Predicting Off-Block Delays: A Case Study at Paris - Charles de Gaulle International Airport

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Abstract: Punctuality is a sensitive issue in large airports and hubs for passenger experience and for controlling operational costs. This paper presents a real and challenging problem of predicting and explaining flight off-block delays. We study the case of the international airport Paris Charles de Gaulle (Paris-CDG) starting from the specificities of this problem at Paris-CDG until the proposal of modelings then solutions and the analysis of the results on real data covering an entire year of activity. The proof of concept provided in this paper allows us to believe that the proposed approach could help improving the management of delays and reduce the impact of the resulting consequences.

1 INTRODUCTION

In the context of an airport, there are several typical problems of artificial intelligence, such as planning, optimization, simulation, and prediction. Indeed, many air transport problems exist where decision support systems are used while integrating artificial intelligence components.

Before the COVID-19 health crisis, the International Air Transport Association (IATA) forecasts showed that passengers would double by 2036, reaching 7.8 billion. The COVID-19 pandemic has slowed air traffic considerably, especially in 2020 and early 2021, but competitive pressure is always present, even in reduced activity. In recent months, air traffic has picked up in several world regions. In France, Paris-Charles de Gaule airport (Paris-CDG) Air France's main hub will see its passenger numbers increase by 35 to 40 million to reach 100 million by 2036. This will require around 400 additional aircraft movements (take-offs and landings) per day. The development project for Paris-CDG airport does not include any extension or new runway. It is, therefore, essential to improve the following:

- passenger flows by offering a simplified, fluid, and personalized route;
- the punctuality of flights by anticipating delays as far as possible;
- aircraft movements with optimized and adaptive planning of resources such as aircraft parking lots, check-in counters, baggage chutes, etc.

The problem of flight delays, for example (landing and take-off delays), does not only have immediate financial consequences. These delays can also cause a chain effect, other delays, and problems that affect the delays and rankings of airlines and airports.

In (Xu et al., 2008), the authors point out that about 84% of delays are generated by the airports. The problem of delay prediction is studied in a few works, but it mainly concerns landing or taxiing delays. The delay at departure from the parking lot (the delay between the scheduled time and the actual time at which an aircraft leaves its parking position or gate) depends on several factors. Many of these are specific to each airport (such as the amount of traffic and resources, passenger processes, weather conditions, air traffic control, Etc.). At Paris-CDG, there is a take-off almost every minute, and the slightest delay can have a cascading effect on the takeoff schedule, which can take several hours to be resolved and return to a normal situation. Predicting and forecasting delays in real-time will allow us to anticipate management by providing delay management plans and adjustments to established schedules such as gateway, check-in, and baggage chutes.

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One of the specificities of our work is that we focused on very fluctuating data due to the COVID-19 pandemic. The main contributions of the paper are the study of the existing situation at Paris-CDG, the needs, and then the identification of three main tasks real-time prediction of parking delays, forecasting, and explicability of predictions. Concerning the modeling, we have identified five categories of data for our problem: flight data, data on the progress of passenger processes (security, boarding, Etc.), weather data, current delay status data, Etc. Finally, we have conducted an empirical study to perform the data, feature, and model selection, and we provide an overview of the results obtained.

2 FLIGHT DELAYS: STATE OF THE ART

The problem of aircraft delays is a well-known problem. Different models among random forests, support vector machines and logistic regression have been studied (Natarajan et al., 2018) to predict whether a flight will be delayed. A logistic regression model to predict a class of departing flights is proposed in (Nigam and Govinda, 2017). In (Venkatesh et al., 2017), the authors study arrival delays and propose different approaches to predict whether a specific flight will be delayed. In (Ibrahem et al., 2021) the authors compared different machine-learning approaches (random forest, logistic regression, Bayesian naive classifier, and decision trees) for delay prediction on arrival. In (Tang, 2021), a comparison of seven binary models is performed. In (Yi et al., 2021), the authors have proposed several stacked approaches for the Boston Logan International Airport flight dataset from January to December 2019.

We also find different studies on the impact of different factors on flight delays. For example, the authors of (Wang et al., 2003) studied the impact of flight connections on delay. In (Markovic et al., 2008), a statistical study on the impact of weather at Frankfurt airport is proposed. In (Yogita Borse et al., 2020), the authors focused on weather data as the main feature to predict the delay class. In (Esmaeilzadeh and Mokhtarimousavi, 2020), a support vector machine (SVM) model is used. Based on 20 days, this latter study examines some causes of air traffic delays at the three major airports in New York City. In the study (Cai et al., 2021), a deep learning approach for flight delay prediction considering a multi-airport scenario is proposed. Regarding regression-based approaches, the authors (Rebollo and Balakrishnan, 2014) have proposed approaches based on classification and regression with random forests for US airports.

To our knowledge, there is only one study that attempts to predict takeoff delay, but it only attempts to predict one hour before the estimated takeoff time, and it is intended for the Maastricht (Dalmau-Codina et al., 2019).

3 Paris-CDG AIRPORT

In this section, we provide factual information about Paris-CDG airport. Paris-CDG airport is the most important airport in France. It was opened in 1974 to cope with the saturation of Paris Orly airport (the main Parisian airport before the opening of Paris-CDG). It is located north of Paris and is the hub of Air France. This company represents 50% of the traffic at Paris-CDG. Three main terminals numbered 1 to 3 makeup Paris-CDG.

At Paris-CDG, there is more than one flight departure per minute. There are about $720,000$ flights per year, or about $2,000$ flights per day. On average, there are 145 passengers per flight. At Paris-CDG, resources are currently planned using solutions powered by constraint solvers. Among the critical resources are the parking lots (or ”stands”) assigned to the flights. When a parking lot is released late, this can lead to complex scheduling changes and cascading delays. It is, therefore, essential to anticipate and predict these delays as accurately as possible, explain them, and propose actions to limit them. Before presenting the problem, we will first introduce some terms. We call *rotation* the set composed of an arrival flight and a departure flight. This set generally consists of two flights, but there may be only one, in which case the flight begins a new rotation. The rotation period is the time between the arrival of an aircraft (landing) and its departure (takeoff). A flight has a scheduled departure time, called SOBT (Scheduled Off-Block Time), at which it is supposed to leave its parking area. The moment when the flight leaves its parking position is called AOBT. The delay is then the period between AOBT and SOBT.

3.1 Milestones Before Off-Block

We present here the main milestones preceding the pushback of an aircraft. These milestone stands are presented in Figure. 1. Before the flight arrives at the airport, the flight estimates its arrival time at the block (EIBT: Estimated In-Block Time). The AIBT (Actual In Block Time) is the right time when the

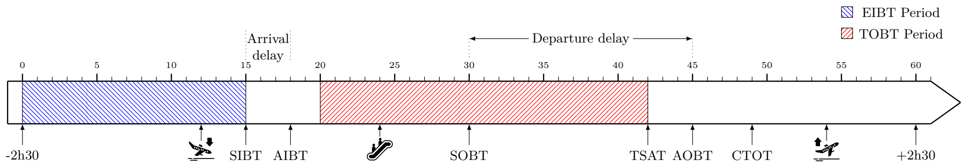


Figure 1: Milestones of a flight at Paris-CDG.

flight arrives at its stand. We call *arrival delay* the difference between AIBT and SIBT. The boarding starts between 1 hour and 30 minutes before SOBT. During the turn-around period (or rotation), the airline sends an estimated time that the aircraft is ready (TOBT: Target Off Block Time) to the management system. For heavy traffic in the sky or congestion on the runway, air traffic control can ”slot” a flight, i.e., force its takeoff between a calculated time called CTOT (Calculated TakeOff Time) and CTOT plus 15 minutes. If the aircraft fails to takeoff during this period, it can be slotted again. The last milestone is the TSAT (Target Start-Up Approval Time) is the time provided by air control taking into account TOBT, CTOT and/or the traffic situation that an aircraft can expect startup/pushback approval.

3.2 Off-Block Delays at CDG

Punctuality is a sensitive issue in large airports and hubs for passenger experience and controlling costs at the airport level. Paris-CDG is ranked[1] in 2018 in 10th place in terms of punctuality. Around half of the flights arrive on time, but only 20% take off on time.

A study of delays at Paris-CDG has highlighted different causes (eg. extreme weather conditions, congestion, breakdowns, incidents at the airport, passenger processes, etc.) of these delays at different phases (parking/pushback, taxi-ing, etc.). Figure. 2 gives an overview of off-block delays over the year considered in our study (March 2021 - March 2022). It should be noted that during this period, some terminals were closed and are still closed, while some other terminals have reopened. Over this period, the proportion of flights with off-block delays is 77%. Figure. 2b shows the number of delayed flights per terminal. We can observe that the two terminals corresponding to Air France (2E and 2F) have the most delayed flights. Figure. 2c shows the number of flights and the mean of delay for each terminal. Terminal 2E has an average delay 37% above the airport average. Figure. 2e shows the cumulated delays (in minutes) each day of the considering period. We can observe an increase during summer 2022, corresponding to a resumption of traffic and some terminals' reopening. Figure 2f depicts the sum and the mean of the delays for each time band of the day, ranging from $p1$ (6am - 8am) to $p6$ (8pm - 11pm). We can observe that the morning periods, particularly $p2$ (9am - 11am) and $p3$ (12pm - 2pm), accumulate most of the delay. Since the majority of delays occur in the morning and there is a cascading delay effect, it is crucial to predict and manage these delays in these time slots accurately.

4 PROBLEM STATEMENT AND OBJECTIVES

This section presents the problem and the objectives of our off-block delay prediction approach at Paris-CDG. Recall that we call off-block delay the time separating the moment that the aircraft leaves the boarding gate (this operation is called *pushback*) from the scheduled off-block time (between Actual Off-Block Time and Scheduled Off Block Time).

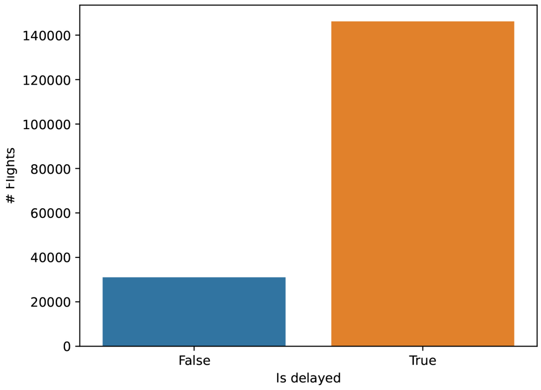
Let Y be the target variable to predict for an input sample describing the flight under study. We distinguish two regression tasks:

4.1 Real-Time Off-Block Delay Prediction

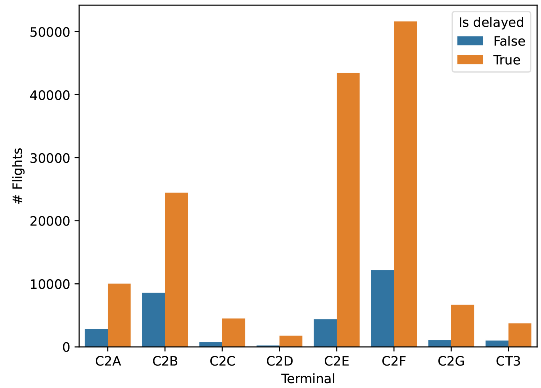
The problem considered here is the one of predicting at any time t, the off-block delay Y (expressed in minutes) that this flight will indeed have. These predictions are updated every 5 minutes until the flight leaves its stand. Indeed, for every slot (each slot lasts 5 minutes), we can acquire new relevant data from the Paris-CDG operational information system. These data can be used to update the predictions (this is valid for dynamic variables such as weather conditions, the progress of passenger processes, etc.). Real-time off-block delay predictions are intended mainly to:

- Draw managers' attention in real-time to flights likely to have significant delays and which may have cascading consequences.
- Explain and identify actionable causes if necessary to resolve the situation.

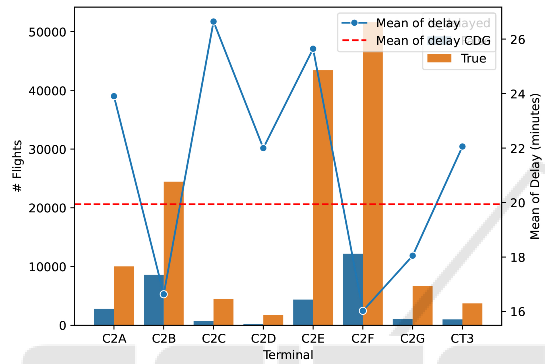
[1]According to OAG Flightview



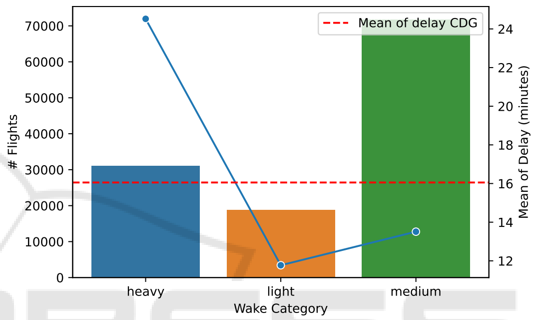
(a) number of on-time flights vs. number of late flights.



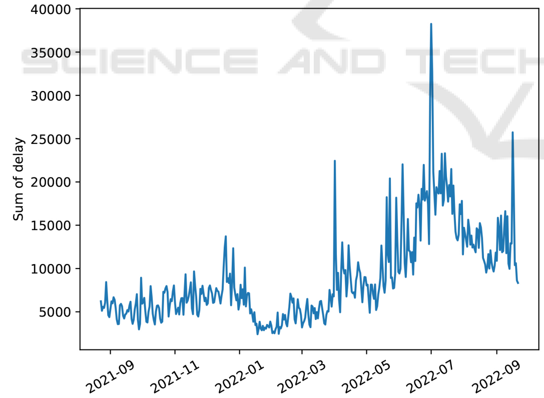
(b) proportion of off-block delayed flights per terminal.



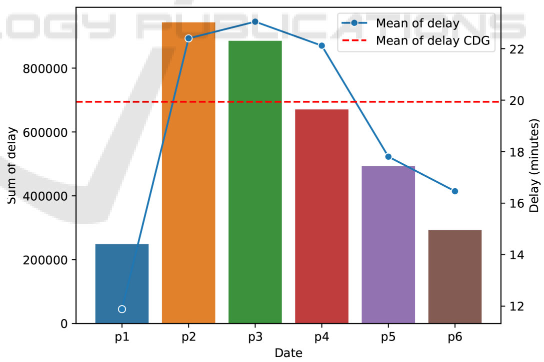
(c) number of delayed flights and mean delay per terminal.



(d) Number of flights by wake category and mean of the delay by wake category.



(e) Cummulative delay for each day of the considering period.



(f) Cummulative and mean delay for each period of a day.

Figure 2: Overview of off-block delays at Paris-CDG from August 2021 to September 2022.

4.2 Off-Block Delay Forecast

We call forecasts the prediction of delays before the opening of the flights. This may be a few hours or several days before the flight. In our case, the forecast cannot rely on dynamic information on the progress of passenger processes, weather conditions, Etc. A such forecast may serve to :

- Establish several plans and mitigation measures according to the expected delays. Then managers can activate the plan provided for each situation when it occurs.
- Identify the causes and anticipate the chaining effect and the consequences.
- Use forecasts to make plausible simulations on

Table 1: Basic flight features (BFF).

Feature	Description	Type	Example
Airline	airline unique company code	Categorical	AF
AircraftType	aircraft type code	Categorical	77W
Destination	IATA code of the destination airport	Categorical	JFK
Terminal	CDG Terminal	Categorical	C2E
Customs	Customs Criteria	Categorical	Schengen
Season	The IATA Season	Categorical	W
Week	A week index calculated from a reference date.	Numeric	1000
Day	Day number in the week (1-7)	Numeric	1
Bus	True if the flight has bus access.	Boolean	True
Parking	True if the arrival flight and the departure flight have the same parking	Boolean	False
SOBT	The Scheduled off-block time in minutes since midnight	Timestamp	360
Rotation	duration between landing and takeoff in minutes	Numeric	300
Pax Count	Number of passengers on the flight (estimated)	Numeric	140
Total Pif Passenger	Number of passengers that must pass through the security point (estimated)	Numeric	75
Service Type	Transport category	Categorical	J

congestion and queues according to delay forecasts, then consider solutions and management plans.

5 MODEL DEFINITION

In this section, we present and motivate the essential information currently available in the Paris-CDG operational information system and which is likely to be relevant for predicting off-block delays. The proposed features come from the analysis of a recent report on takeoff delays at Paris-CDG and the analysis of an entire year of real data.

5.1 Basic Flight Features (BFF)

These are the basic characteristics of a flight, and they do not change over time (these features are listed in Table 1). For example, the name of the airline operating the flight, the type of the aircraft, the IATA code of the destination of the flight, the terminal, the type of customs (national, Schengen, or international), and the IATA season (Summer or Winter).

5.2 Off-Block Milestone Features (OMF)

These are milestones corresponding to each off-block and its management by the various stakeholders, such as air traffic control, the airline, and the airport. For this study, we focused on milestones around the SOBT (-2h30 to +2h30, see Figure. 1). This period is split into 60 slots of 5 minutes. Each new milestone (EIBT, TOBT, CTOT, TSAT) has a timestamp. The OMF features are listed in Table. 2.

5.3 Previous and Current Flights Delay Features (PCFDF)

Relevant information on the probability of a delay for a given flight is the proportion of flights scheduled just before the flight under study and which are late. This could, for example, be due to congestion, a breakdown at the airport, or extreme weather conditions.

We compute the proportion of late flights and the average duration of these delays for each flight slot. At a time t, these features are calculated during a time window w, ranging from a few minutes to a few hours. As we will show empirically, the optimal window duration is a few minutes. For example, if $w = 10$ minutes and the current slot of the flight is 25, we compute the different values from the flights whose AOBT is between slot 23 and slot 25.

Table 2: Off-block milestone features (OMF).

Feature	Description	Type
Arrival Delay	Time in minutes between the last EIBT and the SIBT.	Numeric
$TOBT_{diff}$	time in minutes between the last TOBT and the SOBT.	Numeric
$TOBT_{count}$	The number of TOBTs	Numeric
$CTOT_{diff}$	time in minutes between the last CTOT and the SOBT.	Numeric
$TSAT_{diff}$	time in minutes between the last TSAT and the SOBT.	Numeric

Table 3: Previous and current flights delay features (PCFDF).

Feature	Description	Type
Delay Airport	Mean off-block delay from all the airport (regardless of the terminal)	Numeric
Delay Terminal	Mean off-block delay from the same terminal	Numeric
Delay airline	Mean off-block delay from the same airline	Numeric
Percent delayed flights Airport	Proportion of off-block delayed flights over all the airport (regardless of the terminal)	Numeric
Percent delayed flights Terminal	Proportion of off-block delayed flights from the same terminal	Numeric
Percent delayed flights Airline	Proportion of off-block delayed flights from the same airline	Numeric

5.4 Weather Condition Features (WCF)

Certain weather conditions, such as low visibility and strong winds, are known to be factors that can cause takeoff delays and therefore delay the departure of the flight from its stand. Table 4 shows examples of weather-related faults.

5.5 Passenger Flow Features (PFF)

These features provide information at any time on the progress of specific passenger processes, which may cause an off-block delay. In particular, the relevant information is the percentage at slot t of passengers who have already passed boarding or passed security checkpoints. These features are used only to predict and update the off-block delay prediction in real-time (each flight slot).

6 DATA AND FEATURE EXTRACTION, PREPROCESSING AND SELECTION

In this section, we present our main findings concerning the selection of variables and the selection of data (in particular, the choice of the best parameters for the time window duration, the training data amount, Etc.).

6.1 Data Extraction and Preprocessing

Paris-CDG's operational information system (called AOP for Airport Operation Plan) collects much information about each flight and its progress. For our prediction tasks, a new flight entry is created with the associated time stamp and updated data at each time slot. It is, therefore, possible to trace the status of a flight back to its departure. Therefore, for static

Table 4: Weather condition features (WCF).

Feature	Description	Type
Low Visibility Procedures	These procedures are applied at an airport to ensure safe operations when there is low visibility.	Boolean
Humidity rate (in percent)	Humidity rate	Numeric
Wind speed (in meter/sec)	Wind speed	Numeric
Air pressure (in hectoPascal)	Air pressure	Numeric
Temperature (in degrees Celsius)	Temperature	Numeric

characteristics, we extract them only once. For dynamic characteristics, such as delays of other flights, these are calculated variables that we perform with queries on past flights. For example, to compute the proportion of flights that have been delayed in the last w minutes, we need to review all flights involved in the w time window. The delay characteristics of previous and current flights (PCFDF) are computed after extraction with different w windows. In our study, we considered one year of data (August 2021-September 2022) and constructed a dataset with $10,633,920$ rows and 31 columns (each flight is repeated 60 times with dynamic values for each slot).

6.2 Feature Selection

Once our data set was extracted and preprocessed we proceeded to the selection of variables in order to confirm our intuitions and to eliminate attributes that would prove irrelevant to our prediction tasks. We first performed a simple correlation analysis between each characteristic and the target variable (delay to parking departure). The Figures. 3 show the results of the *Pearson* correlation coefficient.

It can be seen in Figure. 3 that the most relevant variables at the slot 0 are :

- the difference between the SOBT and the TSAT with a score of 0.4,
- the difference between the TOBT between TOBT and SOBT with a *Pearson* score of 0.33.

In contrast, the variables representing the rotation time (*Rotation*) and the arrival delay of a flight (*Arrival delay*) seem to have little relevance. These variables have a negative Pearson score of -0.66 and -0.29, respectively. For the slot 30, the order of the essential variables is confirmed. The durations between SOBT and TSAT or TOBT are the essential variables with a *Pearson* score of 0.74 and 0.68.

The importance of the TSAT variable is explained by the fact that it is one of the last pieces of information obtained for a flight before it leaves its parking lot and that departure is most often at the time indicated by the TSAT. Nevertheless, air traffic control may send this information very early before the departure of the aircraft. The variable *Percent Flight Airport*, representing the proportion of delayed flights airport (for the calculation of the values, we used the 10-minute time window), becomes more important with a progression of its score from 0.16 to 0.23. Finally, we can note that the dynamic variables (in particular, the variable concerning the progression of the boarding) have a score in progression. This progression shows the importance of using dynamic flight data for real-time predictions.

In order to validate the findings on the correlation scores obtained, we performed another empirical analysis by varying the set of variables used for delay prediction. We also varied the window w used to calculate the dynamic variables from the nearby history and the amount of history to use (twelve months, nine months, six months, or three months). We used an ensemble model of boosted regression trees regression trees called *LightGbm*. In the following, we denote by $\mathcal{D}_w^m$ the dataset with m the number of months used ($m \in \{3,6,9,12\}$) and w the duration of the window used for the computation of the dynamic variables ($w \in \{10,30,60\}$). $\mathcal{V}$ denote the set of variables used for the dataset ($\mathcal{V} \in \{\{BFF\},\{BFF,WCF,OMF,PFF\},$ $\{BFF,PCFDF,WCF,OMF,PFF\}\}$).

For our study, we tested our configuration on 40 days (from August 12 to September 21, 2022). For each day, we trained the model until the day before the test day and evaluated it on the test day. Table 5 shows the optimal configurations. The errors and R2 score presented in this table are for the 40 days tested. The hyperparameters are noted as *#Tree/#Leaves/LearningRate*.

Table 5 presents the results for the different configurations. The use of dynamic variables dynamic variables bring a real gain, reducing the error by half and significantly improving the R2 score. Thus the best configuration uses all of the history (12 months), with a time window of 60 minutes.

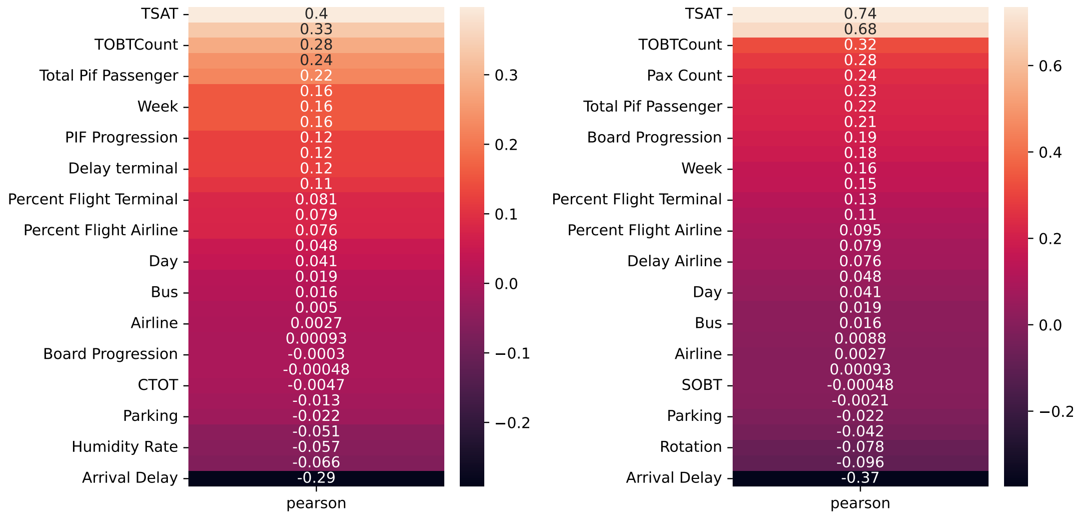


Figure 3: Results of statistical correlation measure at slots 0 (left side figure) and at slot 30 (right side figure).

Table 5: Results of feature selection and historical data.

Dataset	Features ($\mathcal{V}$)	Hyperparameters	MAE	RMSE	R2
$\mathcal{D}^{12}_{60}$	$BFF, PCFDF, WCF, OMF, PFF$	75/256/0.05	9.645	13.858	0.731
$\mathcal{D}^{12}_{10}$	BFF, WCF, OMF, PFF	75/256/0.05	9.709	14.009	0.725
$\mathcal{D}^{12}_{60}$	$BFF, PCFDF, WCF, OMF, PFF$	32/64/0.05	10.376	14.500	0.705
$\mathcal{D}^{12}_{60}$	$BFF, PCFDF, WCF, OMF, PFF$	32/128/0.05	10.473	14.584	0.702
$\mathcal{D}^{3}_{60}$	$BFF, PCFDF, WCF, OMF, PFF$	32/128/0.05	11.637	15.414	0.667
$\mathcal{D}^{12}_{10}$	BFF, WCF, OMF, PFF	32/64/0.05	13.922	20.812	0.393
$\mathcal{D}^{9}_{60}$	BFF	75/256/0.05	17.443	26.576	0.0108

7 REAL TIME PREDICTIONS

Table 6 presents the mean absolute error (MAE) for a subset of the days (for space reasons) tested with the best model selected in the previous section. We notice that the proposed model is more accurate and stable in terms of error than the reference model (e.g., a model predicting the average delay at CDG all the time). However, we can also notice that September 16 significantly increased errors. [2]. The delays could go up to 4h30 (the average delay over the day was 1h20). Addition, as the period covered for each flight is between -2h30 and +2h30, we only collect some of the data on these delays.

Figure 4 gives an overview of the five most important features for our model[3]. The features are sorted by the sum of the SHAP values over all samples at slot 0 and slot 30. The color represents the value of the feature (*red* corresponds to *high*, *blue* to *low*). This reveals, for example, that when the slot is 30, a high value for TSAT increases the predicted delay. Finally, the SHAP values largely confirm the coefficients of *Pearson* from the 6.2 section and the importance of the impact of the TSAT and TOBT variables.

[2]On Thursday, September 16, the delays are due to an air traffic controllers' strike

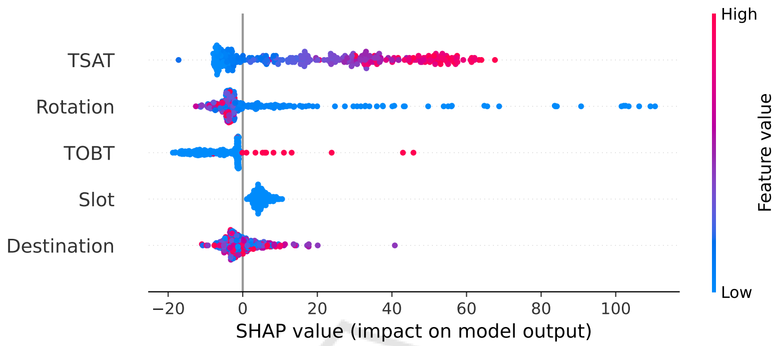
[3]Full figures are available in appendices.

8 CONCLUSIONS

Punctuality is a sensitive issue in major airports and hubs for the passenger experience. In this article, we have addressed the problem of predicting delays at the departure of parking lots at Paris-CDG airport, one of the largest airports in the world and the hub of the airline Air France. Our study started with analyzing the problem (its magnitude, form, causes, Etc.) and the needs (real-time forecasting and prediction) at Paris-CDG. Based on this analysis, we proposed two types of feature categories that could be useful for delay prediction: static features used for the forecasting task and dynamic features (which can be updated in real-time) used for real-time delay prediction. The next step was to build a pipeline to extract the raw data we needed from the operational information sys-

Table 6: MAE for off-block delay forecast.

Date	MAE	Baseline model
2022-08-13	8.196	18.814
2022-08-14	8.490	18.176
2022-08-15	8.026	16.877
2022-08-16	9.911	20.869
2022-08-17	8.288	18.728
2022-09-05	9.340	19.727
2022-09-10	7.429709	16.339208
2022-09-11	8.311289	19.677116
2022-09-12	7.088036	16.854864
2022-09-13	7.252672	15.125720
2022-09-14	8.613775	17.317014
2022-09-15	7.553985	17.969956
2022-09-16	31.250517	65.622123



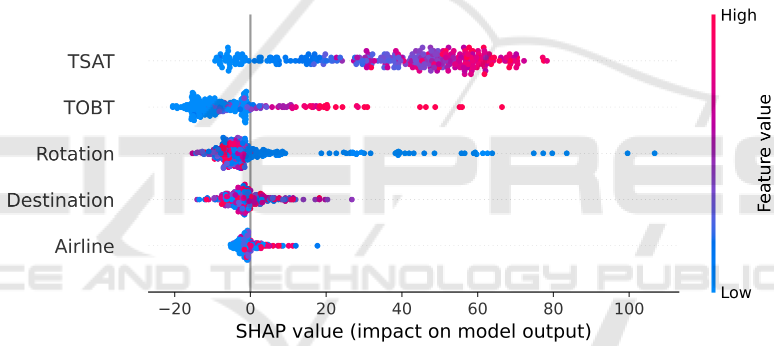


Figure 4: SHAP values for 16th September 2022 at slot 0 (top figure) and slot 30 (bottom figure).

tem of Paris-CDG. This allowed us to build a dataset representing one year of authentic activity. We conducted an empirical study to select the characteristics and the data and then to select the models. One of the specificities of our work is that we worked with very fluctuating data due to the COVID-19 pandemic pandemic and its consequences in terms of air travel restrictions on several occasions, as well as other air traffic hazards. The results show that some delays can be predicted much better than the baseline model. This result can be significantly improved by systematically exploring other models and their best hyper-parameters. In addition to the accuracy improvement, one of the crucial elements for our application will be the explicability of the predictions, in particular, the identification of explanations that can help in delay management.

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