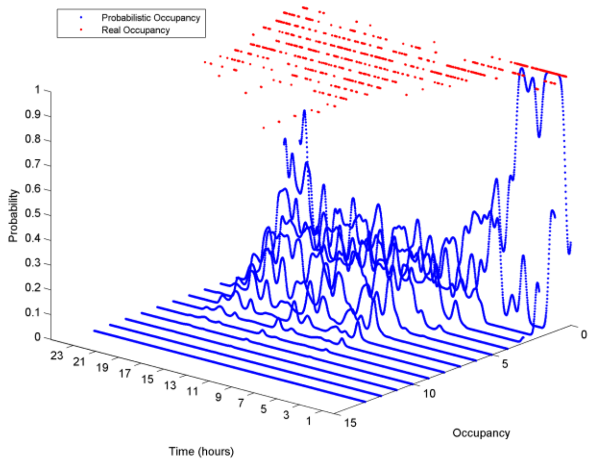

Figure 3 Comparison between measured occupancy (real occupancy) and occupancy predicted using the COPTRA prediction model. 24 hours

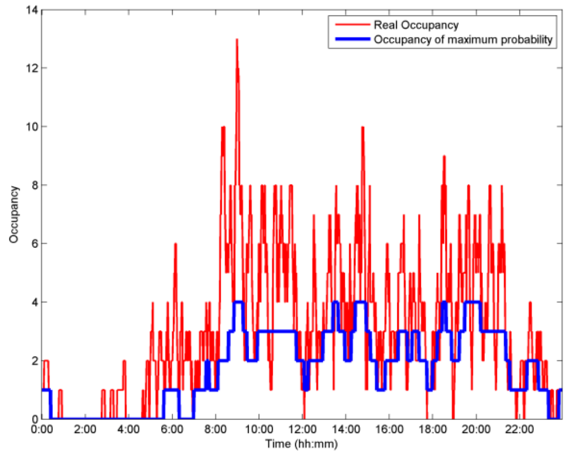

Figure 4 Comparison between measured occupancy (real occupancy) and most likely occupancy using the COPTRA prediction model. 24 hours

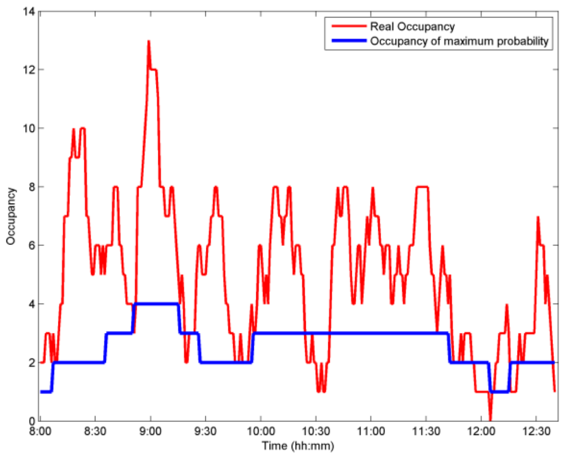

Figure 5 Comparison between measured occupancy (real occupancy) and occupancy predicted using the COPTRA prediction model. Sector LECBP1U, period ranging from 08:00 to 12:40

Table II presents the effect size calculated for the dataset. We can observe an increase in the quality of the predictions as compared with the results of Exercise 01. This increase implies that the performance of the COPTRA prediction model is established.

However, the use of the COPTRA prediction model has a smaller dispersion and provides more consistent results than the current model.

TABLE II. EFFECT SIZE DATA FOR EXERCISE 02.

	SD	MSE	Glass' Δ	CI	t-test
LECBLVL	1,3842	2,5104	0,6456	[0.5688;0.7224]	22,3809
LECBP1L	1,8319	2,1097	0,5061	[0.4307;0.5815]	17,6969
LECBP1U	2,3142	4,3931	0,5191	[0.4437;0.5946]	13,3277
LECBPP2	2,4153	5,8417	0,4630	[0.3880;0.5380]	14,8377

To further gain insight on the performance of the COPTRA prediction model, Table III shows the effect size calculations for the same dataset but for the period ranging from 08:00 – 10:40 (the time at which a regulation was active in LECBP1U). Table III shows a significant improvement of the occupancy estimation for sector LECBP1U performed with the results derived from the COPTRA algorithm.

TABLE III. EFFECT SIZE DATA FOR EXERCISE 02. PERIOD RANGING FROM 8:00 TO 12:40

	SD	MSE	Glass' Δ	CI	t-test
LECBLVL	1,4315	4,4413	1,0952	[0,9062;1,2842]	17,6434
LECBP1L	2,0090	5,6655	0,8744	[0,6935;1,0553]	13,9563
LECBP1U	2,5778	10,9181	0,9398	[0,7566;1,1229]	15,1275
LECBPP2	2,1673	13,0107	1,4133	[1,2102;1,6163]	22,6296

Altogether, the results obtained in Exercise 02 show that the COPTRA prediction model is more capable to estimate the occupancy than the current situation.

C. *Limitations of the results*

It must be pointed out that results are based only on archived data. This implies that the predictions are always made over data which might have been impacted by a previous traffic flow capacity measure. Full validation of the results would require the use and test of the algorithms on a real-time data.

Additionally, the dataset was constructed using a partial view of the European Air Traffic Management network limited to Spain. Given the nature of a-DCB, the study should be enlarged to include the complete ECAC area.

The identification of hotpots currently relies strongly on the value of the pre-established sector capacity. This fixed value has less meaning within a context in which an aircraft can be estimated to be in different sectors simultaneously with different probabilities due to the use of uncertainty. To account for this effect, a-DCB should propose the identification of hotpots using complexity calculations based on the occupancy sector probabilities.

Lastly, the validation performed in Exercise 01 and Exercise 02 is strictly based on mathematics. Its objective was to establish the viability of the proposed COPTRA algorithms. To complete the validation process, the validation exercise must focus on the application of the algorithm to an operational environment.

D. *Summary of the findings*

Exercise 01 has established the limitations of present day estimations. As seen in the analysis of the data, the performance of the current prediction model is strongly dependent on the quality of the available FPL. Furthermore, even if the FPL was optimal (in the sense that it would present little or no difference with the flight trajectory), the predictions are of limited quality. This situation is corroborated from the observation of current a-DCB operations.

Exercise 02 has proven the viability of the COPTRA algorithms. The performance of the prediction model is significantly improved over the baseline established in Exercise 01. When the prediction is focused on a specific time range, the prediction model performs significantly better that the baseline.

E. *Practical implications of the results*

Having more information related to the estimation of occupancy for a given sector and time will lead to fewer false positives (hotspots declared and not occurring) and negatives (hotspots not declared and occurring). This will occur once the performance of the prediction models is improved from today's standards. COPTRA has already established the theoretical ground to proceed along this path. The initial results (as shown in this report and on the ongoing validation efforts) are promising and show an improvement from present conditions.

V. Conclusions

Based on the probabilistic model and algorithms presented in this paper and in [9]–[12] the paper has described the operational context of the use of uncertainty in a trajectory based operations environment, to address the advanced Demand and capacity balancing. The paper also described the validation approach that COPTRA is applying to ensure that the model and algorithms have operational use.

The paper focuses on the initial validation steps taken by COPTRA to establish a baseline and the technical viability of the algorithms used within an operational environment.

The results obtained in Exercises 01 and Exercise 02 show a clear improvement of the occupancy prediction model proposed by COPTRA vs. current operations. These results will be completed in further ongoing validation exercises that will establish the operational use and validity of the results.

The work presented here has opened further research questions amongst which we can highlight the need to redefine our understanding of sector capacity within an environment in which uncertainty is taken into account. Attention must also be paid to the smoothing effect observed when making predictions based on uncertainty.

References

[1] H. H. Harada, John Moore, Takayuki Harada, Ruben Flohr, Jorge Woods, and Yasushi Inoue, "Trajectory Based Operations Concept Document (TBOCD)." ICAO, Mar-2015.

[2] I. Wilson and A. Sipe, "Six blind men and Trajectory based Operations," in *2016 Integrated Communications Navigation and Surveillance (ICNS)*, 2016, p. 6F1-1-6F1-11.

[3] SESAR J.U., "Transition ConOps SESAR 2020 - Consolidated deliverable with contribution from Operational Federating Projects." B.04.02-D106, 2016.[4] C. Wanke, M. B. Callaham, D. P. Greenbaum, and A. J. Masalonis, "Measuring uncertainty in airspace demand predictions for traffic flow management applications," in *AIAA Guidance, Navigation and Control Conference. Austin, TX, USA*, 2003.

[5] C. Wanke, S. Mulgund, D. Greenbaum, and L. Song, "Modeling Traffic Prediction Uncertainty for Traffic Management Decision Support," in *AIAA Guidance, Navigation, and Control Conference and Exhibit*, American Institute of Aeronautics and Astronautics.

[6] E. P. Gilbo and S. B. Smith, "New method for probabilistic traffic demand predictions for en route sectors based on uncertain predictions of individual flight events," in *Ninth USA/Europe Air Traffic Management Research and Development Seminar (ATM2011)*, 2011.

[7] E. Gilbo and S. Smith, "Probabilistic prediction of aggregate traffic demand using uncertainty in individual flight predictions," *Pap. Number AIAA*, vol. 6494, 2009.

[8] E. Gilbo and S. Smith, "A New Model to Improve Aggregate Air Traffic Demand Predictions," in *AIAA Guidance, Navigation and Control Conference, AIAA Paper*, 2007, vol. 6450.

[9] COPTRA Consortium, "D2.1 Techniques to determine trajectory uncertainty and modelling." Feb-2017. Available at: http://coptra.eu

[10] COPTRA Consortium, "D2.2 Quantification of trajectory prediction uncertainty." Feb-2017. Available at: http://coptra.eu

[11] COPTRA Consortium, "D3.1 Probabilistic Traffic Demand Models V1." Aug-2017. Available at: http:/coptra.eu

[12] F. Gonze, A. Simonetto, E. Huens, J. Boucquey, and R. M. Jungers, "Probabilistic Occupancy Counts and Flight Criticality Measures for ATM," 2017.

[13] C. P. M. Dallchampt, "Hourly Entry Count Versus Occupancy Count Relationship Definitions and Indicators (I)." EUROCONTROL, 2007.

[14] T. Vacha-Haase and B. Thompson, "How to estimate and interpret various effect sizes.," *J. Couns. Psychol.*, vol. 51, no. 4, p. 473, 2004.