Performance-based analysis of aerodrome weather forecasts

Francesco Simone
Department of Mechanical and Aerospace Engineering
Sapienza University of Rome
Rome, Italy
francesco.simone@uniroma1.it

Giulio Di Gravio
Department of Mechanical and Aerospace Engineering
Sapienza University of Rome
Rome, Italy
giulio.digravio@uniroma1.it

Riccardo Patriarca*
Department of Mechanical and Aerospace Engineering
Sapienza University of Rome
Rome, Italy
riccardo.patriarca@uniroma1.it

*corresponding author

***Abstract*— Weather forecasting is a critical aspect for optimizing aerodrome operations. It allows ensuring on-ground and en-route safe and efficient air traffic management. Being a continuous and mandatory operation for aerodrome systems, it routinely produces large amounts of data. This paper suggests a customized performance-based analysis of weather forecasts accuracy in line with ICAO (International Civil Aviation Organization) standards. The analysis is instantiated into operational settings of a European Weather Service Provider (WSP), and its implications for operations of an Air Navigation Service Provider (ANSP), by means of exemplary data intelligence reports including accuracy indicators. The analysis is meant to support decision makers in managing aerodrome weather forecasting gaining knowledge from past operations.**

Keywords—Weather forecasting, aerodromes, weather service providers, data analytics, data intelligence.

I. Introduction

Accurate weather prediction by Weather Service Providers (WPS) is critical for aviation services. Airport operations for example are exposed to large safety and economic losses in case of adverse weather [1]. Weather phenomena such as thunderstorms, snow, low visibility, or gusts are frequently the causes of delays and flight rescheduling [2]. Access to timely and accurate weather forecasting is thus fundamental to support decision makers from Air Navigation Service Providers (ANSPs) in planning, routing and managing flight operations, and to ensure a safe and smooth management of air traffic. ANSPs take as reference two main drivers for weather management [3]:

- METeorological Aerodrome Reports (METARs), which contain observations and measures about actual weather conditions. METARs are generated manually or from automatic observing systems. A METAR follows peculiar hourly or half hourly intervals. If atmospheric conditions have a higher variability, a SPECI (SPECIal Report) may be released. SPECIs do not follow the hourly/half hourly emission frequency.
- Terminal Aerodrome Forecasts (TAFs), previsions for future weather conditions. An aerodrome forecast shall be issued at a specified time and shall consist of a concise statement of the expected meteorological conditions at an aerodrome for a specified period (e.g., 9h, 24h or 30h). A TAF remains valid for its overall time validity. Nonetheless, the meteorological offices preparing TAFs should keep the forecaster under continuous review and, when necessary, should issue new TAFs, or amend promptly the previous ones. The use of modern technologies in aerodrome weather forecasting produces large amount of data stratified by geographical area, and time of the day. This generates a higher potential for syntax errors in forecasts being done manually. Such problem has been acknowledged in (e.g.) [4], where a Python code for TAFs error checking has been produced to spot major criticalities and correlations over six year of data collected in Czech airports.

Besides syntax errors, understanding weather forecast accuracy for a certain region in a certain time span means comparing what has been forecasted, i.e., relevant TAF data, versus what really happened corresponding to METAR data. The way the comparison is run is suggested by ICAO, leaving room to state the operationalization of the methodology under certain boundaries [5]. Despite the number of research contributions available in literature, either deterministic [6] or stochastic [7], forecasts accuracy analysis still presents uncertainties to be resolved [8]. For example, data aggregation techniques to allow shifting from individual TAFs' accuracy to organization-wide dynamic sets of TAFs seems to be a partially open challenge. In this regard, some limitations can be acknowledged: (i) limited periods of analysis (e.g., [9], where authors evaluated forecasting performance based on 24h operations data); (ii) restricted geographical area (e.g., [10], where authors evaluated forecasting performance using data from 5 Czech airports).

An advancement of the state of the art in terms of organizational solutions can be represented by the usage of Business Intelligence (BI). This latter is defined as the set of methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information to ensure a more effective strategic, tactical, and operational decision-making [11]. Acknowledging the limitations of available approaches, the aim of this paper consists of proposing data analytics which may serve as a basis for BI technologies to help systematic analyses of weather forecasts. The paper will go through each step, from the data pre-processing to establish a data mart towards data analysis by means of specific Key Performance Indicators (KPIs) to be captured in data intelligence reports.

The remainder of this paper is organized as follows. Section II presents each step of the proposed methodology. Section III instantiates the proposed methodology on data in order to propose exemplary results. Section IV lastly discusses the obtained results in light of future applications.

II. MATERIALS AND METHODS

This work details methodological steps and results of weather forecast accuracy evaluation.

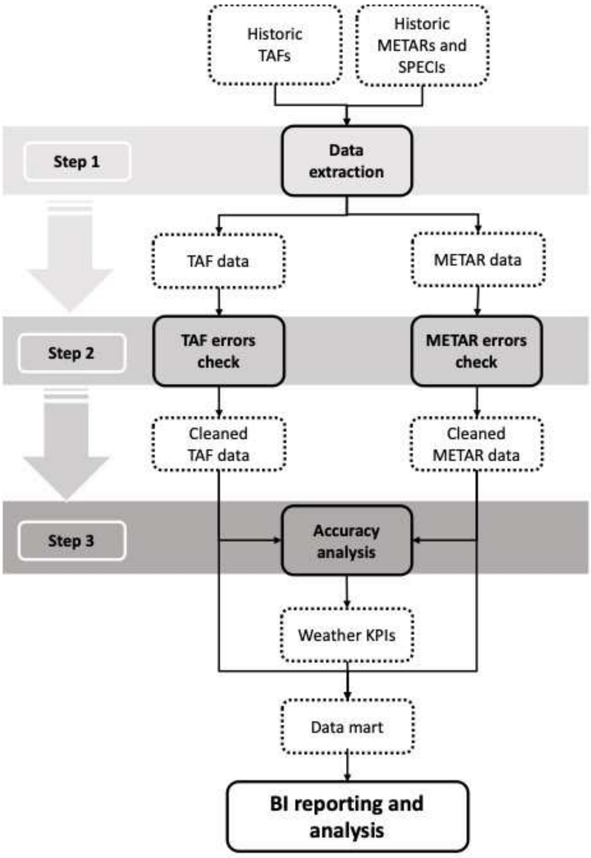

Fig. 1. Methodological steps of the weather data pre-processing for accuracy analysis.

Fig. 1 presents the methodological steps being developed for the purpose of the paper. It is worth noticing that the blocks with dashed edges in Fig. 1 represent data to be used as input, and data generated as output. Data to be analyzed are constituted by historic weather data collected from aerodromes. These data comprehend bulletins regarding: (i) observed weather conditions, i.e., METAR and SPECI, and (ii) forecasted weather conditions, i.e., TAF. The BI data model is then built on three main phases:

- Data extraction: to retrieve information about observed and forecasted weather conditions from the bulletin strings.
- Errors checking: to spot syntax errors, typos and unallowed elements. This step is meant to isolate the consistent data for the subsequent analysis.
- Accuracy analysis: to compare weather data from both observations and forecasts. At this stage, weather KPIs are calculated to assess forecasts accuracy.

A. *Data extraction*

Basic weather information codified in METARs, SPECIs and TAFs strings comprehend (among others) location, time of emission, wind direction and speed, horizontal visibility, meteorological phenomena (present weather e.g., rain, snow), cloud amount, cloud type and height of cloud base, temperature, pressure. Besides the static value in the bulletins (i.e., baseline value in the period of interest of a certain bulletin), each parameter may have a dynamic evolution which needs to be captured in the string. This dynamicity (change groups) adds complexity to the comparisons, and analysis. From an IT perspective, the structure of the main field of the weather database used in the analysis are summarized in Table 1.

B. *Errors checking*

The main goal of a BI solution is to support operators, managers, and analysts in making better and faster decisions [12]. To do so, a BI model must enable operations such as filtering, joining, and aggregating data. Accordingly, the BI model is developed based on Extraction-Transformation-Loading (ETL) process [13]. All information about observed and forecasted weather are stored in a single field of the input database (i.e., “TEXT”, cf. Table 1).

A proper data model for errors checking and accuracy analysis requires a de-codification process to deconstruct this data into relevant fields. A decoding script has been developed to parse METAR, SPECI and TAF strings and split them into their relevant elements. The script follows ICAO codification [3], as well as documents from the World Meteorological Organization (WMO) [14].

Subsequently, data transformations are put in place to: (i) remove not compliant records to avoid noise in data; (ii) gain additional information on aerodrome performance through the calculation of weather KPIs. The decoding script is then paired with a second script to perform formal syntax checks and spot errors run on all database records.

The script procedure is the following:

- Type check. Individual weather data fields can be numerical or categorical. This distinction is established *ex ante* for the extracted data, so a formal control on data type can be performed accordingly. For example, wind velocity is expected to be always made up of digits, any letter would generate a wind velocity type error.
- Length check. Element’s length is calculated for fields that must be reported through a precise number of characters and compared against their prescribed length. For example, since the visibility value must be reported in four digits, a visibility value of 100 meters must be coded as “0100”; (e.g.) “100” would be marked as a visibility length check error.
- Spell check. This check is performed on categorical fields to be completed with predefined values. These latter are evaluated by searching their value within a list of all possible items for that specific field. For example, since each aerodrome has a fixed and individual code (i.e., the ICAO Location Indicator [15]), a list of all possible codes is made available to verify each string includes one of them in the right position.

TABLE 1. INPUT DATABASE STRUCTURE FOR WEATHER DATA.

Field	Description
ID	Unique identification code for the record
KIND	Type of the record, it can be METAR, SPECI or TAF.
AD	Aerodrome of the record

Field	Description
TEXT	Metar or TAF, i.e. alphanumerical string coded following [3] that carries on information about weather condition, either actual or foreseen.
TIME STAMP	Time stamp (i.e. date and time) at which the record is stored in the database

Similarly, the list of weather phenomena is fixed *ex ante* and it can be used to perform the a spell check: "RA" is acceptable sign for rain phenomenon, but "RAS" would be a weather phenomenon spell check.

- Numerical feasibility check. Additional rules are developed to spot feasibility errors in numerical fields. These rules check a record is included within certain thresholds to verify specific requirements. For example, wind direction cannot be more than 360° and must be reported with intervals of 10° each: a value of 370, or 355 would then generate a numerical feasibility error.

Errors checks run on extracted METARs, SPECIs and TAFs. Those strings presenting at least one of the errors mentioned above are excluded from any subsequent analysis. As a result of the errors checking procedure, less than 0.1% of METARs/SPECIs records, and about 3% of TAFs records have been proved to contain errors.

C. Accuracy analysis

At this stage, KPIs can be defined and computed to assess forecasts accuracy for each string parameters. Six weather parameters are prioritized for a set of corresponding KPIs: wind direction (ddd), wind velocity (ff), wind gust (fmfm), visibility (VVVV), weather phenomena (ww), cloud height and amount (NsNsNs and nsnsns). Weather KPIs rely on the usage of contingency tables. They provide relations between two variables, in this case observed and forecasted parameters. A representation of a generic contingency table for weather forecast is presented in Fig. 2. [16]

One should note that for binary parameters (i.e., presence or not presence, in or out a fixed threshold) there are fewer chances of relationships and only four possible outcomes are present (c.f. Fig. 2):

- Hit (*a*): number of times forecasted an event has been observed.
- False alarm (*b*): number of times an event has been forecasted but not observed.
- Miss (*c*): number of times an event has been observed but not forecasted.
- Correct rejection (d): number of times an event has neither been observed nor forecasted.

Specific criteria for each weather parameter have been defined to assess whether their occurrence should be listed as hit, false alarm, miss or correct rejection in the corresponding contingency tables. Individual criteria are defined for each parameter recalling ICAO Annex 3 [3]:

- Forecasted wind direction is considered correct if it does not exceed 60° difference with the observed one. Moreover, if the observed and forecasted intensity is less than 10kt forecasted direction is always considered correct. Notice that false alarm and correct rejections make no sense in wind direction contingency table.
- Forecasted wind velocity is considered correct if the difference between its value and the observed one does not exceed 10 kt. Notice that false alarm and correct rejections make no sense in wind velocity contingency table.

		Event observed				
		Class 1	Class 2	...	Class N	Not specified
Event forecasted	Class 1	*a*	*b*	*b*	*b*	*b*
	Class 2	*c*	*a*	*b*	*b*	*b*
	...	*c*	*c*	*a*	*b*	*b*
	Class N	*c*	*c*	*c*	*a*	*b*
	Not specified	*c*	*c*	*c*	*c*	*d*

Fig. 2. Exemplary multi-category contingency table.

- Gust is treated as a binary parameter: occurrence or non-occurrence versus forecasted or not forecasted. The intensity of the gust is not considered.
- Visibility relies on a multi-category contingency table since it is evaluated through eight classes distributed in accordance with the following thresholds: 150 m, 350 m, 600 m, 800 m, 1500 m, 3000 m, 5000 m.
- Weather phenomena are grouped in different categories based on their severity. Up to three weather phenomena can be included in a TAF. Accordingly, the forecast is considered correct if the class of the more severe phenomenon (i.e., lower class) forecasted corresponds to the class of the more severe phenomenon observed. Weather phenomena are evaluated as a multi-category parameter.
- Cloud height and amount are evaluated by considering the height of the bottom clouds layer. Moreover, this latter must refer to broken amount clouds (i.e., 5 to 7 okta) or overcast amount clouds (i.e., equal or more than 8 okta) with a height of base less than 1500 ft. If the forecast does not satisfy these hypotheses, it is always considered correct. In all other cases, five ceiling classes are defined for a multi-category contingency table. Thresholds between classes are: 100 ft, 200 ft, 500 ft, 1000 ft, 1500 ft.

Additionally, other rules are established for managing the change groups. When a TAF includes the BECMG (becoming) indicator, it means that for a certain time interval weather conditions are expected to reach or pass-through specified thresholds. In this interval, from a KPI perspective, both values (the basic and the change group) are considered valid. At the end of the BECMG validity, the BECMG parameters overwrite the ones declared in the basic forecast. On the other hand, the TEMPO indicator describes temporary fluctuations of certain weather parameters. In a TEMPO interval, both the main and the change parameters are considered valid. Outside the TEMPO interval, the main parameters apply. Note however that the expected fluctuations should last less than one half of the time period of the TEMPO group, as per ICAO recommendations [3]. The KPIs accuracy reflects these assessment in terms of scoring penalties, as inspired by previous research [17]. The intent of this work is to measure the accuracy of TAFs being emitted. Accordingly, in those cased where a later TAF that overlaps a former one both TAFs are considered as distinct entries.

On this basis, five types of weather KPIs can be calculated from corresponding contingency tables, as summarized in TABLE 2. Once syntax errors have been isolated, and KPIs been calculated, data are stored into the data mart which serves as an input for business analytics. The data model is built following a snowflake data architecture, i.e., the fact table to be the core of the model, and its dimensions to be in the branches. Two fact tables have been identified, a first one for METARs and SPECIs, a second one for TAFs. Both fact tables relate to dimension tables which enable data exploration, calendar date/time, region, location, etc.

III. RESULTS

The steps from Section II are applied on a database of historic weather data. The database used for this work contains a whole year dataset, i.e., about 600000 METARs and SPECIs, and 60000 TAFs. Reports are collected from about 40 different aerodromes. Following the prescribed steps, report can encompass a pure descriptive perspective (e.g., number of reports produced over time, number of incorrect reports per airport over time), towards more specific analyses for weather parameters (e.g., frequency of a certain combination of wind intensity and wind direction in an aerodrome). Some exemplary analyses are presented in Fig. 3 for a single airport, whose reference values have been de-identified. Specifically, a report on gusts is shown in Fig. 3a. Gust is a critical phenomenon in aerodrome operations with serious implications for aircraft landing. Unforeseen wind gusts may generate aircraft go-arounds or hazardous landings. Fig. 3a shows the number of METARs which include a gust (red line chart) against the number of METARs without it (light blue line chart) over a quarter. It is noticeable how, for the analyzed airport, the second and third month are historically more subjected to gusts. Particular attention should be paid in managing landing movements over these months, putting in place preventing strategies, where possible. Fig. 3b and Fig. 3c show wind parameters (i.e., velocity and direction) in scenarios with or without gusts. The box plots in Fig. 3b demonstrate how gusts, if present, are more concentrated in a specific direction. On average, gusts usually occur from 260° and in 50% of cases they occur between 240° and 330°. In case of no gust occurrence, it is more difficult to assess what the most probable wind direction may be. For example, in 50% of cases, wind blows between 110° and 330°. Concerning wind intensity, in the histogram in Fig. 3c the average wind intensity in case of gust presence (light blue) or absence (dark blue) is compared.

TABLE 2. TYPES OF WEATHER KPIS FOR ACCURACY ANALYSES.

KPI	Analytical expression	Range	Perfect score
Frequency Bias Index (FBI)	$\mathrm{FBI} = \frac{a+b}{a+c}$	$-\infty < \mathrm{FBI} < \infty$	$\mathrm{FBI} = 1$
Proportion Correct (PC)	$\mathrm{PC} = \frac{a+d}{a+b+c+d}$	$0 < \mathrm{PC} < 1$	$\mathrm{PC} = 1$
Critical Success Index (CSI)	$\mathrm{CSI} = \frac{a}{a+b+c}$	$0 < \mathrm{CSI} < 1$	$\mathrm{CSI} = 1$
Probability Of Detection (POD)	$\mathrm{POD} = \frac{a}{a+c}$	$0 < \mathrm{POD} < 1$	$\mathrm{POD} = 1$
False Alarm Ratio (FAR)	$\mathrm{FAR} = \frac{b}{a+b}$	$0 < \mathrm{FAR} < 1$	$\mathrm{FAR} = 0$

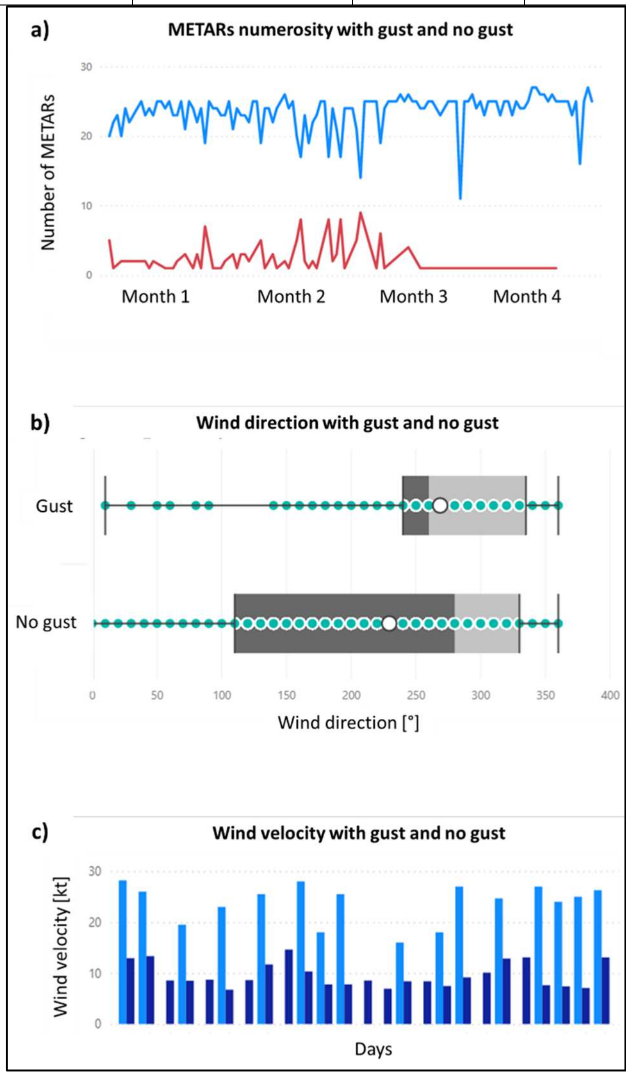

Fig. 3. Exemplary data analytics visualizations to analyze wind gust.

This observation confirms that on average, a wind gust is larger than a normal wind (i.e., almost double than the normal condition. In case of no gust occurrence, it is more difficult to assess what the most probable wind direction may be. For example, in 50% of cases, wind blows between 110° and 330°. Concerning wind intensity, in the histogram in Fig. 3c the average wind intensity in case of gust presence (light blue) or absence (dark blue) is compared. These three visualizations exemplify possible time-dependent analyses on wind parameters. Within the scope of this manuscript, special attention is devoted to KPIs accuracy analyses through an exemplary case sketched in Fig. 4 for two selected airports.

Concerning FBI (Fig. 4a), both airports behave similarly in forecasting clouds and visibility. Even if both FBIs for clouds and visibility are close to FBI = 1 (perfect score), Airport 1 shows a slightly higher tendency in overestimating visibility. In both airports, forecasted gusts are overestimate

(FBI > 1), which is a critical parameter for aircraft take-off and landing operations affecting both safety and cost-effectiveness since heavy gusts force flight re-scheduling. Overlapping the graphs of the two stations, it can be noticed that forecast numerosity of gusts in Airport 2 are overestimated. Concerning weather phenomena, the accuracy of the forecasts on Airport 1 is perfect (FBI=1), way better than Airport 2 (FBI=0.05).

As far as the PC index is concerned (Fig. 4b), forecasts on both airports behaved very similarly for each parameter. High scores close to the optimal value PC = 1 are reported. Anyway, as long PC considers correct rejections, it is easier to gain higher score if compared to the other indexes.

More detailed observations arise in terms of CSI, which does not consider correct rejections. It is clear how a good score on weather phenomena forecast heavily depends on correct rejections: CSIs from both airports (Fig. 4c) for phenomena are low, with Airport 2 CSI being close to the bottom value CSI = 0. On both airports the forecasts underestimate gusts: a performance loss of almost an order of magnitude (compared to PC values) is due to correct rejections. Even if Airport 1 obtains a better score concerning weather phenomena, its overall CSI performance is worse than Airport 2 with lower values for both clouds and visibility. On the other hand, Fig. 4d shows POD that simply considers correct forecasts over all event observed and can be calculated for every weather parameter. The two airports have similar POD performance for ddd, ff, VVVV, NsNsNs and largely different ones for gusts and weather phenomena. The POD score confirms Airport 2 shows inaccuracy to forecast weather phenomena (i.e., number of hits). Gust detection for both airports is sub-optimal but noticeably better than CSI scores, with Airport 2 outperforming Airport 1. A low POD score, yet higher than CSI, is representative of many false alarms on gusts, being fmfm a boolean parameter. The same observation is backed by the overestimation in terms of FBI.

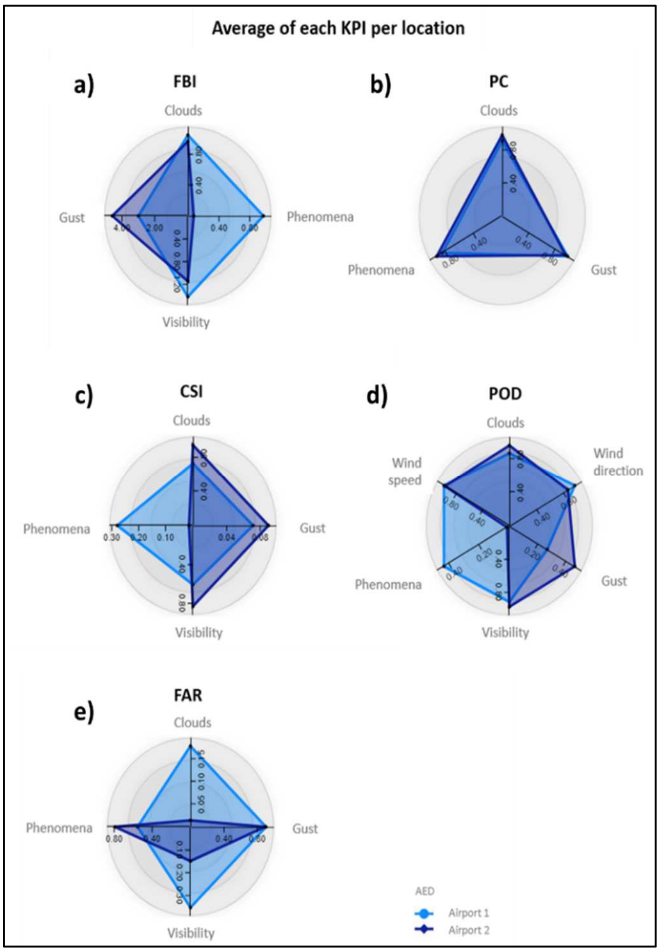

Fig. 4. KPIs comparison between two aerodromes in five different KPIs (FBI, PC; CSI, POD, FAR) for different weather parameters. Note for the construction of some contingency tables not all KPIs can be computed for each weather parameter.

Finally, an investigation on FAR allows complementing previous observations. An aspect to be investigated is the higher score by Airport 2 for weather phenomena: while FBI suggests underestimation in this regard, FAR suggest large number of false alarms. Overall, Airport 2 observes weather phenomena much more than it is able to capture in forecasting, and even when it forecasts any of them, they are frequently false alarms (i.e., high FAR).

Comparison between more than two airports can be made too. In Fig. 5, seven airports belonging to the same region are compared in terms of POD index for visibility (VVVV). This visualization allows observing and comparing trends in terms POD index over time. For a given period, airports are positioned within the matrix showing a snapshot of system performance. On the x-axis, the POD performance value is reported vs the number of METARs on which it is calculated (on the y-axis). Airports are depicted with different colors based on certain performance thresholds: airports in green obtained a POD value equal or major than 95%, for airports in yellow a value of POD between 80% and 94% is reported, the red ones are airports with POD value less than 80%.

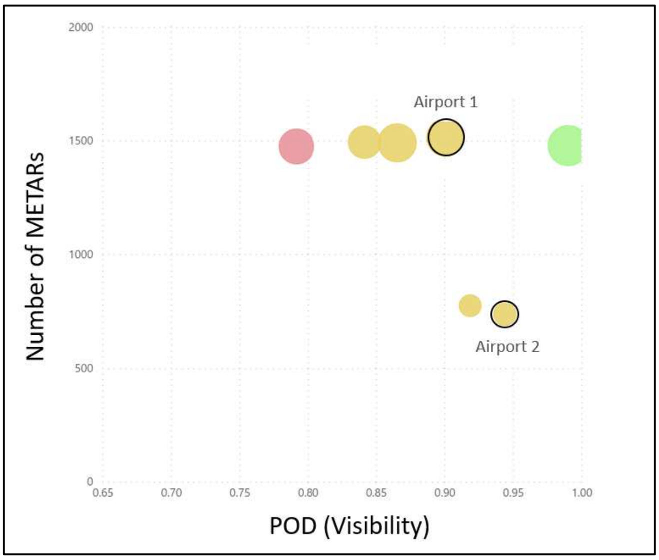

Fig. 5. Comparison of Number of METARs (y-axis) vs POD for visibility parameters (x-axis).

When used on continuously updated data, this type of analysis allows mapping dynamically aerodromes to prioritize intervention on areas that are performing below expectations.

IV. Conclusion

In this paper an application of data analytics on weather data has been presented. The proposed methodology to construct the data mart opens almost limitless possibilities in terms of data to be processed and moreover flexibility of the analysis. The obtained results can be of interest under multiple management perspectives. WSP decision-makers, ANSPs, and airport authorities can benefit of data analytics to monitor system's performance at different locations and in terms of different KPIs. It is worth highlighting that the methodology is conceived from ANSPs perspective: the timing issues regarding long haul flights as experienced by airlines flight planners are neglected. KPI scores can support improvement and interventions, but they can also facilitate sharing best practices among diverse forecasters and business units. At a pure operational level, dashboards and reports can guide the forecasters in the definition of TAF based on historic events as reported in METARs. A clear and user-friendly view of historic information can be arranged to convert multiple analyses into BI dashboards.

While this paper focuses on descriptive analysis, business analytics at large comprehends predictive and prescriptive dimensions, too. Future developments may be devoted to extending this pure descriptive approach via Machine Learning techniques. This retrospective data may be also used to predict future phenomena, (e.g.) gust occurrence, direction and intensity. On the other hand, clustering algorithms may be used to define families of reports, or anomaly detection algorithms may highlight patterns and atypical behaviors within data and KPIs. ML solution could be aggregated in a decision support tool to guide future decision regarding weather forecasting.

In conclusion, the present study provides some examples on a systematic methodology to pre-process and analyze weather bulletins and forecasts for aerodrome weather forecasting, showing the potential for their adoption at a larger scale in any aviation management system.

Acknowledgment

The authors deeply thank ENAV, the Italian Air Navigation Service Provider for sharing data, feedback and expertise that greatly assisted the research.

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