Low-level Wind Shear Prediction based on Machine Learning Techniques: a Case Study of Palermo-Punta Raisi International Airport

Patrizio Ripesi
ATM System Evolution and Strategic Services Planning
Enav S.p.a.
Via Salaria 716, 00138 Rome, Italy
Patrizio.ripesi@enav.it

Patrizia Criscuolo
Long Term and Exploratory Research
Enav S.p.a.
Viale Fulco Ruffo di Calabria snc, 80144 Naples, Italy

***Abstract*—Low-level wind shear (LLWS) is one of the most prominent aviation hazards impacting safety, punctuality, and the environment. To mitigate its effects, several aerodromes have been equipped with dedicated systems capable of recognizing the presence of LLWS in the proximity of a runway. These systems usually comprise a collection of different devices, including a Terminal Doppler Weather Radar, a Doppler Light Detection and Ranging, and a network of anemometers spread along the airport grounds. The LLWS recognition technique is based on the measurement of the vertical wind profile, issuing a warning when a rapid change in wind direction or intensity is detected. Since this methodology is based on real-time data, no useful prediction is provided regarding the possibility of upcoming LLWS events. Furthermore, the costs associated with an LLWS detection system, in terms of purchase and maintenance, are very high making its installation quite prohibitive.**

In this study, we investigated the development of a new methodology for the prediction of LLWS events, based on the use of Machine Learning (ML) techniques applied to wind data obtained from ground station observations and pressure-level Numerical Weather models. The study is carried out considering the site of Palermo-Punta Raisi International Airport since it is the Italian airport most subject to LLWS phenomena. Historical data series from 2007 to 2022, extracted from the Era-5 reanalysis and Enav's meteorological and aeronautical databases, were used to train and test different ML classification models, searching for the best-performing one through the analysis of specific evaluation metrics.

The results we obtained are very encouraging and we are confident that our work could be very useful in developing a new generation of low-cost and high-efficiency ML-based LLWS prediction tools.

Keywords —Low-level wind shear; Airport; Machine Learning; Safety; Aeronautical Meteorology.

I. INTRODUCTION

Low-level wind shear (LLWS) is one of the most prominent aviation hazards. Caused by a sudden change in the wind direction and intensity, it can severely impact airport flight operations causing missed approaches, diversions, holdings, and, in some cases, accidents.

The term "low-level" refers to wind shears that occur below 1600ft i.e. during the approaching or departing phase of the flight [1]. Since these phases are characterized by the low speed and low altitude of the aircraft, we have that any variations in the wind components will result in a variation in the aircraft's stability with a potentially high impact in terms of safety [2].

According to past ICAO investigations [1], from 1964-1983 LLWS was cited in at least 28 large transport aircraft accidents with over 500 fatalities and 200 injuries worldwide. Recent studies [3], have set the final count of fatalities from 1943 to 2022 to over 1400. In addition to this, since LLWS are often the cause of aircraft holdings, missed approaches, and diversions, the delay associated with these actions strongly affects the airport and ATM network while the consequent extra-fuel consumption increases the impact of aviation on climate [4].

Several phenomena can be responsible for the development of LLWS such as thunderstorm microbursts, frontal systems with step wind gradient, tropical cyclones, low-level thermal inversion, land and sea breeze, terrain roughness, and the presence of obstacles in the vicinity of the aerodrome, like buildings or mountains [5].

Due to the potentially fatal impact of the LLWS, many aerodromes have been equipped with dedicated systems capable of recognizing its possible occurrence in the proximity of the runways. These systems are usually composed of a collection of different devices that include a Terminal Doppler Weather Radar (TDWR) [6], a Doppler Light Detection and Ranging (LIDAR) [7], and a network of anemometers located at different points near the runways [8][9][10]. The simultaneous presence of multiple devices is due to the fact that each of these instruments performs differently based on different weather conditions. In particular, the LIDAR can be very useful in recognizing the possible presence of LLWS during clear-sky conditions, while under rainy weather conditions, the signal can be disturbed by rain droplets [7]; on the contrary, the TDWR performs very well in the presence of raindrops, while under clear-sky conditions its reliability drops significantly [6].

The associated LLWS recognition methodology is based on the measurement of the vertical wind profile, followed by the issuing of a warning signal whenever a rapid change in the

SESAR Innovation Days 2024
12 - 15 November 2024. Rome

wind direction or intensity is detected. Based on this, we can find the following limitations affecting the existing LLWS detection systems:

- The LLWS recognition methodology is based on real-time measurements, so no useful information or prediction is provided regarding the possibility of upcoming events.
- Given the need to install several different devices simultaneously, the costs related to an LLWS system, in terms of purchase and maintenance, are very high, making its installation quite prohibitive [11].

In recent years, different methodologies have been investigated to overcome these problems, for example by making use of high-resolution Numerical Weather Prediction models (NWP) [12][13], and Machine Learning (ML) techniques applied to wind data obtained from LIDAR and ground sensors [14][15][16][17]. While the use of high-resolution NWP data does not seem to be the most suitable solution, due to low precision and high computational costs, the use of ML algorithms provides satisfactory results in terms of operational efficiency and resource consumption. Anyway, the exclusive use of wind data measured by ground sensors and remote sensing instruments limits their application to the only real-time context, missing any useful prediction about possible upcoming LLWS events.

Forecasting LLWS events is therefore a real challenge for aeronautical meteorologists, whose only option is to make use of empirical methods based on their professional experience.

In this work, we present a new methodology for the prediction of LLWS events, based on the use of ML techniques applied to wind data obtained from ground station measurements coupled with wind at altitudes obtained from a coarse-grained NWP. Concerning the state of the art, the main novelty that we introduce with our study are:

- The use of a NWP to get the vertical wind profile, instead of making use of dedicated ground sensors like TDWR and LIDAR.
- The ability to predict possible upcoming LLWS events over a time interval that is not strictly limited to the real-time frame.

The study is conducted considering the site of Palermo-Punta Raisi International Airport since it is the Italian airport most subject to LLWS phenomena [18]. Historical data from 2007 to 2022 were used to train and test several ML classification models and, as far as we know, this represents the largest dataset ever used for this type of application.

The paper is organized as follows. In Section II, we describe the study area, the LLWS report procedure, the data, and the methodology used to train and test the Machine Learning models. In Section III, we present a statistical analysis of the LLWS events recorded at the site, and we show the main results obtained from the investigation of the LLWS predictions based on ML techniques. In Section IV, we describe the proposed technical-operational scheme. Finally, Section V provides a summary of the findings and future proposals.

II. Data and Methods

A. *Study area and Low-level Wind Shear report procedure*

The international Airport of Palermo-Punta Raisi, named also Falcone and Borsellino (ICAO code: LICJ), is located on the north coast of Sicily, at 38.18° N and 13.10°E. The aerodrome site is characterized by the proximity of the sea to the north, and by the presence of a mountain massif with an average height of about 800 meters a few km to the south (see Figure 1).

The airport has four runways: the primary RWYs 07/25 are oriented along the 070°-250° direction and have a total length of 3326 meters, while the secondary RWYs 02/20 are oriented along the 020°-200° direction and have a total length of 2068 meters.

Meteorological parameters such as surface wind, QNH, temperature, humidity, present weather, and cloud coverage are measured by a network of ground sensors located in the proximity of each runway touch-down zone. The meteorological data are collected by the airport's Automated Weather Observing System (AWOS) and then used by the Aeronautical Meteorological Observer (AMO) to emit the meteorological aviation report (METAR), a routine weather message issued every half-hour (at HH.20 and HH.50) [19][20].

Figure 1. View of the Palermo-Punta Raisi International Airport site. The runways are marked with black lines while white labels correspond to the runway's orientation and name. (Image taken from Google Earth with Data SIO, NOAA, U.S. Navy, NGA, GEBCOLandsat / Copernicus)

Regarding LLWS phenomena, since no automatic LLWS detection system is currently operational on LICJ, the only way to recognize their presence is through the direct reports made by pilots.

In fact, in Italy, the well-established procedure provides that every time a pilot experiences an LLWS during its approaching or departing phase, he immediately makes a radio communication to the airport control tower (TWR) reporting the time and the position where the aircraft encountered the phenomenon. The AMO present in the TWR then forwards the LLWS report to the Enav Meteorological Office i.e. the Meteorological Forecast Unit (MFU), which will issue an aerodrome warning message (WRNG) for observed LLWS valid for one hour. Within the validity period of the WRNG, if an aircraft reports the cessation of the phenomenon, the warning will be deleted, while if the LLWS continues to be reported in the proximity of the end of the warning validity time, this latter will be extended over the next hour.

The presence of an active LLWS WRNG will be then highlighted within the additional body of the METARs issued during its validity time and notified to the aeronautical and aerodrome users via Automatic Terminal Information System (ATIS) diffusion and METARs dissemination.

B. Data Selection and Preparation for Machine Learning

When dealing with Machine Learning techniques, it is important to carefully select and prepare a dedicated dataset that will be used for training and testing the model. To this end, in our study, we have considered the 2007-2022 historical time series of:

- The LICJ METAR reports, issued every half-hour and containing information regarding:
  - the direction, intensity, and gusts of the surface wind averaged over 10 minutes,
  - the presence of an active LLWS aerodrome warning.
- The number of LICJ hourly movements, corresponding to the sum of the number of arrivals and departures totaled in an hour over LICJ.
- The 875hPa pressure-level wind data, obtained from the European Centre for Medium-range Weather Forecast (ECMWF) ERA-5 reanalysis with a global coverage of 0.25° latitude by 0.25° longitude resolution and a temporal resolution of one hour.

The ERA-5 wind data were taken considering the four grid points closest to the airport (see Figure 2), in order to train the ML model considering the general atmospheric circulation present at altitude in addition to the local ground wind measured at LICJ. Moreover, since the orography is generally poorly resolved by the numerical weather models, to mitigate the effects induced by the bad resolution of the orography on NWP wind data we opted for the use of the 875hPa as the pressure-level positioned immediately above the mountain massif's summit.

Figure 2. Map of the data source points. The blue markers ($V_{1\text{-}4}$) represent the ERA-5 grid point locations, while the red marker represents the airport location. (Image taken from Google Earth with Data SIO, NOAA, U.S. Navy, NGA, GEBCOLandsat / Copernicus).

Analyzing our dataset, we found an amount of 2607 LLWS reports for over 240000 No-LLWS reports, resulting in a highly unbalanced distribution between the two classes (i.e. LLWS and No-LLWS), with a ratio of approximately one to hundred. Since this imbalance can lead to difficulties during the training of the ML model, as the majority class tends to prevail over the minority one, specific mitigation strategies need to be adopted. The most common techniques include minority class upsampling, majority class downsampling, and class weight balancing during ML model training [21][22].

Regarding our case study, we have addressed the data imbalance problem by taking the following actions:

- Downsampling of the majority class, comparing the METAR issuing time and the airport hourly movements and filtering out all the No-LLWS data where the number of movements is less than ten flights per hour. This action is motivated by the fact that the LLWS reports are based on pilot communications, therefore in case no aircraft is departing or landing at LICJ it is not possible to have any information regarding the eventual presence of the LLWS.
  The choice to set the filter to ten movements per hour is motivated by the intention to consider an adequate temporal sampling for LLWS detection.
- Upsampling of the minority class, considering the data corresponding to the time-step immediately preceding the LLWS warning METAR emission as

part of the LLWS class. Since the LLWS report present in the additional body of METAR refers to an active warning issued before the METAR issuance time, data taken from the time step preceding the LLWS METAR warning could also be compatible with LLWS conditions. Therefore, we opted to classify the data corresponding to the previous LLWS METAR warning emission time as part of the LLWS class.

After applying these resampling techniques, the data imbalance was significantly reduced, with a ratio of minority vs majority classes of approximately one to nine. To mitigate this latter imbalance, we applied a stratified random sampling technique splitting the dataset into 80% for training and 20% for testing. Then, we used a class weight balance during the training of the ML model.

III. Results

A. *Historical analysis of Low-level Wind Shear at LICJ*

In Figure 3 we show the results of the statistical analysis for the LICJ LLWS events, extracted from the METAR collected from 1 January 2007 to 31 December 2022.

As said before, during this period we found a total of 2607 METAR messages reporting an active LLWS warning, whose annual distribution is shown in Figure 3a. The number of LLWS warning reports ranges from a maximum of 325 in 2009 to a minimum of 35 in 2020, with an average annual value of about 163 reports per year. Regarding the minimum value in 2020, we note that this is largely influenced by the reduced number of movements registered over LICJ due to the COVID-19 pandemic phase.

Net of the effects of the year 2020, we can observe a general decreasing trend in the number of LLWS reports during the years. Since the volume of air traffic on LICJ has constantly increased over time, is our opinion that this trend is intricately connected to the prevalent synoptical configuration changes that have occurred over the Tyrrhenian area in recent years.

To better explain this statement, we refer to Figure 3b showing the monthly distribution of the LLWS warning reports. As we can see, this distribution follows a marked seasonal pattern, characterized by a maximum of LLWS activity from late autumn to early spring and a minimum of LLWS activity during the summer months. This seasonality is easily explainable by considering the climatology of LICJ [23], where:

- Summers are characterized by the presence of high-pressure ridges, which determine stable meteorological conditions with winds driven by the action of the land and sea breezes.
- Winters are characterized by the development of Tyrrhenian low-pressure systems, which cause severe weather conditions with precipitation, thunderstorms, and strong winds.

Recent studies have found that one of the effects of climate change over the Mediterranean area is characterized by the reduction in the number of the Tyrrhenian low-pressure systems, due to a reinforcement of the North African high-pressure system that affects the south Tyrrhenian area also during autumn and winter [24][25]. Considering the above-mentioned effects of the large-scale synoptical configuration on the LICJ climatology, it is our opinion that the decreasing trend of the LLWS reports shown in Figure 3a is due to the change in the prevailing synoptical configuration, related to the observed increase of the persistence of the African high-pressure system during autumn and winter seasons. In any case, despite the observed trend showing a decrease in the frequency of LLWS, their potential operational impact in terms of safety and airport performance remains high.

Looking at the hourly distribution of the LLWS (see Figure 3c), we can see that it follows the air traffic operational pattern present at LICJ, which is characterized by a reduced number of movements from 23UTC to 5UTC. Due to this, it is not possible to identify the presence of a privileged time interval for the development of LLWS on LICJ.

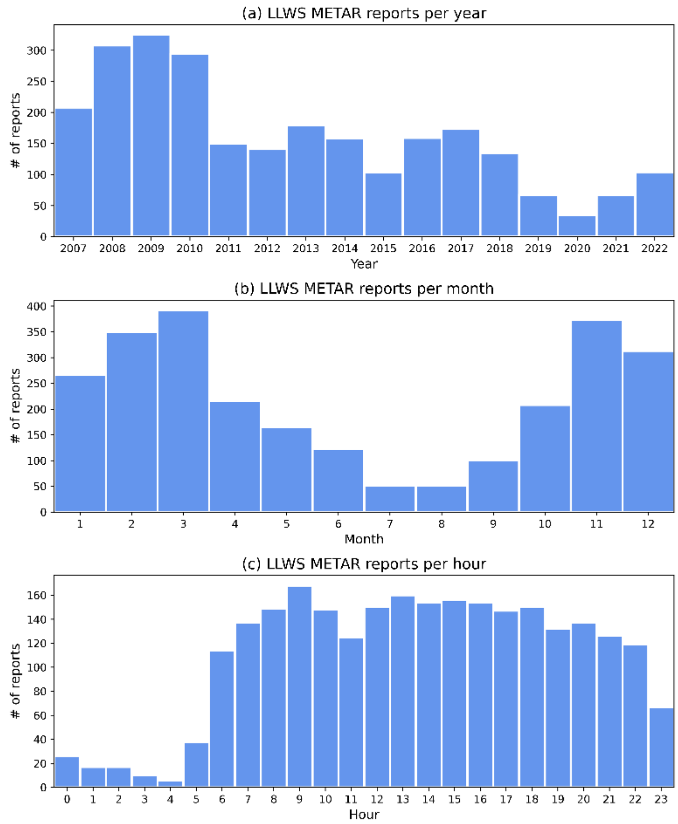

Figure 3. Annual (a), Monthly (b), and Hourly (c) distribution of LLWS reports over LICJ, obtained from the 2007 to 2022 historical METAR data series.

Figure 4 shows the results obtained from the statistical analysis of the surface and 875hPa wind direction and intensity reported during LLWS events. As we can see, the distribution of the ground wind direction (Figure 4a) follows two distinct peaks: a major one, centered around the 190°S and reflecting the position of the mountain massif respect to the aerodrome, and a minor one, centered around the 060°N and related to the circulation induced by the sea breeze. Looking at the 875hPa pressure level wind direction, we can instead observe that it is almost exclusively from the southern quadrants. Therefore, we can affirm that the LLWS events connected to the sea breeze circulation are mainly forced by the vertical shear of the wind, characterized by northerly circulation at the ground and southerly circulation at the altitude.

Analyzing the wind intensity shown in Figure 4b, we can see a wide distribution for the surface and the 875hPa pressure-level wind, without well-defined preferential intensities. A similar distribution is also present for the surface wind gusts, which result in about half of the LLWS METAR reports.

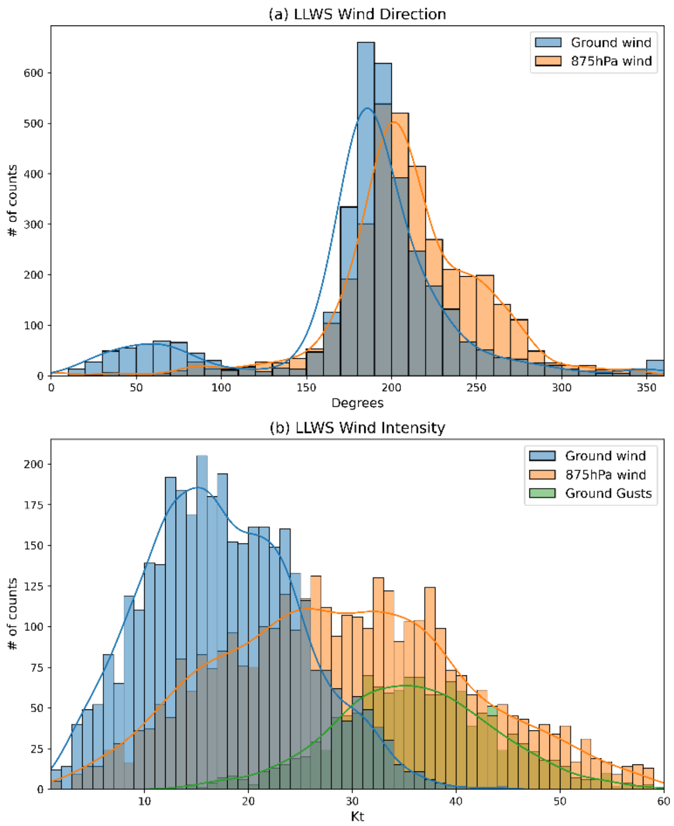

Figure 4. Distribution for the 2007-2022 historical LLWS events of (a) wind direction (degrees); (b) wind intensity (kt). Ground wind (in blue) and gusts (in green) are obtained from the METAR reports, while 875hPa level wind (in orange) is obtained from the ERA-5 reanalysis data as V_{1-4} average. The solid lines correspond to the Gaussian Kernel Density estimated for each of the distributions.

Regarding the presence of convective phenomena (e.g., thunderstorm microbursts) that could act as a forcing factor for the LLWS development, we observed that thunderstorms are reported in just two percent of the 2607 LLWS events and almost always in conjunction with the presence of southerly winds.

Based on that, we can assume that on LICJ, the prevailing factor for the development of the LLWS is correlated to the interaction between the wind circulation and the local orography which leads to the development of several flow instabilities, such as gravity-lee waves, von Karman vortices, and Kelvin-Helmholtz waves [26].

B. *Low-level Wind-Shear prediction based on Machine Learning techniques*

In order to evaluate the degree of reliability of the proposed methodology, we carried out a punctual analysis of the results obtained from the prediction of the LLWS events made with the use of Machine Learning models. Given the physical nature of the system, consisting of a binary classification problem among the majority No-LLWS and minority LLWS classes, we opted for the use of ML classifiers.

Since the performance of the ML models could differ sensibly from one typology to another, several ML classifiers have been investigated to find the best-performing one. The training of the models was performed following the procedure described in Section II, applying supervised learning techniques based on the use of vectors composed of eleven predictors (the four points V_{1-4} wind directions and intensities, the LICJ wind direction and intensity plus the gusts intensity) and one output binary variable related to the presence of the LLWS, as indicated by the following Equation (1):

$$LLWS = \begin{cases} 1 & for \ \ LLWS, \\ 0 & for\ No\ LLWS, \end{cases} \tag{1}$$

Each vector corresponds to a different METAR issue time, where the values of the corresponding variables were taken at the same time interval.

In order to assess the performance and effectiveness of the classifiers, given the imbalanced data distribution of the system, we opted for the use of the Precision-Recall area under curve (PR-AUC) as the evaluation metric [21], where the Precision and Recall are defined respectively as follows:

$$\textit{Precision} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FP}), \tag{2}$$

$$\textit{Recall} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FN}), \tag{3}$$

where TP is the number of true positives, FN is the number of false negatives, and FP is the number of false positives.

In Figure 5, we show the PR curve for several typologies of ML classifiers tested in our study: Logistic Regression (LR), K-nearest neighbors (KNN), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), and XGBoost (XGB). The hyperparameter values are the default ones in the Python Scikit-learn package.

The PR-AUC score ranges from 0 (fully incorrect) to 1 (perfectly classified), estimating the level of performance obtained. In our case study, Random Forest is the best-performing classifier, with a PR-AUC score of about 0.87.

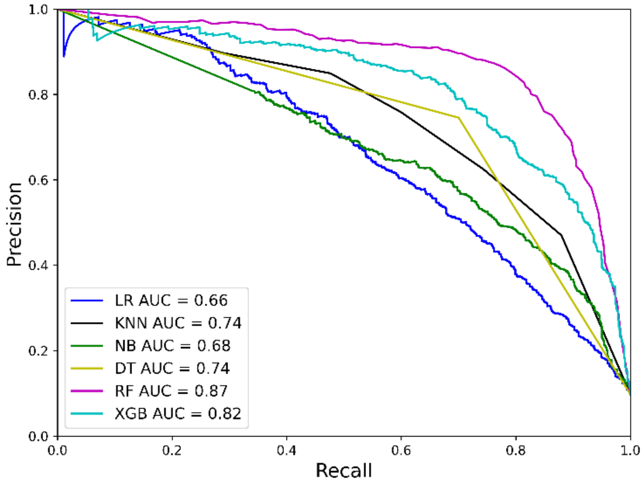

Figure 5. Precision-Recall curve and AUC score for Logistic Regression (LR, blue line), K-nearest neighbors (KNN, black line) Naïve Bayes (NB, green line), Decision Tree (DT, yellow), Random Forest (RF, purple line), and XGBoost (XGB, cyan line) classification model.

Figure 6 shows the correlation matrix associated with the Random Forest classification. As we can see, the No-LLWS vs. No-LLWS true negative count (TN) is sensibly higher than the others due to the imbalance between the majority and minority classes. However, since the PR-AUC doesn't depend on the TN, the class imbalance does not affect the metric results [22].

Comparing the TP values with the FN and FP ones, we can observe that the RF classifier shows a good Precision and Recall score, corresponding to a good predictability of the LLWS events referred to in our case study. As for the FP and FN classifications, we can state that these are mainly due to the lack of information on the LLWS type and the weight class of the aircraft encountering the phenomena.

To better explain this point, we note that since the LLWS reports are based on pilot sensitivity, some pilots may report light events while others report only moderate to severe events. Moreover, small-class aircraft are more sensitive to the LLWS than medium to high-weight ones, and this factor could represent a further possible source of error.

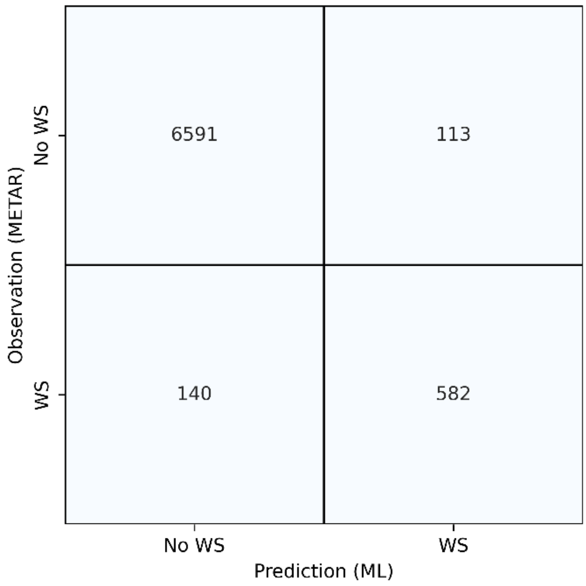

Figure 6. Confusion Matrix obtained for the LLWS Random Forest classifier.

IV. Operational Integration Scheme

In this Section, we discuss the concepts elaborated for the future operational integration of the ML-based LLWS prediction system. The proposed technical-operational scheme is shown in Figure 7.

As we can see, the core of the system consists of a Machine Learning tool which, taking as input the surface wind measured by the LICJ AWOS and the 875hPa pressure-level wind forecasted by the NWP model, will provide as output a

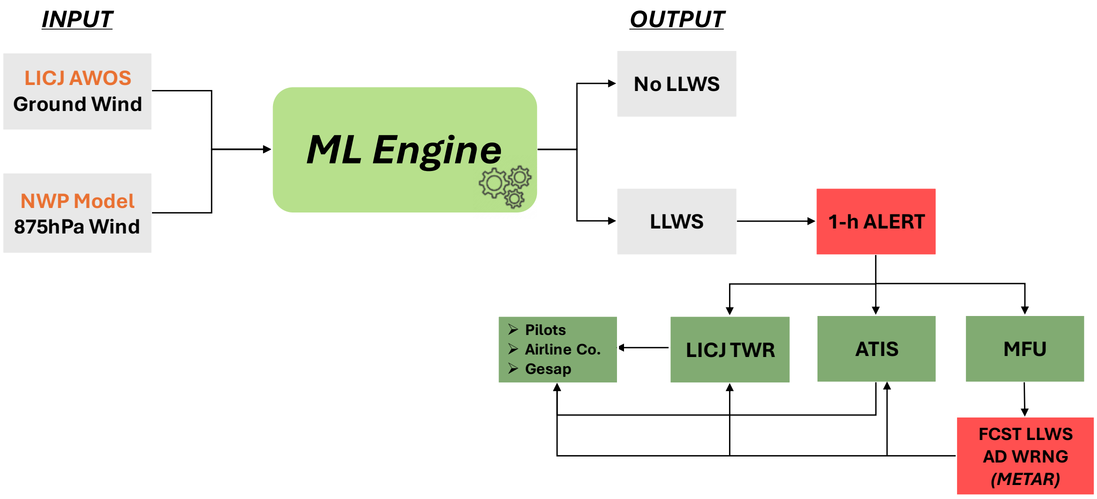

Figure 7. Technical-operational scheme for the Machine Learning based LLWS prediction tool.

prediction regarding the possibility of incoming LLWS events.

Based on the results obtained from our study, the Machine Learning engine will consist of a Random Forest classifier trained with the data and the methodologies previously presented. The tool will run at each METAR issuing time (HH.20 and HH.50), providing a prediction of possible LLWS events over the next hour.

To better explain this point, let's take a practical example considering the case of the 12.20UTC issue time. At this time, the tool will:

- Take as input the ground wind measured by the AWOS at 12.20UTC and the 875hPa pressure-level wind forecasted by the NWP at 12UTC.
- Provide as output a prediction for possible or not LLWS, ranging from 12.20UTC to 13.20UTC.

The tool will then rerun at the issuing time of 12.50UTC, taking as input the ground wind measured at 12.50UTC and the 875hPa pressure-level wind at 13UTC, providing as output the prediction about possible LLWS ranging from 12.50UTC to 13.50UTC.

Whenever the system provides a positive prediction about the possible LLWS occurrence, an alert signal will be displayed on a dedicated Human-Machine web-based Interface which will be available on the operating systems in use at the LICJ TWR and the MFU. Once the alert is received, this latter will issue an aerodrome warning for forecasted LLWS, valid for one hour and renewable at the end of the validity period if the LLWS continues to be predicted.

After its emissions, the warning will be highlighted in the additional body of the METAR reports and disseminated to aeronautical and aerodrome users such as pilots, airline companies, and the airport management company (i.e. the Gesap S.p.a. for LICJ) via METAR diffusion, ATIS and TWR communications.

V. Conclusion

In this paper, we have studied the development of a new Low-level Wind Shear prediction methodology based on Machine Learning techniques. Our study considers the site of Palermo-Punta Raisi International Airport since it is the Italian airport most affected by LLWS phenomena.

A statistical analysis of the LLWS events is presented, finding a strong seasonality connected to the prevailing atmospheric circulation and a strong correlation between the wind direction and the local orography, due to the instability effects generated by the action of gravity, von Karman, and Kelvin-Helmholtz waves.

Several Machine Learning classifiers have been trained and tested using ground and 875hPa pressure-level wind data, obtained from the METAR and the ERA-5 reanalysis respectively. To mitigate the effects induced by the strongly imbalanced LLWS-No LLWS data distribution, we applied specific methodologies based on the resampling of the data and class weight balancing. The performances of the ML classifiers are evaluated using the PR-AUC metric, obtaining good scores for all the tested models. In particular, the Random Forest turns out to be the best-performing classifier, with a PR-AUC score of about 87%.

In conclusion, we can assert that the methodology presented in this paper shows good results in terms of performance and effectiveness. Although our case study focuses on LICJ, the methods and considerations presented can be generalized to any airport (Italian or not) with a long history of non-convective LLWS events. The findings we obtained are very encouraging and we are confident that our work could be very useful in developing a new generation of low-cost and high-efficiency LLWS prediction tools based on ML techniques.

As the next activities, we will investigate the possible extension of the LLWS prediction time up to 24 hours, by integrating the ground wind measured by the AWOS with the surface wind forecasted by the NWP model. This activity is crucial to provide a forecast about the possibility of LLWS events within the LICJ Terminal Aerodrome Forecast (TAF), thus ensuring better planning of the mitigation actions (e.g. airport capacity reduction by the ANSP, fuel planning and optimization of flight schedules by the airlines, optimal aircraft configuration and increase of responsiveness by the pilots) from the aeronautical and airport users.

Finally, as the last step, we will focus on developing a fully operational LLWS prediction tool to support Enav's provision of MET and ATS services on LICJ.

Acknowledgment

The authors thank the Copernicus Climate Database for providing the historical ERA-5 reanalysis data.
Historical LICJ METAR reports were obtained from the Enav Banca Dati Meteo (BDM).
The authors would like to acknowledge the contribution of Giuseppe Gangemi (Enav S.p.a) for kindly providing the historical data series of aircraft hourly movements over LICJ.
Special thanks also go to Paolo Nasetti, Giorgio Berti, Luna Babusci, Luigi Perrotta, Ramona Santarelli, and Giuseppe Labanca (Enav S.p.a.) for providing useful discussions and support during the project development.

References

[1] ICAO, "Manual on low-level wind shear and turbulence," 1st edition. Montreal, Canada: International Civil Aviation Organization.

[2] F.H. Proctor, D.A. Hinton, and R.L. Bowles, "A windshear hazard index," Preprints of the 9th conference on aviation, range and aerospace meteorology, Orlando, FL, American Meteorological Society, paper 7.7.

[3] J. McCarthy, R. Serafin, J. Wilson, J. Evans, C. Kessinger, and W.P. Mahoney, "Addressing the Microburst Threat to Aviation: Research to Operations success story," Bull. Amer. Meteor. Soc., vol. 103, pp. E2845-2861, 2022.

[4] EASA, "Updated analysis of the non-CO2 climate impact of aviation and potential policy measures pursuant to the EU Emissions Trading System Directive Article 30(4)," Final Report, 2020.

[5] G.H. Fitch, D.W. Camp, and W. Frost, "Sources of low-level wind shear around airports," J. Aircr, vol. 14, pp. 5-14, 1977.

[6] J.W. Wilson and R.M. Wakimoto, “The discovery of the downburst,” Bull. Amer. Meteor. Soc., vol. 82, pp. 49-62, 2001.

[7] C.M. Shun and P.W. Chan, “Applications of an infrared Doppler lidar in detection of wind shear,” J. Atmos. Oceanic Technol., vol. 25, pp. 637-655, 2008.

[8] C.M. Shun, “Wind shear and turbulence alerting at Hong Kong International Airport,” WMO Bull., vol. 53, pp. 316-320, 2004.

[9] N. Matayoshi, T. Ijima, K. Yamamoto, and E. Fujita, “Development of Airport Low-level Wind Information (ALWIN),” 16th AIAA Aviation Technology, Integration, and Operations Conf., Washington DC, AIAA 2016-4362, 2016.

[10] D.C. Robinson, D. Collins, J. Brett, J. Klewicki, and P. Murray, “Airport building development: Towards a framework for managing building-induced wind shear and turbulence risks,” J. Airport Manage, vol. 11, pp. 369-385, 2017.

[11] R.G. Hallowell, J.Y.N. Cho, “Wind-Shear System Cost-Benefit Analysis,” Lincoln Lab. Jour., vol. 18, pp. 47-68, 2010.

[12] P.W. Chan and K.K. Hon, “Performance of super high resolution numerical weather prediction model in forecasting terrain-disrupted airflow at the Hong Kong International Airport: case studies,” Meteorological Application, vol. 23, pp. 101-114, 2016.

[13] K.K. Hon, “Predicting Low-level Wind Shear using 200-m-Resolution NWP at the Hong Kong International Airport,” J. App. Meteor. And Clim., vol. 59, pp. 193-206, 2020.

[14] A. Khattak, P.W. Chan, F. Chen, and H. Peng, “Prediction and interpretation of low-level wind shear critically based on its altitude above runway level: application of Bayesian Optimization-Ensamble learning classifiers and Shapley additive exPlanations,” Atmosphere, vol. 13, pp.1-19, 2022.

[15] A. Khattak, P.W. Chan, F. Chen, and H. Peng, “Time-series prediction of intense wind shear using Machine Learning algorithms: a case study of Hong Kong International Airport,” Atmosphere, vol. 14, pp.1-14, 2023.

[16] J. Huang, M.K. Pong, and P.W. Chan, “Wind Shear prediction from light detection and ranging data using Machine Learning methods,” Atmosphere, vol. 12, pp.1-13, 2021.

[17] M. Ryan, A.H. Saputro, and A. Sopaheluwakan, “Intelligent Low-Level Wind Shear alert prediction system based on anemometer sensor network and temporal convolutional network,” Geo. Tech., vol. 17, pp.92-103, 2022.

[18] V. Iannotti, “Studio del fenomeno del wind shear e analisi dei principali sistemi di rilevamento,” Master Degree Thesis, University of Bologna, 2019.

[19] Enac, “Meteorologia per la navigazione aerea,” Regolamento, vol. 2, pp.1-212, 2017.

[20] P. Ripesi, “Automatic cumulonimbus and towering cumulus identification based on the Italian weather radar network data,” Weather, vol. 79, pp. 163-1699, 2024.

[21] A. Fernandez, S. Garcia, M. Galar, R. Prati, B. Krawczyk, and F. Herrera, “Learning from imbalanced data sets,”, Springer, vol. 10, 2018.

[22] S. Kotsiantis, D. Kanellopoulos, and P. Pintelas, "Handling imbalanced datasets: A review," GESTS international transactions on computer science and engineering, vol. 30, pp.25-36, 2006.

[23] Enav, “Palermo Punta-Raisi Airport,” Climatic Atlas, pp.1-79, 2017.

[24] L. Aragao, F. Porcu, “Cyclonic activity in the Mediterranean region from a high-resolution perspective using ECMWF ERA5 dataset,” Clim. Dyn., vol. 58, pp.1293-1310, 2022.

[25] E. Flaounas, S. Davolio, S. Rubin, F. Pantillon, M. Miglietta, M. Gaertner, M. Hatzaki, V. Homar, S. Khodayar, G. Korres, V. Kotroni, J. Kushta, M. Reale, and D. Ricard, “Mediterranean cyclones: current knowledge and open question on dynamics, prediction, climatology and impacts,” Weather Clim. Dynam, vol. 3, pp.173-208, 2022.

[26] P.G. Baines, “Topographic Effects in Stratified Flows,” Cambridge University Press, Cambridge, 1988.