Learning Methods for Air Traffic Management

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Abstract. Weather is an important source of delay for aircraft. Recent studies have shown that certain weather factors have significant influence on air traffic. More than 50% of all delay accounts to weather and causes among others high costs to airlines and passengers. In this work we will show to what extent weather factors in the closer region of Frankfurt Airport have an impact on the delay of flights. Besides the results of a linear regression model we will also present the results of some modern data mining approaches, such as regression trees and fuzzy clustering techniques. With the clustering approach we will show that several weather conditions have a similar influence on the delay of flights. Our analyses focus on the delay that will be explicitly caused by weather factors in the vicinity of the airport, the so-called terminal management area (TMA). Thus, delay caused by weather at the departure airport or by other circumstances during the flight will not bias our results. With our methods it becomes possible to predict the delay of flights if certain weather factors are known. We will specify these factors and quantify their effects on delay.

1 Introduction

Traffic at Frankfurt Airport is increasing every year. As for car traffic, obstruction or delay in air traffic is mostly caused by high traffic volume. Apart from this, weather is an important source of delaying, particularly in the vicinity of an airport. In this paper we discuss which weather factors at Frankfurt Airport may have an effect on the travel time on approaching aircraft. Delays according to a certain schedule will not be concern of this work. To be independent for the most part from any delay that might be caused at the departure airport or during the flight (*en route*), we only consider in this study the travel time that aircraft need from the entrance in the terminal management area (TMA) until landing. In average, this travel time is about 30 minutes.

Our analyses focus on a weather dataset that consists of more than ten weather factors which are captured at the airport at least half-hourly by different sensors. Another dataset that contains all flights for the same time period is used to bring it in correlation with the weather data. The objective of these analyses is the prediction of the travel time of an aircraft given a comparable weather description. With this information it is possible to manage landside procedures, such as the disposition system, taxing, arrangement on the apron and the aircraft's stand. Optimising these procedures could afford saving money since these resources are always scarce.

We will present in this paper the results of three statistical methods, which we apply on this data. Beside linear regression, we use two modern learning methods namely regression trees and fuzzy clustering. The clustering of the weather data shows that there are some significant weather conditions at Frankfurt Airport which have a certain effect on the travel time.

2 Related Work

There are several publications on this topic analysing only a short time period or considering only a few different weather factors.

In [4] a model is described that predicts a daily flight time index for Los Angeles Airport. This index represents the daily flight time by weighting several factors such as weather but also origin airport departure delay. The problem of weather normalisation is addressed in [3] to improve a performance measure which aims at comparing different airspace systems.

The effect of thunderstorms on delay at Frankfurt Airport is discussed in [7]. This study shows that one thunderstorm affects the air traffic in the TMA at Frankfurt Airport for three hours and causes approximately one thousand minutes delay for one hundred aircraft.

[8] investigates the effects of weather at Frankfurt Airport to compute the daily punctuality at Frankfurt Airport. These analyses base on daily indices of punctuality and local weather data of the airport. By means of multiple linear regression, more than twenty weather parameters are determined with effect on punctuality. With this model it can be estimated the punctuality of one day, given the expected weather conditions.

3 The Weather Data

This study is based on the ATIS* weather dataset of the years 1998 and 1999. This dataset consists of more than ten attributes, describing certain weather factors at Frankfurt Airport which where captured by different sensors over a timeframe of some minutes. The following table shows these weather factors.

ATIS
atmospheric pressure
temperature
visibility
cloud coverage
cloud layers
precipitation
precipitation intensity
wind speed†
wind direction†

We will call a datum that is composed of these attributes a weather report. Regularly, weather reports will be recorded in an ATIS dataset every 30 minutes. Only when the weather changes quickly, weather reports will be recorded in a shorter interval.

Apart from the precipitation attributes, these weather factors are described by means of numerical values. For certain methods, precipitation, which is actually nominal, must be converted into numerical values, too.

* Automatic Terminal Information Service
† from two different sensors

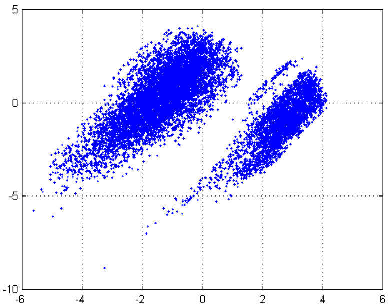

Fig. 1. Two Components of the Weather Data after PCA

4 The Flight Data

For the observed time period, we use a flight dataset, which contains the arrival times of all aircraft. Since we are mainly interested in the delay that is caused by certain weather factors in the vicinity of the airport, we consider the point in time of the aircraft's entrance in the TMA and the time when the corresponding aircraft is landing. As mentioned above, this travel time is about 30 minutes in average.

Additionally, the dataset contains the identification of the runway that was used for the respective landing. The runway configuration, the direction that is actually used for approaches and departures, is of importance when analysing the effect of certain wind components, such as headwind and tailwind.

5 Data Preprocessing

The weather dataset consists of attributes which have different ranges of values. For the linear regression method and the clustering, which we intend to use, it is essential to normalise the data. Thus, coefficients resulting from linear regression can be interpreted directly as degree of importance. Clustering is sensitive to different scaled variables, too. Without normalising the data large distances that may occur regarding wide range attributes such as visibility and atmospheric pressure would result in misleading clusters.

A first insight into the weather data we obtain by applying a principle component analysis (PCA). The first three components have eigenvalues which are greater than 1. These three hypothetical components cover more than 70% of the variation in the data.

Figure 1 shows two components of the weather data, which result from applying PCA. Obviously, there are two linearly separable clusters. The clear separation of the data into two clusters is due to two different weather conditions: cloudy weather and cloudless weather.

Atmospheric Pressure	Temperature	Visibility	Precipitation
1015	30	30000	-
1020	22	25000	SHRA
1020	8	20000	BCFG
1018	6	2000	BR

$\longrightarrow$

Atmospheric Pressure	Temperature	Visibility	Precipitation		
			SHRA	BCFG	BR
-0.06	2.5	0.53	0	0	0
0.5	1.4	0.16	1	0	0
0.5	-0.5	-0.21	0	1	0
0.27	-0.77	-1.55	0	0	1

Table 1. Data Preprocessing

When considering the precipitation attribute, another important conversion has to be made. Some statistical methods can not deal with nominal attributes directly. Usually, a numerical representation for such variables has to be found. In most cases, values of such nominal variables will be converted into dichotomous (0/1-coded) variables. That means, that for every value that occurs in column precipitation a new variable will be created, that is either 1 if this kind of precipitation has been recorded or 0 otherwise. Thus, normalising and converting variables for a small extract of the data (see left part of table 1) leads to the right part of table 1.

From the flight data two additional variables can be extracted. It is obvious, that the travel time depends to a high degree on the capacity of the airport. Thus, shortages mainly result from the demand, that is a factor determined by means of the amount of aircraft that wish to land.

Another essential attribute is the travel time. We intend to assign a specific travel time value to each weather report. Since weather reports occur usually half-hourly and arrivals may occur with inter-arrival times of a few minutes, it is necessary to determine a specific value for the travel time. To obtain these values for a certain weather report, we propose to consider all approaching flights, that have entered the TMA already and those flights that have been landed after that point in time where the preceding weather report has been recorded. Thus, we count the number of flights according to the above definition and call this attribute *traffic*. Further, we examine all travel times of those flights and choose the median travel time. In some cases, the mean estimator would be not appropriate, particularly when some normal flights will be pooled with one flight that has an extreme long travel time.

For some data mining methods, such as for clustering and regression trees, it is advisable to eliminate the dependence of the travel time on the traffic. Since traffic is very important to predict the travel time, regression trees would mostly use the traffic attribute for the prediction and weather factors would be rarely represented in the tree. Further on, clusters of weather conditions would not be meaningful when comparing them with average travel times.

For each flight in the flight dataset, the corresponding landing runway can be read. Because the wind sensors measure wind speed and wind direction one can compute the related headwind components and crosswind components. This might be of interest, since runway configuration changes, when tailwind exceeds five knots.

6 Statistical Analyses

In this section we describe the results of three statistical methods. For a more detailed description of the principles of the algorithms we refer to the literature.

6.1 Multiple Linear Regression

Linear regression aims at estimating the conditional expected value of one variable y given the values of some other variable or variables x. The variable of interest, y, is called the *dependent variable*. The other variables x are called the *independent variables*. A multiple linear regression model is typically stated in the form

$$y = a_0 + ax_1 + a_2x_2 + \ldots + a_px_p.$$

Usually, the parameters $a_1, a_2, \ldots$ will be estimated by the method of least squares. In our context, the dependent variable is the travel time. The independent variables are the weather factors and the traffic. Including the new variables when converting the precipitation attribute, the coefficients for more than 40 independent variables have to be determined.

Usually, one starts applying linear regression using all given variables and eliminating variables stepwise that do not contribute significantly to the prediction. From air traffic experts we know that some variables might have a non-linear, for instance logarithmic or quadratic influence. Therefore, we also extended the regression function correspondingly.

Table 2 shows the final results applying this procedure. Since most of the variables are normalised, the values of the estimated parameters can be directly interpreted as degree of impact. For the precipitation variables the 0/1-coded values are used, traffic is used as described in section 5 and for visibility we recommend to used the logarithm of visibility. With these variables we obtain a model with a coefficient of determination $R^2 = 0.63$.

Obviously, a certain kind of precipitation affects the travel time significantly. Thus, snow prolongs the travel time by some minutes. Snowfall decreases visibility and occurs often in conjunction with iced runways. In such cases, runways but also aircraft must be cleared and deiced. This may cause delay if traffic volume is high, because these procedures take some time and must be repeated as the case may be.

Mist near the ground might be problematic, since the airport is often still visible from a larger height, but when approaching visibility decreases dramatically. Also fog, thunderstorms and rain affect the air traffic in terms of visibility. When visibility decreases, then separation of aircraft must be enlarged. Rain leads to wet runways and causes therewith a risk of skidding and elongated braking distances. Thunderstorms imply very high risks for air traffic, since they are associated with a number of weather phenomena. Generally, their avoidance leads to significant impairment.

Increasing values for temperature, cloud layer$_1$ and visibility favour short travel times. Increased temperatures and high cloud layers stand often for good

Variable	Parameter Estimate	P
traffic	0.05	≤ 0.0001
traffic^2	-1.3	≤ 0.0001
traffic^3	22.4	≤ 0.0001
log(visibility)	-22.3	≤ 0.0001
temperature	-25.5	≤ 0.0001
cloud coverage$_2$	-34.1	≤ 0.0001
cloud layer$_1$	-41.3	≤ 0.0001
headwind	12.8	0.0029
south wind	9.1	≤ 0.0001
wind speed$_1$	41.9	≤ 0.0001
wind speed$_2$	12.5	≤ 0.0001
fog	385.9	≤ 0.0001
fog patches	86.9	≤ 0.0001
mist	48.4	≤ 0.0001
rain	26.3	≤ 0.0001
rain, mist	111.1	≤ 0.0001
snow grains	658.5	≤ 0.0001
snow grains, mist	287.1	≤ 0.0001
snow, mist	-183.7	0.0095
snow shower	286.8	≤ 0.0001
thunderstorm, rain	422.6	≤ 0.0001

Table 2. Results for Linear Regression

weather conditions at all. Wind speed is an important source of delay at Frankfurt Airport. The high probabilities for the two measured wind speed values and the computed wind components ascertain that these variables contribute significantly to the regression model. Depending on the wind speed and the wind direction the runway configuration changes. Since high wind speed correlates mostly with other bad weather conditions separation will be enlarged and therefore delay increases.

6.2 Regression Trees

Regression tree learning is a method for approximating continuous-valued target functions, in which the learned function is represented by a tree. Learned trees can also be represented as sets of *if-then* rules. Such rules can be easily interpreted by humans.

With the well known CART (Classification and Regression Tree) [2] algorithm we aim at inducing such trees, with the objective to determine important weather factors and significant values for these weather factors, which enable us to predict the travel time.

Figure 2 shows a simple tree that consists of fifteen nodes and eight leaves. Each node represents a decision based on a certain weather factor and an associated value. The leaves of the tree stand for the predicted travel time that will be measured in average when applying the respective rule. CART determines

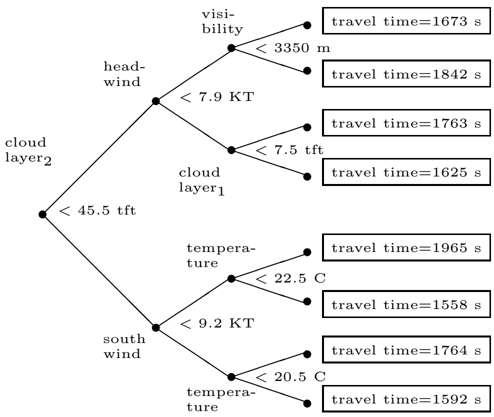

Fig. 2. A simple Regression Tree for Travel Time Prediction

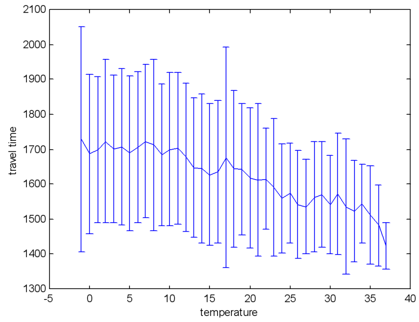

Fig. 3. Temperature affects the Travel Time

the optimal split in a greedy way considering every single attribute and dividing the dataset at this point that minimises the variance for the child nodes and maximises the difference between the sum of quadratic deviations in the parent node and those in the child nodes.

When inducing different regression trees with different datasets by means of cross validation one can observe that these trees have not always the same structure. But in general, attributes that are represented in top levels of one tree will be also represented in the top level of most other trees. We consider these attributes as important ones, which can be found very often in the tree and whose values are quite similar.

The following table shows some results. Analysing a set of regression trees, for some weather factors, such as visibility and certain wind components, a specific value can be obtained. Thus, wind speed about a value of 7-10 kt in average, which includes very high peaks of about 35 kt, leads to long travel times. Also low visibility complicates the air traffic. Although, temperature is represented very often in regression trees, no specific value can be given. This is due to a main disadvantage of regression trees, which can only produce orthogonal data splits. A diagonal curve progression as shown in figure 3 will be stepwise approximated be several nodes with different values.

frequently represented attributes	rarely represented attributes
head wind (7-10 kt)	cross wind
south wind (9 kt)	cloud coverage$_1$
visibility (2000-3500m)	cloud coverage$_2$
temperature	atmospheric pressure
cloud layer$_1$	
cloud layer$_2$	

Nevertheless, some attributes that the experts suspect to be important, such as crosswind and cloud coverage, occur quite rarely in the regression trees. Obviously, the other wind components are mostly higher and therefore represented in the top levels of the trees. As well, cloud coverage, that affects actually visibility, is according to our results less important to predict the travel time than the height of cloud layers or visibility.

Finally, we produce regression trees of different complexity to acquire the appropriate size for these trees. Generally, trees becoming more and more complex can predict the travel time for the training dataset better and better. With hundreds of branches, a training dataset can be adapted nearly perfectly. Since outliers and natural deviations may occur in such datasets, those complex trees cannot predict the travel time very well for new data. Quite the contrary, rather small trees are capable to predict well even for new data.

As a result we can make good predictions of similar quality as with linear regression, with regression trees of depth eight. Bigger trees tend to overfit the training data and yield poor results on test data.

6.3 Clustering

Even though, it is valuable to know which single weather factors affect the air traffic, due the complex interaction of different weather factors it is essential to inspect real weather conditions as a whole and their effect on the air traffic.

With clustering is becomes possible to partition the weather data into groups, the so called clusters. Such a weather cluster might describe a certain weather condition by means of a prototype, that is the centre of the respective cluster. As it can be clearly seen in figure 1 the dataset contains two separable clusters. These two clusters mainly describe the difference between weather reports referring to cloudy weather and those referring to cloudless weather. Beside this, other weather conditions seem not to be separated linearly that clearly. If these clusters differ also relating to the travel time, then we can predict this value for future flights, too.

Nevertheless, even if weather is subject of smooth transitions, one may distinguish some weather conditions anyway. We apply the fuzzy clustering algorithm *fuzzy c-means* (FCM), which allows us – as our tests have shown – to find stable weather clusters. As always when clustering with a prototype-based clustering technique, the number of prototypes is of concern. Common validity measures [6, 9, 1, 5] give no definite answer toward the question, how many prototypes should be used for the clustering on this dataset. Therefore, it is recommended to experiment with different numbers of clusters in order to minimise the prediction error as well as maintain the interpretability of the clusters in terms of weather situations.

Table 3 shows the most interesting prototypes which result from partitioning both the cloudy weather reports and the cloudless weather reports separately

cluster	temperature	cloud coverage$_1$	cloud coverage$_2$	atmospheric pressure	visibility	cloud layer$_1$	cloud layer$_2$	headwind	crosswind	southwind
1	22.9	-	-	1017.4	30166.4	-	-	1.6	2.0	-0.1
2	14	-	-	1013.5	29109.9	-	-	10.2	7.9	10.7
3	16.5	2.1	3.5	1014.8	29127.9	3.32	6.91	4.9	3.4	1.7
4	13.4	2.2	3.7	1014.1	25703.5	4.06	24.57	4.9	3.3	2.5
5	6.7	2.1	3.6	1022.0	21926.3	2.02	3.63	5.8	6.7	-6.2
6	4.7	2.1	3.8	1021.1	9705.5	1.24	3.15	3.5	3.0	2.3
7	12.2	2.1	3.3	1009.1	35328.9	2.63	5.1	12.9	4.4	6.7
8	10.6	2.1	3.7	1008.2	20356.5	1.76	3.6	9.2	8.8	11.2

Table 3. Prototypes of FCM Clustering

into eight clusters. The prototypes appear in ascending order regarding the average travel time for flights that correspond to the described weather conditions.

Cluster 1 and 2 describe weather conditions of cloudless weather. The estimated travel time for flights corresponding to the weather conditions of cluster 1 is $1566s$ in average with a standard deviation about $157s$. Therefore, this cluster represents the best weather conditions regarding the travel time. Obviously, the reason for this are increased temperatures, good visibility and almost no wind. The second cluster represents weather conditions which lead to the longest travel times when considering only cloudless weather. Although most weather factors indicate quite good flight conditions, the strong wind leads to these long travel times ($1687s/254s$)*.

Cluster 3 ($1606s/183s$) and cluster 4 ($1639s/187s$) represent good weather conditions when cloudy weather was recorded. Both clusters indicate increased temperatures, good horizontal and vertical visibility and moderate wind speed. Increased temperatures mostly represent physical conditions, which attend higher approach speed and consequently shorter travel time. The connection between temperature and the travel time, that can also be observed in figure 3, is revealed in cluster 5 ($1675s/235s$) and cluster 6 ($1676s/257s$), too. Additionally, cluster 6 is featured by lowest visibility be it horizontal or vertical. The longest travel times due to the weather conditions are represented by cluster 7 ($1715s/252$) and cluster 8 ($1737s/231s$). Wind has the most important effect on the travel time in these two clusters. As other studies have shown, reduced approach speed (i.e. due to headwind) affect the capacity of the airport. Particularly when approaching, due to strong wind flight paths are deformed, which forces pilots to enlarge separation to preceding aircraft. If in addition to this visibility is reduced due to a low cloud layer and a visual approach is not possible, this might lead to a considerable enlargement of separation and to significant delay consequently. Cluster 7 mainly contains weather reports where rain and also snow was recorded, which additionally affects visibility and thus the air traffic.

* notation: (average travel time/standard error)

7 Conclusions

In this paper we have discussed some learning methods to predict the travel time of approaching aircraft at Frankfurt Airport with the emphasis to gain knowledge about the influence of the weather conditions. By means of linear regression we have investigated which weather factors affect the air traffic to which extent. With regression tree induction, we have applied a method whose results are easy to interpret. Such trees give hints toward the question, what the critical values are for certain variables to predict the travel time. Clustering enables us to examine weather conditions by partitioning the weather dataset into weather clusters. As the results indicate, weather clusters have characteristic travel times. The results of the different learning methods have one thing in common, there is a considerable variance, which is not explained yet by these models. Hence, future work will be to improve accuracy of the prediction. To achieve this, we plan to estimate missing values so that we can use such weather reports that have been left out so far. Furthermore, an additional treatment of outliers could lower the prediction error.

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