

Development of Safety Performance Functions (SPFs) to analyse and predict losses of separation in accordance with the characteristics of the airspace.

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1. Abstract.

This research demonstrates the feasibility of extrapolating the concept of Safety Performance Function, used to predict safety events in other modes of transport based on the characteristics of the infrastructure, to air transport.

The work illustrates how the techniques used to develop SPFs in road transport are applicable to the study of safety data on the evolution of aircraft in an airspace. Statistical and predictive models are developed that allow the number of losses of separation between aircraft in an airspace segment to be predicted, based on the characteristics of the segment. They also provide information on the magnitude of the risk involved and enable predictions to be made.

These models can be used in preventive and predictive methodologies to improve the safety conditions under which airlines operate, thereby minimising the level of risk.

2. Introduction.

Air transport has grown significantly in recent years, with almost 3.8 billion passengers and 52.8 million tonnes of cargo transported in 2016 [1]. It plays a key role in social and economic development, contributing 3.0 trillion dollars to GDP (Gross Domestic Product) and approximately 67.7 million jobs in 2016 [2].

To ensure the viability and vitality of the sector requires exceptional safety figures [3]. The accident ratios currently experienced in commercial air transport are difficult to improve. According to ICAO figures [1], during 2016, only one out of every 2.1 million commercial flights had an accident; the accident rate that year being the lowest per million departures (0.48) since 1945. However, the continuous development of air transport, with average annual growth of 5%, requires us to continue reducing the accident rate to satisfy the expected demand while at the same time achieving a number of fatalities similar to current, socially acceptable levels [4],[5].

One of the areas of greatest concern to the aviation industry, due to the anticipated growth in traffic and exhaustion of the current ATM (Air Traffic Management) model, is the **occurrence of losses of separation between aircraft in an airspace** that could lead to Mid Air Collisions (MAC) [6], [7] [8]. However, within the industry there is little knowledge about the factors that give rise to loss of separation between aircraft and, consequently, the ability to predict them is limited.

Much of the research in this area has focused on the development of collision risk models based on aircraft trajectories [9], [10],[11]. The most noteworthy of these are the Reich model [12], the TOPAZ (Traffic Optimization and Perturbation AnalyZer) methodology [13] and the ICAO

collision risk model, which are used to determine separation criteria when designing airspace. The limitation of these models is that most of them are exclusively based on the trajectories of aircraft or their flight mechanics, and many are not able to make predictions with a high number of aircraft, in some cases more than two.

There have also been initiatives to monitor and measure the safety of the air transport system, such as the Airspace Performance Factor (APF) [14] which attempts to monitor safety via a combination of safety indicators such as reported incidents, causal factors and other factors or operational restrictions. Other studies and models have focused on intervention and human error as the main cause of unsafe situations due to a loss of separation between aircraft [15].

Some authors have studied the influence of the structure of the air traffic network on the occurrence of security events through the Theory of Complex Networks, which studies the relationships between different parts of a system to understand a specific behaviour [16], [17]. Most of these studies focus on the analysis of airports as nodes and the routes between them as boundaries [18], [19],[20],[21]. Others focus on the air traffic network and take account of the way that airplanes fly, considering the points defined in the airspace as nodes and the airways that connect them as boundaries [22], [23]. Hossain et al. [24] analysed the effect of intermediate points on collision risk assessment. The most recent contribution in this area is from [25] with a model based on aviation networks to evaluate losses of separation between aircraft, generated using radar data of aircraft trajectories.

In recent decades, substantial research has been carried out on the use of modern statistical techniques to predict safety incidents and accident precursors in other modes of transport, specifically road transport [26]. The commonly used statistical models include Binomial, Poisson and Poisson-gamma (or negative binomial). The tools used to develop predictive models include random-effects models [27], Generalized Estimation Equations (GEE) [28] and Markov chain Monte Carlo Methods (MCM) [29]. However, in the context of aviation, there is little available research that compares the different approaches used in predictive models, identifies the most appropriate statistical models for predicting safety events, or helps predict safety performance. [30], [31], [32], [33], [34], [35], [36], [37].

This research uses statistical inference to develop models to estimate and predict losses of separation between aircraft in an airspace based on the intrinsic characteristics of the routes and segments; the traffic and its evolution; and airspace management. These functions will enable us to evaluate, determine and predict the results of a given airspace in terms of safety; and will allow us to detect and differentiate singular points or risk areas that will require action to improve safety. These models are known as **Safety Performance Functions (SPFs)**. Furthermore, most of these prior studies on air traffic networks use flight plans based on airline intentions and, therefore, add uncertainty to the results [38]. To overcome these limitations, this study uses an approach based on leveraging big data from real trajectories flown by aircraft. This gives a realistic network representing flown trajectories and we analyse the influence of its structure on the issue of loss of separation.

3. The concept of SPF.

The concept of SPF has been used in land transport to quantitatively measure the safety of a road in terms of the number of collisions. In this context, SPFs are collision prediction models that incorporate known information about a specific feature of a road, such as an intersection

or stretch of road, in an equation that estimates the safety of that feature as an annual collision frequency [39].

SPFs have been developed in the field of land transport for various types of features, such as rural roads, urban arteries, intersections, highways and even motorway ramps [40], [17], [41], [42], [43], [44], [45].

SPFs developed from different studies for similar features may have the same type of model but incorporate differences due to local characteristics and traffic. SPFs can take the form of simple exponential functions that determine the expected number of collisions from simple and general parameters such as the length of the stretch of road and the average daily traffic. These simple models only consider exposure data (traffic volume and length of the stretch of road) and are applicable to those stretches that satisfy specific conditions.

When the characteristics of the scenario deviate from the standard ones used in the primary model, there are several ways of dealing with this. A simple way is to define Modification Factors (MF) that multiply the base prediction (N_{spf}), i.e. predicted value for base conditions, to adjust the frequency of expected losses of separation to that of the actual conditions. Therefore, an MF of greater than 1.0 indicates an increase in the expected incidents due to a condition that is not a base condition, while an MF of less than 1.0 represents a reduction in the number of incidents.

A more complex alternative used in certain cases has been to resort to Empirical Bayes (EB) models [46], [47], [48], [49]. These enable us to address two problems associated with safety prediction models. On the one hand, they allow us to consider Regression to the mean (RTM) and, on the other hand, to handle situations where there is a lack of data due to an insufficient length of time or a very small number of occurrences. RTM is a common bias when evaluating a network in terms of accident rate or safety, since a point or element of the network may experience a high frequency of occurrence one year and the following year experience a much lower and more characteristic frequency of occurrence. The accuracy of a separation loss model will be very low when it is based on a limited period of time, since the small time period is unlikely to be representative of the actual average frequency of occurrence.

The EB method allows us to better estimate the safety of a part of the transport system taking into account not only the number of safety occurrences in that location, but also the occurrences observed in places with similar characteristics, as well as a priori knowledge of experts as to the reasons why these occur. In this context, empirical Bayesian models that consider Poisson and negative binomial functions have been developed and validated; as well as hierarchical Bayesian models. Losses of separation between vehicles within a space and in a small time interval are traditionally assumed to follow a Poisson distribution. A mixed Poisson distribution has been used where the data on traffic conflict consists of non-negative, discrete and rare events (compared to the volume of circulating traffic) [50]. They also recommend the use of more elaborate hierarchical models to identify stretches of the road network where the frequencies of accidents or collisions are such that safety improvements are required.

In general, SPF models can be conceptually extrapolated to airspace by considering the geometry and segments of the routes followed by the aircraft, traffic volume, traffic mix and the different dynamic variables of the aircraft, etc.

The objective of this paper is to demonstrate that the techniques used to develop SPFs in road transport are applicable to the study of safety data on the evolution of aircraft in an airspace;

and that they enable information to be extracted on the magnitude of the risk involved thereby allowing us to make predictions. As such, they can be used in preventive and predictive methodologies to improve the safety conditions under which airlines operate, thereby minimising the level of risk.

The research presented in this article sets out a new approach to defining safety patterns by using predictive functions in air traffic networks based on real losses of separation between aircraft. Actual losses of separation are defined as conflicts between a pair of aircraft in which separation minima (horizontal and/or vertical) are violated in the controlled airspace, which generates a collision risk.

These predictive safety functions will enable us to:

- Explore security incident data and effectively identify anomalies;
- Evaluate the level of risk;
- Define an objective framework to allow comparison between different airspaces, including their design and the way they are managed, and finally;
- Predict and anticipate incidents.

These models will be used in two ways. Firstly, to predict the safety of an airspace for a future period of time, for example, after an increase in traffic. Secondly, to identify routes, segments or other elements of the airspace that experience abnormally high and unusual frequencies of losses of separation; as well as to identify the cause of these.

An understanding of the factors that affect the number of losses of separation in a given airspace can help system planners make decisions that improve safety. A model that accurately predicts the number of losses of separation and their cause will help locate hot spots and evaluate how to best reduce the number of accidents in future years.

4. Methodology.

4.1. Methods for modelling and predicting count data.

In this study we seek to develop SPFs capable of predicting the number of losses of separation that occurred in a segment of air space, that is, the number of occurrences of an event given certain variables. Because the variable to be predicted is an integer greater than or equal to zero, an optimised prediction model for count data must be applied. Most multiple regression models assume that the residual values of a model follow a normal distribution, and this is because they typically follow the distribution of the variable to be predicted. This leads to problems when working with count data, because as a rule these do not follow a normal or even symmetric distribution [51], [52], [53], [54]. The most appropriate and commonly used models for the treatment of this type of data are discussed below.

- **Poisson Model**

This is the most common model for count variables. It uses the Poisson distribution [55], which is a probability distribution for non-zero integer values. The Poisson probability function is given by the following equation:

$$f(k, \lambda) = \frac{e^{-\lambda} \lambda^k}{k!} \quad (1)$$

Where:

- K = number of occurrences of the event or phenomenon
- λ = expected number of occurrences during a time Interval

The function is defined by a single parameter (λ) that estimates both the mean and the variance, and therefore controls the shape of the distribution.

Unlike typical regressions, this model assumes that the residual values follow a Poisson distribution. Furthermore, the prediction variables are related to the result by means of a logarithmic transformation, thus avoiding negative predicted values. The logarithmic transformation is given below in a simplified way [55].

$$\begin{aligned} E(Y) &= \mu \quad (\text{Expected value of } Y) \\ \mu &= e^{\alpha + \beta x} \quad (\text{Generalised linear model} - \text{Linear regression}) \\ \log(\mu) &= \alpha + \beta x \quad (\text{Generalised linear model} - \text{Poisson regression}) \end{aligned} \quad (2)$$

Where:

- α = Intercept
- β = Regression coefficient

A typical regression is characterized by two main parameters, namely the intercept and the regression coefficients. The intercept enables us to know the expected value when all the prediction variables have a value of zero. The regression coefficients represent the expected change in the prediction due to the variation in one unit of the predictor variable (the other variables remaining constant).

In the Poisson and negative binomial models (described below) this interpretation is more complex. The regression coefficients in these two models also show the degree of change in the prediction due to variations in the parameters. Based on the above formulae on the logarithmic transformation in the Poisson model, we can deduce the equation to be:

$$\mu = e^{\alpha + \beta x} = e^{\alpha} e^{\beta x} \quad (3)$$

Where β is the regression coefficient. If β varies by one unit the value of μ would be affected in the following way:

$$\mu_1 = e^{\alpha} e^{\beta x}; \mu_2 = e^{\alpha} e^{\beta(x_1+1)} = e^{\alpha} e^{\beta x_1} e^{\beta} = \mu_1 e^{\beta} \quad (4)$$

As can be seen, a change of one unit in variable x has a multiplier effect of e^{β} in the value of μ .

The simplicity of the Poisson model comes with a great restriction. It assumes that the variance and the mean of the count variable are equal. This is not necessarily so and the difference between the two may be considerable, which is known as "overdispersion" [56]. The number of losses of separation in the data used in this study has a mean of 0.1684 and a variance of 1.3023, which is a clear case of overdispersion.

Although the most typical regression models tend to use least squares regression to estimate the parameters, in this case the maximum likelihood estimation is used to estimate the

parameters. The maximum likelihood seeks to find the values for the regression coefficients that have the highest probability of having produced the observed data [57].

- **Negative Binomial Model**

When data is over dispersed, we can resort to the negative binomial distribution model [58] instead of the Poisson distribution model. In this model, a negative binomial distribution is used for the distribution of residual values. This model gives the variance of the data to be predicted as:

$$\vartheta = \lambda + \frac{\lambda^2}{\theta} \quad (5)$$

Where:

- θ = overdispersion parameter

As can be seen in equation (5), if the overdispersion parameter is increased sufficiently, the variance and the mean converge, and the negative binomial distribution becomes a Poisson distribution. As in the Poisson model, the maximum likelihood estimation is used to find the parameters of the model.

- **Zero-Inflated Models**

When working with count data it is common to have a large amount of data with null values, as in this case. There are some regression models that take into account this excess of zeros in the sample and are known as "Zero-inflated models".

Within this category, there are two principal regression models called Zero-inflated Poisson (ZIP) and the Zero-inflated negative binomial (ZINB) that take into account an excess of zeros in the prediction. They achieve this because they generate a model from a combination of two other models. The first of the models that is combined is a logistic regression model whose objective is to predict whether or not there will be occurrences (i.e. in the case of this study, to predict if losses of separation occur in a segment). The second model predicts the number of times the occurrence happens (the number of conflicts or losses of separation that occur in the segment). This second model is a Poisson model (ZIP) or a negative binomial model (ZINB). The predictors of both models may differ. Like the Poisson and negative binomial models, the parameters of these are calculated using maximum likelihood estimation.

Because the ZIP and ZINB regression models are composed of two different models, two groups of coefficients are produced: one for the count part of the model and the other for the logistical part. The first ones (count part) are interpreted in the same way as those described for the Poisson models and the negative binomial. The coefficients of the second group (logistical part) are found using the logit scale:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta x; \quad p = \frac{1}{1+e^{(-\alpha-\beta x)}} \quad (6)$$

Where:

- p = Probability of occurrence of the event

When proposing a model for the available data, the nature of the loss of separation data was considered. This data is characterised by:

1. Large excess of zeros ($\approx 93\%$).
2. The variance of the variable to be predicted (number of conflicts or losses of separation) is greater than its average (overdispersion).

Bearing in mind these characteristics, the model that will best fit the data and predict the number of losses of separation occurring in a segment is the Zero-inflated negative binomial.

4.2. Methodology used to develop the models.

In this study we have used an iterative methodology to develop and adjust the models. This enables us to analyse and understand, based on the data, how different parameters, related to a segment of air space, affect the occurrence of a loss of separation in the segment.

To achieve this, different regression models are generated, based on a negative binomial Zero-inflated distribution. The regression models use different variables and the effect of these on the prediction is analysed.

In the Zero-inflated negative binomial model, two groups of variables must be provided, one for each of the independent models that make up this regression model. The variables of each group can be the same or different. If it is known with certainty which variables are related to the occurrence or not of losses of separation and which variables are related to the frequency of occurrence of these losses of separation, two different groups may easily be generated. However, as there is in general a total lack of a priori knowledge both groups will be formed by the same variables.

To determine which of the possible models gives the prediction that best fits the data, and therefore which variables are the most adequate to predict the occurrence of losses of separation in a segment, we use the Akaike information criterion (AIC) [59].

The AIC is defined for a large number of models adjusted by maximum likelihood factors. The formula for calculating the AIC is as follows:

$$AIC = \frac{1}{n\hat{\sigma}^2}(RSS + 2d\hat{\sigma}^2) \quad (9)$$

Where:

- n = number of observations
- RSS = residual sum of squares
- $\hat{\sigma}^2$ = variance of the distribution of residuals

The general method when applying the AIC is to choose that model that has the lowest AIC value. The AIC values individually are not directly interpretable because they are affected by different factors corresponding to the sample of data used [60].

The iterative process used to develop the models has the following steps:

- Initially an independent Zero-inflated binomial negative model is generated for each variable (Number of flights, % Ascents, Average time, ...); so that each of the independent models only contain that variable.
- A first comparative analysis of the different initial models is carried out using the AIC and the one with the lowest value is chosen.
- The model with the lowest AIC then becomes the "default model".
- Next, based on this default model, new ones are generated, formed by the variables of the default model and adding one of the remaining variables.
- The models are compared again with the AIC and the model with the lowest value is chosen.
- This process is repeated iteratively until one of the following two conditions occurs:
 1. All variables have been used and the resulting model is the one with the lowest AIC value. This will be chosen as the best model.
 2. In one of the repetitions, none of the models created has an AIC smaller than the default model and therefore the default model is chosen as the best model.

One of the advantages of using this methodology is that without having to carry out a preliminary analysis, variables that are highly related to others are discarded. This iterative process is carried out for each of the 7 regions into which the European airspace has been divided. This enables us to identify for each model the regional characteristics of the airspace and traffic in such a vast area.

5. Identification and treatment of data.

5.1. Parameters that characterise the segments and how these operate.

Airspace structures are conceived as the equivalent to the infrastructure that support the application of SPF in other modes of transport. Therefore, the basic elements of the estimation model will be the airspace segments and the number of conflicts or losses of separation that take place in each of them. In addition to these basic elements, the design of SPF enables us to consider a series of factors that may have an impact on the occurrence of safety events, and that affect the infrastructure, procedures and the users themselves.

An **airspace segment** is defined as an entity that represents a segment of an air route. The segment is defined by two points (Way-Points) and the direction of flight is from the first to the second. Figure 1 shows a segment of the European Route Network. As can be seen in the figure, the segment "ADORO_CANAR" is defined by the Way-Points ADORO and CANAR and the direction of flight is from ADORO to CANAR.

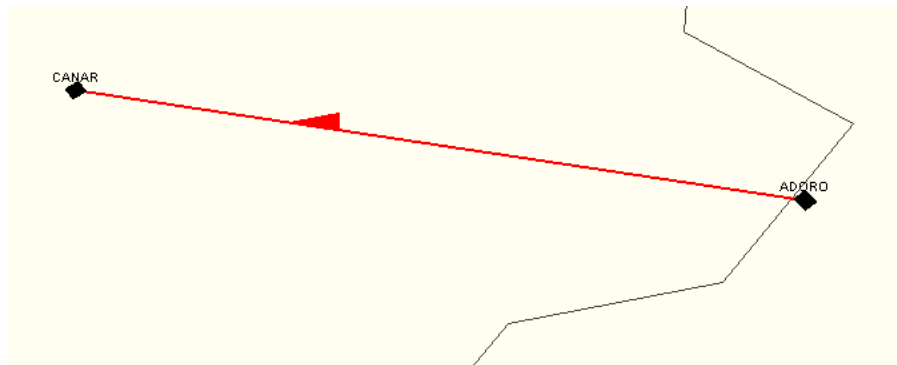


Figure 1. ADORO-CANAR Segment.

The number of segments that make up the Air Route Network (ARN) is not invariant over time. In the airspace of the ECAC (European Civil Aviation Conference), for example, the number of segments can vary by two thousand segments within the same year and up to 10 thousand between different years. A detailed analysis of the AIRAC (Aeronautical Information Regulation and Control) cycles over 5 years (2012-2016) shows a general increase in the number of segments of the network, which went from 30,000 segments in 2012 to an average of 53,000 segments in 2016.

To resolve the problems of data processing resulting from this variability, we have taken 2016 as a reference and used the AIRAC cycle of that year with the largest number of segments, AIRAC number 1611. To guarantee that the data analysed is representative and coherent, we verified that the vast majority of segments belonging to AIRAC number 1611 were also present in the other AIRACs.

A conflict or loss of separation is defined as "a pair of flights for which we have detected a loss of vertical or horizontal separation". In this first analysis, we address the development of SPF for the en-route operation, therefore, the Terminal Manoeuvring Areas (TMA) are considered to be boundary conditions of the problem. In other words, only traffic in ECAC airspace beyond the limits of the TMA boundaries is considered when developing the models. The separation rules that apply in en-route airspace for the possible identification of conflicts are 5NM of horizontal separation and 1000 feet of vertical separation. We consider cruise flight conflicts and evolving and parallel traffic conflicts.

We identified a set of 14 variables that are different for and relevant to each segment studied.

- **Date:** the date (day, month and year) of the remaining data of the segment.
- **Conflicts:** number of losses of separation that have occurred in the segment. A conflict can occur between aircraft in the same segment, or between aircraft in different segments. In this study, we focus on the first type of conflict, i.e. those that occur between aircraft operating in the same segment. We will address the second type of conflict in subsequent studies once we have confirmed that there is interest in this line of research. Different parameters, such as number of crossings with other segments, geometry of the crossings, etc., are required to characterise the predictive functions of the second type of conflict.
- **Number of flights:** number of aircraft that have flown in the segment.

- **Flight attitude:** number of aircraft that are in an attitude of ascent, descent or cruise. This data is subdivided into three categories: 1) Ascent, 2) Descent and 3) Cruise. This data reflects the predominant flight attitude (if any) of the aircraft passing through the segment being studied. To facilitate the presentation of the results and their comparison with those of other segments, the values are given as a percentage.
- **Wake Turbulence Category:** classification of the different flights of the chosen segment according to their WTC.
- **Schedules:** time distribution of the different flights.
- **Traffic in opposite directions:** number of aircraft that fly in the segment in one direction and in the other.
- **Average FL:** average flight level of the aircraft in the segment.
- **Average Time:** average time taken by the aircraft to cover the segment.
- **Length:** length of the segment being studied.
- **Direction:** Classifies the segment according to the manoeuvres performed by the aircraft in it - arrival, departure or normal.
- **Type:** Permanent, CDR Generic, CDR 1, etc.
- **Network:** VST, DCTRAD, DCTNIGHT, etc.
- **Zone:** geographical area in which the segment is located.

We chose the airspace of the ECAC for this study, bearing in mind that this is one of the busiest airspaces in the world. We analysed traffic and losses of separation in 2015 and 2016. According to EUROCONTROL [15], in 2016, air traffic in the ECAC network reached a historic record of 10,190,903 flights, with an average of 27,844 flights per day, surpassing the previous record set in 2008. The final number of segments studied was 38,956.

The sheer size and variety of the study area prompted us to divide the airspace into different geographical areas, to improve the prediction possibilities. This division will enable specific characteristics of the different zones to become apparent in the study. The decision on the number of geographical zones to be modelled is based on statistical data provided by EUROCONTROL on traffic in European airspace. This is primarily the average daily IFR movements and the predicted growth in the average number of flights between 2014 and 2021.

Table 1 gives the average daily IFR movements in 2015. Figure 2 shows the predicted annual growth in the number of flights for the period 2014-2021 [61]. Based on this data we divided European airspace into 7 zones for modelling purposes, as illustrated in Figure 3.

Zone	Average Daily IFR Movements	Rank	Zone	Average Daily IFR Movements
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	(including overflights)			(excluding overflights)
Germany	8,198	1	UK	5,280
France	7,900	2	Germany	5,010
UK	6,243	3	France	3,801
Italy	4,541	4	Spain	3,120
Spain	4,408	5	Italy	3,087
Turkey	3,647	6	Turkey	2,587
Netherlands	3,158	7	Netherlands	1,491
Austria	3,138	8	Switzerland	1,256
Belgium/Luxembourg	3,128	9	Belgium/Luxembourg	1,055
Switzerland	2,805	10	Austria	835

Table 1. Average daily IFR movements in 2015.

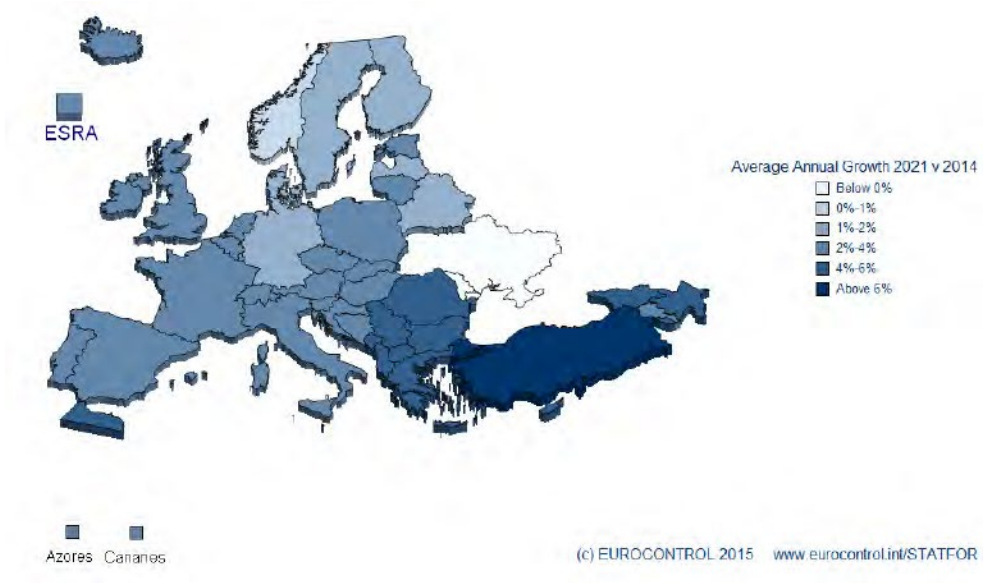


Figure 2. Average annual growth in the number of flights for the period 2014-2021.

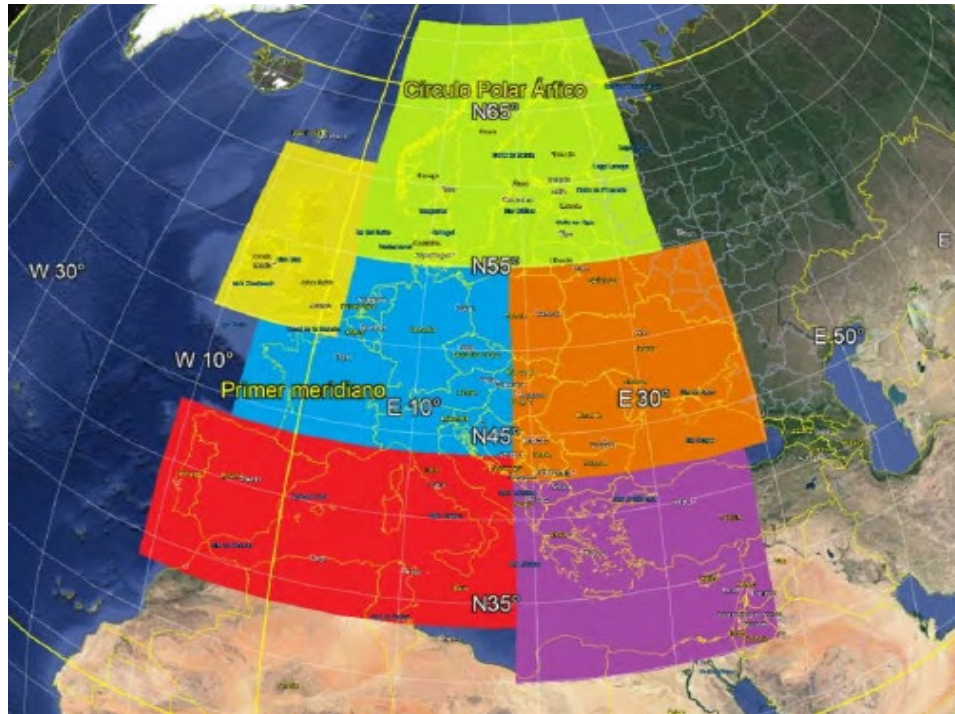


Figure 3. Zones used in the study.

The different zones are described in Table 2.

Zone	Colour in Figure 4	Description	Upper limit	Lower limit	Left limit	Right limit
1	Yellow	United Kingdom (England, Scotland, Wales & Northern Ireland) and Ireland.	61:00'00'' N	49:54'00'' N	11:00'00'' W	02:00'00'' E
2	Green	Denmark, Sweden, Finland, Norway, Latvia, Estonia, northern Lithuania and part of Russia.	71:30'00'' N	54:54'00'' N	02:00'00'' E	35:00'00'' E
3	Red	Spain, Portugal, Italy (except for the north), small areas of Croatia and Bosnia Herzegovina and part of North Africa (the northern zone of Morocco, Algeria and Tunisia).	43:54'00'' N	33:30'00'' N	11:00'00'' W	18:30'00'' E
4	Purple	Greece, Albania, Macedonia, Cyprus, the vast majority of Turkey, Lebanon, Israel, southern Bulgaria, part of Jordan, part of Syria, part of northern Libya and northern Egypt	42:15'00'' N	29:54'00'' N	18:30'00'' E	38:00'00'' E
5	Blue	France (except the south), Belgium, the Netherlands, Switzerland, Germany, Czech Republic. Austria, Slovenia, Luxembourg, most of Croatia, northern Italy, and parts of Poland,	49:54'00'' N	43:54'00'' N	06:00'00'' W	02:00'00'' E
			54:54'00'' N	43:54'00'' N	02:00'00'' E	18:30'00'' E

		Slovakia, Hungary and Bosnia Herzegovina. This area does not have a uniform shape but can be divided into two uniform rectangular shapes (WEST/EAST).				
6	Orange	Belarus, Ukraine, Moldova, Romania, Serbia, Montenegro, part of Russia and most of Poland, Hungary, Slovakia and Lithuania.	54:54'00" N	42:15'00" N	18:30'00" E	40:15'00" E
7		All those segments not located in any of the previous zones are included in this zone. These segments can be classified as non-European (Africa, Asia, ...).				

Table 2. Zones used in the study.

5.2. Data processing.

To build the air traffic scenario, we extract, from the EUROCONTROL Demand Data Repository 2 (DDR2), full actual data on the 4D trajectories flown by aircraft in European airspace [62]. We also obtained the set of airspace data, i.e. the route network and the segments that comprise it, the location of airports, FL restrictions, etc., from DDR2.

For this study, data on losses of separation in each airspace segment was obtained using the Network Strategic Tool (NEST) modelling tool from EUROCONTROL. Using its calculation functionality and based on the radar trajectories of the aircraft that have flown over Europe, we were able to obtain the number of times there was a loss of separation.

Data on the type and category of aircraft involved in each event was obtained from ICAO's API Data Service. API Data Service is a tool developed by ICAO to collect a vast array of aviation safety data that allows existing and emerging global risks to be identified [63]. The data provided by ICAO is grouped by topic: States, Airports, Aircraft, Operators, Airspaces, Occurrences.

The data was extracted and processed using ad hoc software developed with R, the free software environment for statistical computing. Figure 4 gives a flow diagram that shows how the processing algorithm works. The algorithm may be divided into two parts: 1) Processes that occur outside the daily processing loop and 2) Processes that occur within the daily processing loop. All the data that does not vary or is not affected by the day being processed, lies outside the daily processing loop. This data is indicated by the blue blocks in Figure 4. There are two main nodes for the rest of the algorithm. These are the Wake Turbulence Category (ICAO) and the complete information about the segments. Most of the data on the segments (10 of the 14) are included in the daily processing loop.

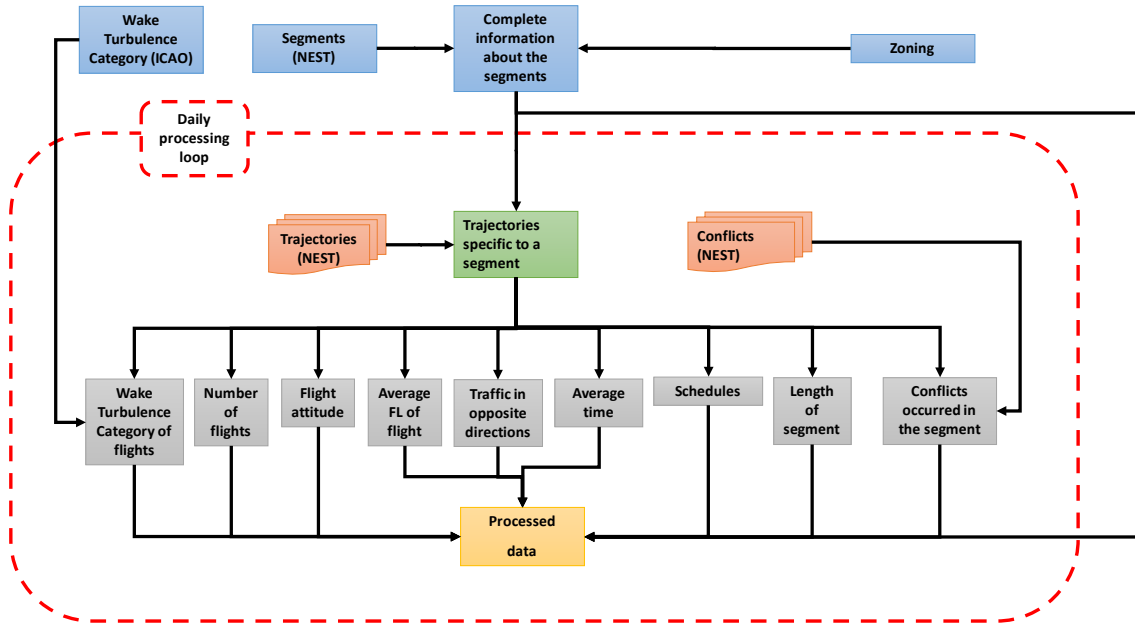


Figure 4. Data processing algorithms.

6. Analysis and results.

6.1. Preliminary analysis of the data.

Preliminary analysis of the data is the first step in the study of the data sample. This allows us to begin to understand the nature of the data and its distribution and values, as well as the direct relationships between data points or with the number of losses of separation.

Table 3 gives the Pearson correlation matrix of the segment data. The Pearson correlation coefficient is a measure of the linear relationship between two quantitative random variables. The Pearson correlation coefficient of two variables (x and y) is calculated as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (7)$$

Where:

- n = sample number.
- x_i, y_i = unique samples of variables x and y.
- $R = 1$, There is a perfect positive correlation (total dependence between the two variables).
- $0 < R < 1$, There is a positive correlation.
- $R = 0$, There is no linear relationship (There could be other non-linear relationships).
- $-1 < R < 0$, There is a negative correlation.
- $R = -1$, There is a perfect negative correlation (total dependence between the variables but with an inverse relationship).

	Losses of separation	Number of flights	% Ascent	% Descent	% Cruise	% Heavy	% Medium	% Light	% Morning	% Tarde	% Night	Crossing Traffic	Average FL	Average Time	Length
Losses of separation	1	0.4882	0.0028	0.1012	-0.0889	0.0047	0.0111	-0.0333	-0.0042	0.0086	-0.0056	0.0189	-0.0603	-0.0025	-0.01210
Number of flights	0.4882	1	-0.0401	-0.0580	0.0815	0.0408	0.0098	-0.1044	-0.0122	0.0222	0.0125	-0.0107	0.1078	-0.0196	-0.1162
% Ascent	0.0028	-0.0401	1	-0.2671	-0.5647	-0.1590	0.1473	0.0115	0.0592	0.0113	-0.0872	0.0601	-0.2649	0.0184	-0.0170
% Descent	0.1019	-0.0580	-0.2671	1	-0.6444	-0.2178	0.1910	0.0389	0.0292	0.0566	-0.1067	0.1053	-0.4650	0.0193	-0.0702
% Cruise	-0.0889	0.0815	-0.5648	-0.6444	1	0.3127	-0.2805	-0.0425	-0.0720	-0.0574	0.1605	-0.1379	0.6083	-0.0312	0.0736
% Heavy	0.0047	0.0408	-0.1590	-0.2178	0.3127	1	-0.8863	-0.1589	-0.1358	-0.1616	0.3694	-0.0633	0.3312	-0.0501	0.2059
% Medium	0.0111	0.0098	0.1473	0.1910	-0.2805	-0.8863	1	-0.3162	0.0870	0.1576	-0.3040	0.0719	-0.1633	0.0363	-0.1570
% Light	-0.0333	-0.1044	0.0115	0.0389	-0.0425	-0.1589	-0.3162	1	0.0928	-0.0049	-0.1086	-0.0237	-0.0330	0.0253	-0.0871
% Morning	-0.0041	-0.0122	0.0591	0.0292	-0.0720	-0.1358	0.0870	0.0927	1	-0.6755	-0.3848	0.0273	-0.0922	0.0759	-0.0652
% Afternoon	0.0086	0.0222	0.0112	0.0566	-0.0574	-0.1616	0.1576	-0.0049	-0.6755	1	-0.4108	0.0294	-0.0576	0.0445	-0.0524
% Night	-0.0055	-0.0124	-0.0872	-0.1066	0.1605	0.3694	-0.3040	-0.1085	-0.3947	-0.4108	1	-0.0705	0.1859	-0.1494	0.1460
Traffic in opposite directions	0.0188	-0.0107	0.0601	0.1053	-0.1379	-0.0632	0.0719	-0.0237	0.0273	0.0294	-0.0705	1	-0.0501	0.0270	0.0253
Average FL	-0.0603	0.1078	-0.2649	-0.4649	0.6083	0.3312	-0.1633	-0.3304	-0.0923	-0.0576	0.1859	-0.0501	1	-0.0221	0.2759
Average Time	-0.0025	-0.0196	0.0184	0.0193	-0.0312	-0.0501	0.0363	0.0253	0.0759	0.0445	-0.1494	0.0270	-0.0221	1	0.0120
Length	-0.0120	-0.1161	-0.0170	-0.0702	0.0736	0.2059	-0.1570	-0.0871	-0.0652	-0.0524	0.1460	0.0252	0.2759	0.0121	1

Table 3. Pearson correlation matrix.

It is possible to know in advance that certain variables are strongly related to one other. These are Flight Attitude (Ascent, Descent and Cruise), WTC Category (Heavy, Medium and Light) and Schedule (Morning, Afternoon and Night). This is because, when dealing with percentages, the sum of the three variables in each category is 100. This relationship can be seen graphically in Figures 5 and Figure 6.

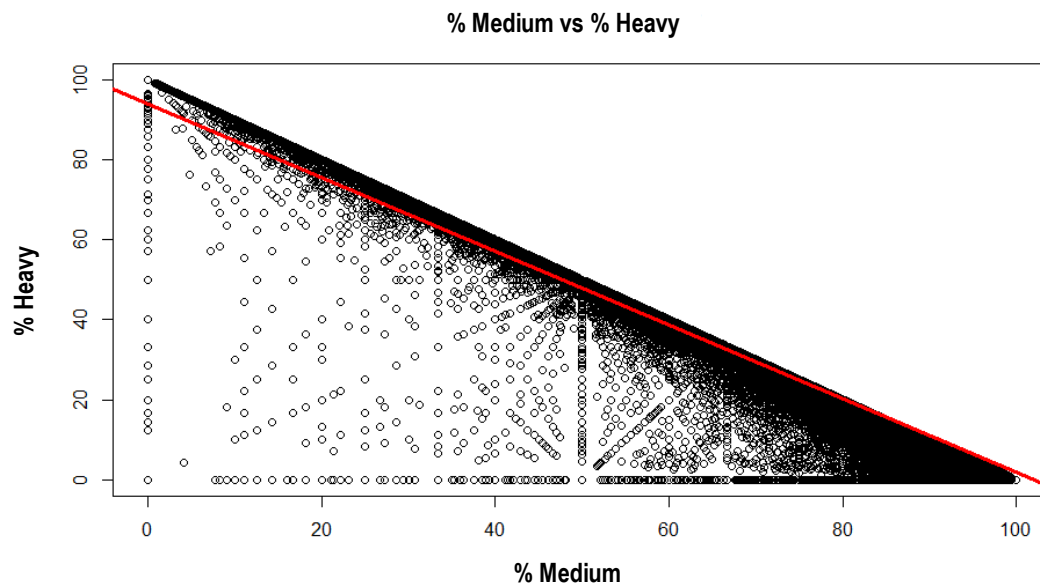


Figure 5. % Medium vs % Heavy.

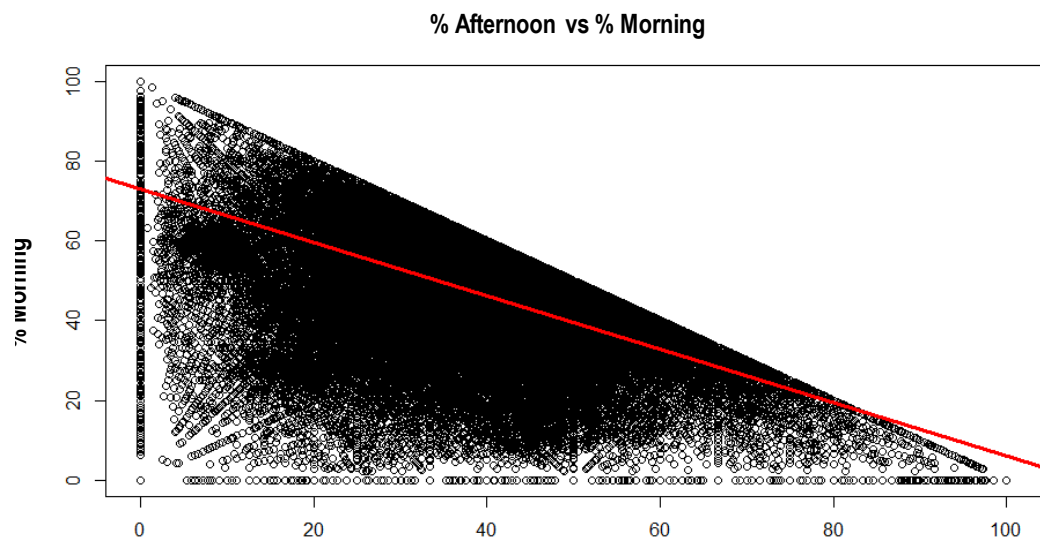


Figure 6. % Afternoon vs % Morning.

As we are dealing with percentages, both figures are bounded by the diagonal that connects the 100 values of both variables. Using linear regression lines (red lines) it is easier to perceive the degree of correlation between the variables. This correlation is greater in Figure 5 ($\approx -0,89$) than in Figure 6 ($\approx -0,68$). Both correlations are negative since, as these are percentages, when one value increases the other necessarily decreases. Finally, there are several segments (points in

the graph) along the zero values of both variables. This is because the data has three variables and it may be the case that on occasions the third variable, not represented in the figures, has a value of 100% meaning that the two variables represented have a value of zero.

There is also a strong correlation between Average FL and % Cruise, as can be seen in Figure 7. The data shows that there is a positive correlation of approximately 0.61. This strong correlation is because aircraft tend to operate in cruise phase when they are at a high FL, while ascent and descent manoeuvres usually occur at lower FLs and close to airports or aerodromes. We can also see that in the vast majority of the segments aircraft operate at an Average FL below FL 360.

Except for the variables mentioned, and as can be seen in Table 3, the correlation coefficients between the remaining variables are low, usually between -0.1 and 0.1.

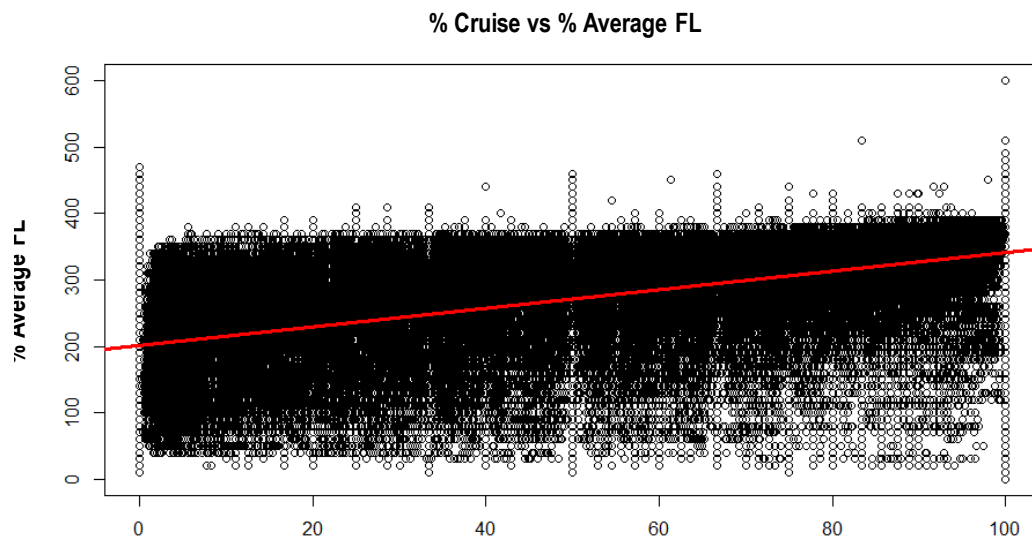


Figure 7. % Cruise vs % Average FL.

Having analysed the correlation coefficients between the different variables we then study the correlation between the data and the number of losses of separation. Figure 8 shows the number of losses of separation losses versus the number of flights. The quadratic regression line enables us to see that the relationship between both variables is non-linear.

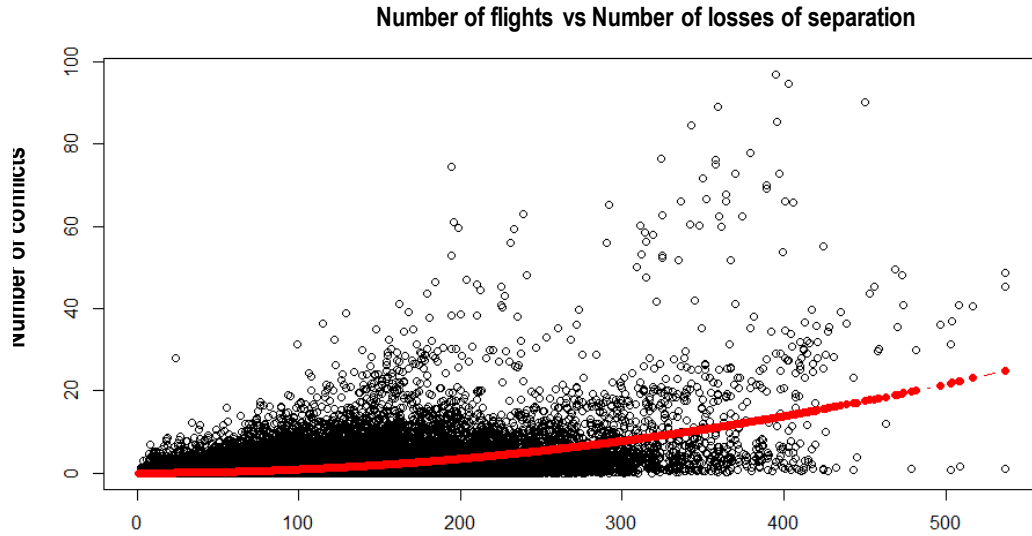


Figure 8. Number of flights vs Number of losses of separation.

One of the limitations of Pearson correlation coefficients is that they only look for linear relationships and those that are not linear may remain hidden. To avoid this problem, we studied the data using Spearman's rank correlation coefficients. The Spearman method is similar to the Pearson method and attempts to assess how well the relationship between two variables can be described using a monotonic function. Interpretation of the results when using Spearman's rank correlation coefficients is similar to the interpretation when using Pearson correlation coefficients. The formula for finding the Spearman's rank correlation coefficients is:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (8)$$

Where:

d = the difference of the range of the values in each row
 n = sample number

The level of Spearman correlation between the different segment data is roughly the same as the level of Pearson correlation, except in two cases. There is an increase in the correlation between Average FL and the length of the segment. The Pearson correlation coefficient is 0.28 while the Spearman method gives a value of 0.39. Figure 9 shows the relationship between these two variables. As can be seen from the graph, there is a positive exponential correlation for the range FL 0 - 320. There is also a strong negative correlation for FL values above 320. In this second case, and as can be seen in Table 4, the Spearman's rank correlation coefficients show a slight increase in the correlation between the different data and the number of losses of separation. One variable that stands out is the number of flights, where the increase in correlation is almost 0.2 points, demonstrating the non-linear relationship between these variables.

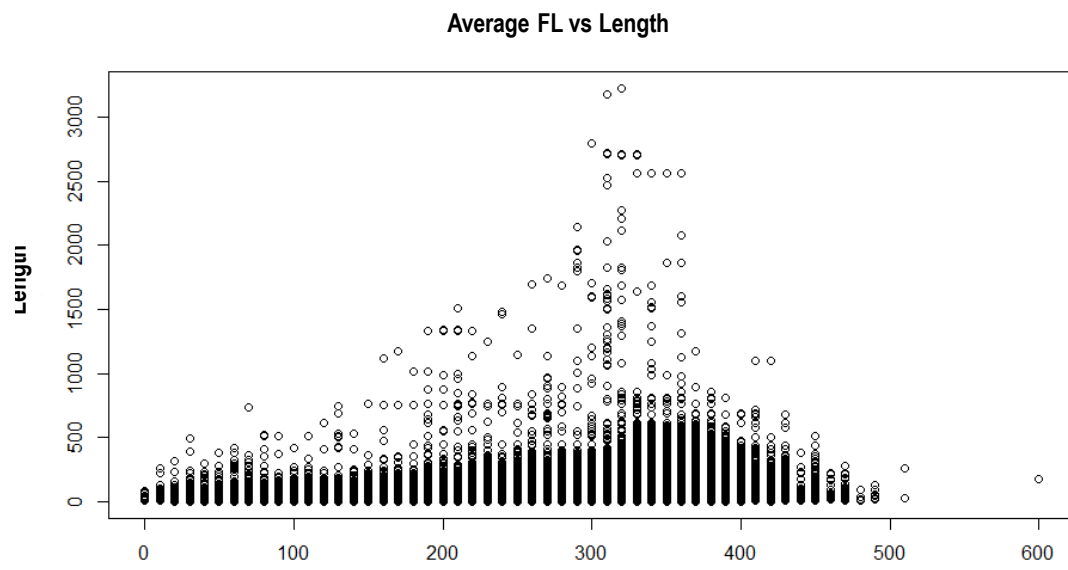


Figure 9. Average FL vs Length of the segment.

Spearman's Coefficient	Losses of separation	No. of flights	% Ascent	% Descent	% Cruise	% Heavy	% Light	% Morning	% Afternoon	% Night	Crossing Traffic	Average FL	Average Time	Length
Losses of separation	1	0.6357	0.1654	0.2038	-0.1698	0.1390	0.1613	0.0121	0.0560	0.1422	0.0055	-0.0626	-0.1031	-0.0209

Table 4. Spearman's Coefficient.

Similar correlations are obtained using both the Pearson and Spearman's coefficients. These shows that there are no two variables that are highly correlated and, therefore, no variable can be eliminated from the study.

We may also conclude the number of flights operating in the segment is clearly related to the number of losses of separation. Figure 10 and Figure 11 show the evolution of flights and losses of separation for 2015. There is a clear difference between the number of flights per day depending on the day of the week, as well as a direct correlation between the number of flights and the number of losses of separation. Both distributions are practically identical, although the distinction between the number of losses of separation depending on the day of the week is not as pronounced as in the case of the number of flights.

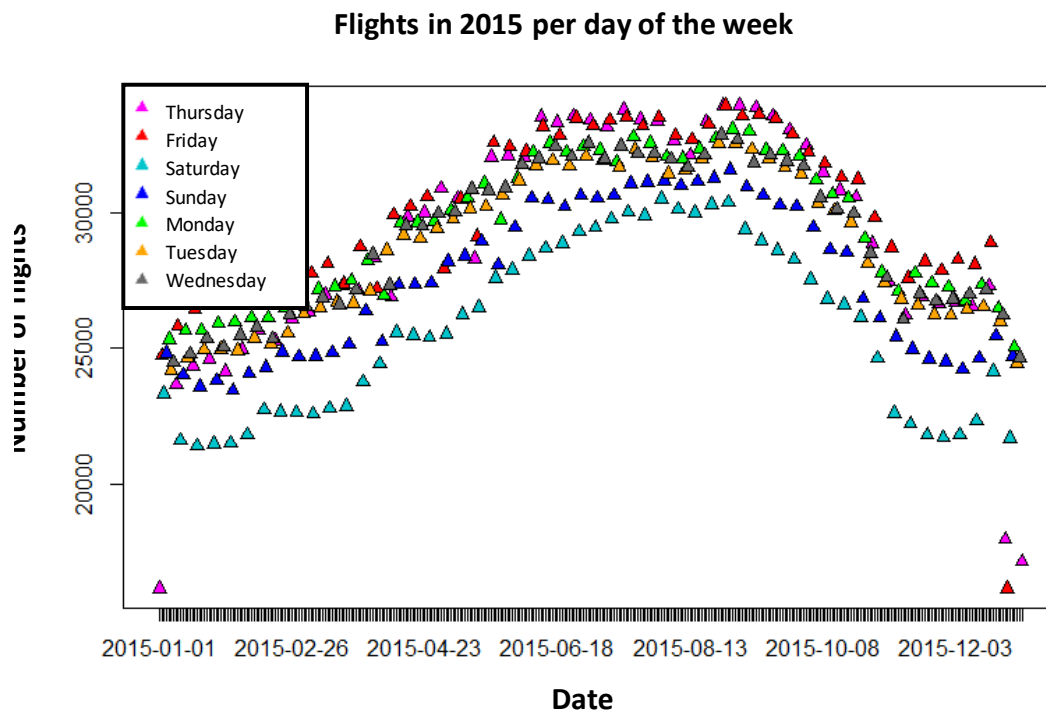


Figure 10. Flights in 2015 per day of the week.

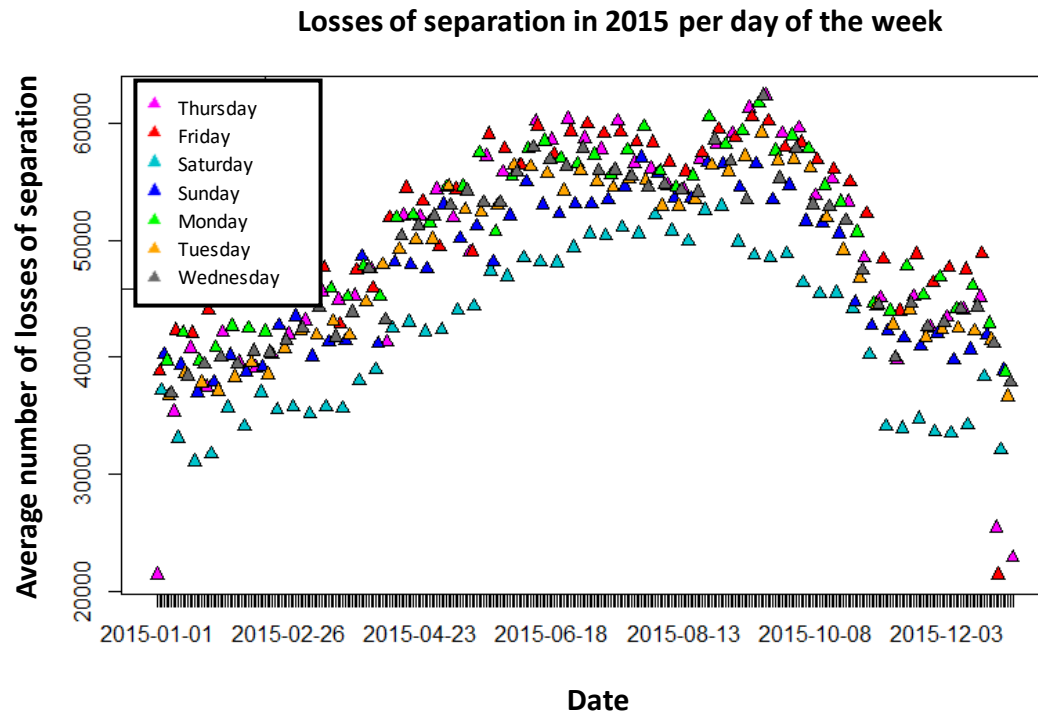


Figure 11. Losses of separation in 2015 per day of the week.

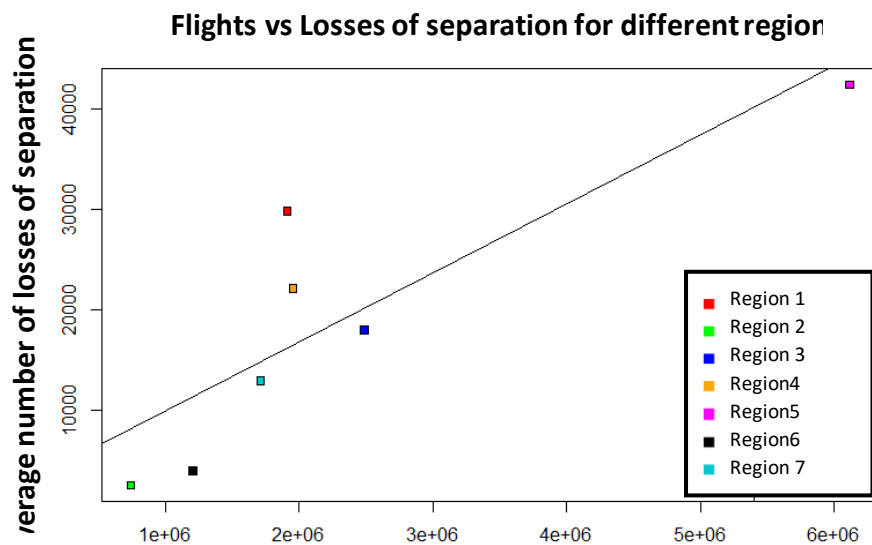


Figure 12. Flights vs Losses of separation in the 7 regions.

An analysis of the flights and losses of separation per region shows how the positive relationship between both variables holds true for all regions, as can be seen in Figure 12. Figure 13 shows a box plot of the distribution of the number of flights per segment for each region.

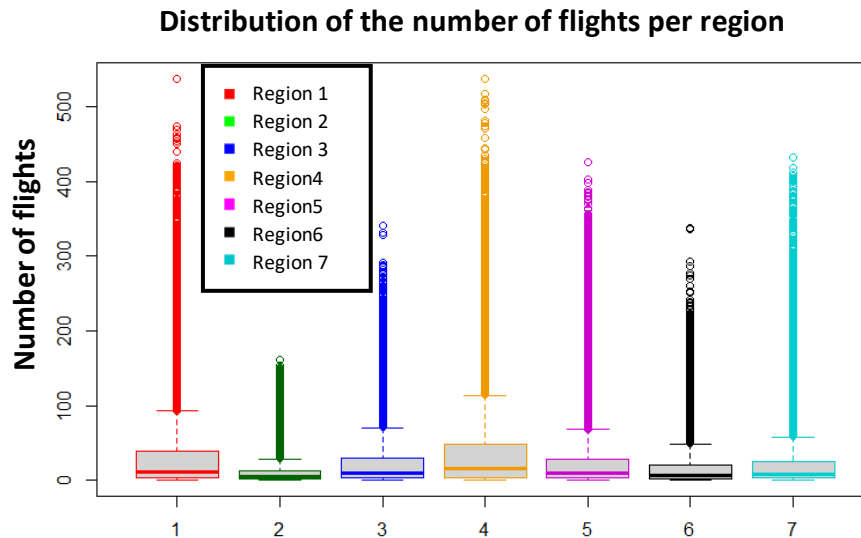


Figure 13. Distribution of the number of flights in each region, with outliers.

We can see that there is a large number of segments with “outlier” flights beyond the whiskers of the diagram. These are values that are at a considerable distance from the rest. Although it is usually up to the analyst to define what an outlier is, in general those values that are below $Q1 - 1.5 \cdot IQR$ or above $Q3 + 1.5 \cdot IQR$ are considered to be outliers where $Q1$ = Lower quartile, $Q3$ =Upper quartile and $IQR=(Q3-Q1)$.

In the figure we can see that, in the different regions, most of the segments have fewer than 100 flights. To make it easier to view the data we show, in Figure 14, a box plot for the different regions without any outliers.

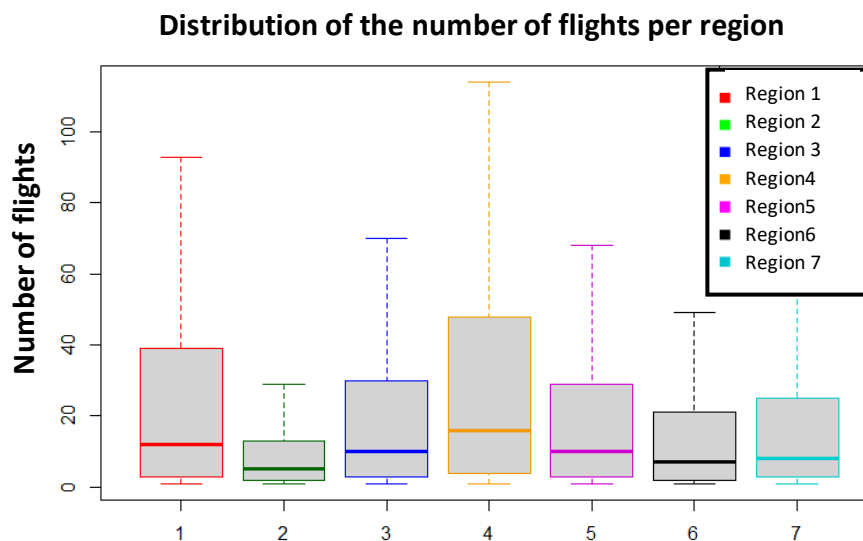


Figure 14. Distribution of the number of flights in each region, without outliers.

As can be seen in Figure 14, there is a certain similarity in the distribution of flights in the different segments for each region. The average in all regions is around 10 flights. Also, the shape of the boxes is similar, them being narrower in the lower part than in the upper part. This means that flights between 50% and 75% of the sample are more dispersed than those between 25% and 50%. Similarly, flights between 75% and 100 % are more dispersed that those between 0% and 25%.

6.2. Results and discussion.

We use the data from Region 1 to illustrate the development of the model and the results. Table 5 shows the results for the model which gave the best AIC value for the data of Region 1. In the table we see the variables chosen in the model, as well as the regression coefficients of the count model used to predict the number of losses of separation, and the corresponding p-values.

Variable	Coefficient	P-value
Intercept	-0.731265	0.0705
% Cruise	0.012975	<2 e-16
% Ascent	-0.011580	<2 e-16
Length	0.010708	<2 e-16
Average FL	-0.003008	<2 e-16
% Afternoon	-0.009007	1.96 e-06
Crossing Traffic	-0.000804	0.0691
% Morning	0.002275	0.2747
% Heavy	0.015410	9.93 e-07
% Medium	0.015410	3.69 e-05

Table 5. Coefficients for the count model of Region 1.

As can be seen, the model for Region 1 only uses 10 of the 16 possible variables. The model does not contemplate any categorical variable (Direction, Type or Network) due to the great imbalance between the different groups in the category. The model considers there to be a high correlation between these variables, or between them and other variables, and, therefore, discards them. The absence of the variables % Descent, % Night and % Light is also noteworthy. Their absence is not due to the fact that they have little influence on the prediction of the number of losses of separation, but because they are highly related to other complementary variables and their effect is, therefore, already included in the model.

The coefficients of the model are interpreted below in an integrated manner. A direct comparison of the coefficients between variables would be misleading and could lead to false conclusions because the magnitude of the coefficient is closely related to the magnitude of the variable.

Analysis of the coefficients shows that three variables have a relatively high p-value. These are Intercept, Crossing Traffic and % Morning. The p-value is defined as the probability of obtaining the observed results when the null hypothesis of the study is correct. In this study the null hypothesis is that the variable in question does not have a significant impact on the number of losses of separation that occur. The level at which a variable is considered to be significant is not fixed and it is generally up to the analyst to determine. In this study, the level of significance has been set at 95% which means that variables with a p-value > 0.05 are considered to be not significant. The three variables mentioned above exceed this value and, therefore, may be eliminated from the model.

Continuing the analysis, we see that % Cruise, % Ascent and % Afternoon, as well as Crossing Traffic and Average FL all have negative coefficients. This means that a positive variation in the value of these variables causes a decrease in the number of losses of separation. Looking at % Cruise, assuming that the rest of the variables remain constant, an increase of one unit implies a decrease of 2.84% ($e^{-0.028803} = 0.9716$) in the number of losses of separation. Similarly, an increase of one unit in Average FL results in a decrease of 2.96% ($e^{(10 \cdot -0.003008)} = 0.97$) in the number of losses of separation. It is worth mentioning that in the case of the variable Average FL one unit corresponds to a value of 10, i.e. 1000 ft.

To validate the model and evaluate how well it fits the data, we analyse the residual values (residuals) and the fitted values of the model. The fitted values are the values predicted by the model, in this case the predicted values of the number of losses of separation. A residual is the difference between the fitted value and the actual value; and there should be no relationship between these two values.

$$e_i = y_i - \hat{y}_i \quad (10)$$

Where:

- e_i = Residual value
- y_i = Actual value
- $\hat{y}_i$ = Fitted value

Fitted values vs Residuals - Model for Region 1

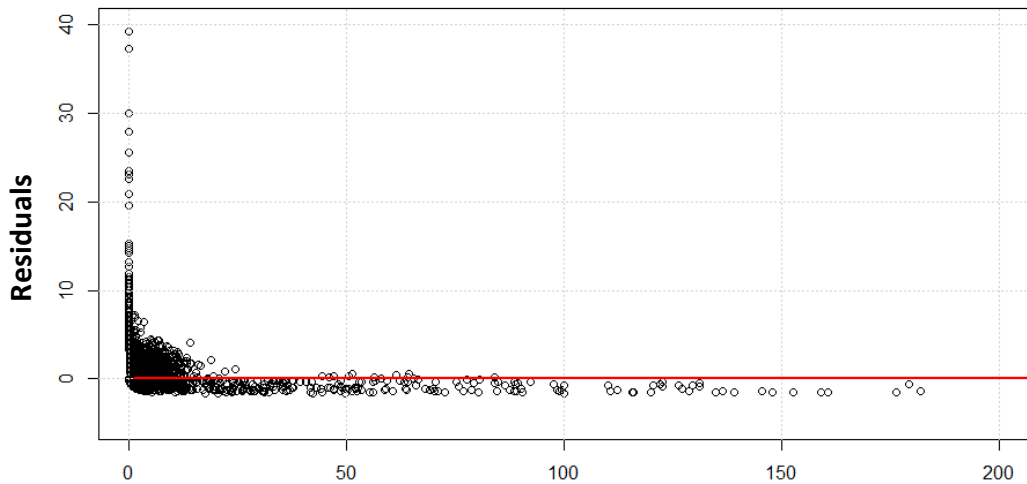


Figure 15. Fitted values vs Residuals- Model for Region 1.

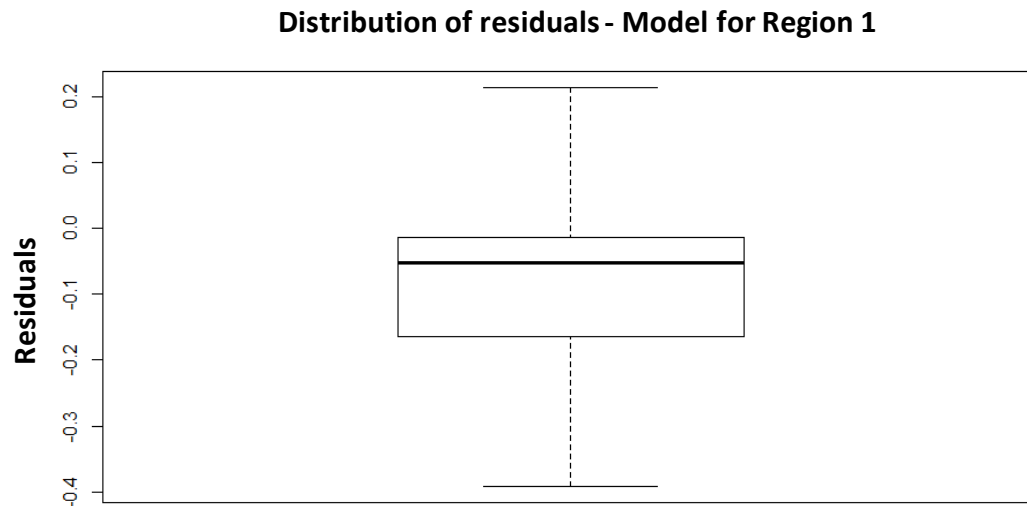


Figure 16. Distribution of residuals – Model for Region 1.

As can be seen in Figure 15, the model fits the data quite well. However, as can be seen in Figure 15 and Figure 16, the model tends to overestimate the number of losses of separation in the segments. Figure 15 shows that there are a number of predictions below the zero line (red line). This overestimation can be more clearly seen in the box plot in Figure 16 which gives the distribution of the residual values. We see that both the first and third quartiles are below zero. The average residual value in this model is -0.0214083.

To graphically illustrate the accuracy of this model, the adjusted and residual values of a linear model created using the same variables as those used in the model for Region 1 are shown in Figure 17 and Figure 18.

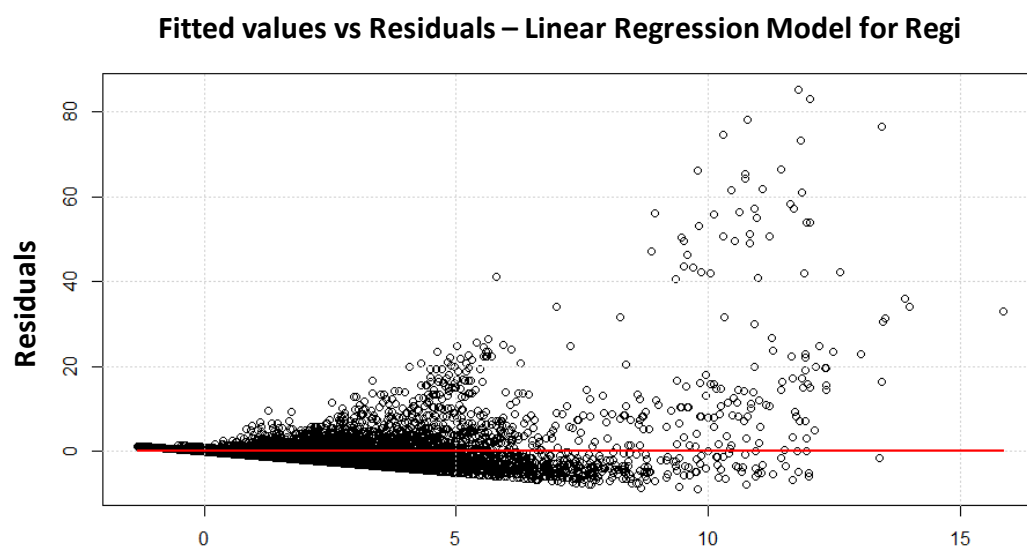


Figure 17. Fitted vs Residuals - Linear regression model for Region 1.

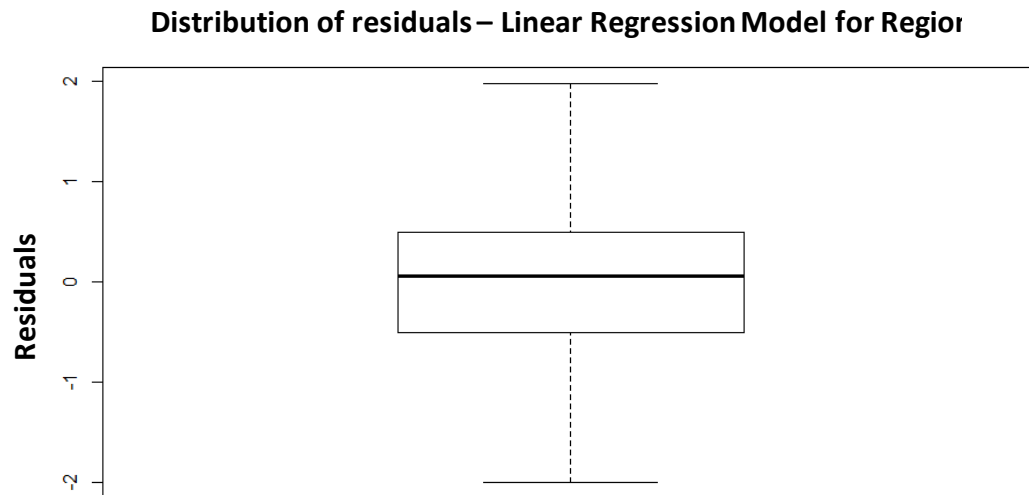


Figure 18. Distribution of residuals - Linear regression model for Region 1.

It can be clearly seen that the linear model gives a very poor fit to the data, especially in segments with losses of separation. Due to the excess of zeros in the data, the linear model tends to predict in almost 100% of the cases that the number of losses of separation is zero. In Figure 17 we see that the linear model does not predict a number of losses of separation greater than 20 for any of the segments. This means that the residual value can be as high as 80.

Figure 19 shows the residual and fitted values of the models for Regions 2 – 7. Table 6 gives, for each region, the variables included in the model that best fit the data as well as the coefficients and p-values for each variable. The table enables us to compare the models generated for each region.

	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	Region 7
Mean residual value	-0.0214083	0.001169074	-0.00501231	-0.01943389	-0.0002604214	-0.001991476	-0.01606784
Number of flights	0.012975	0.035196	0.020949	0.012762	0.017114	0.019528	0.013950
% Ascent	0.011580			0.004882		0.001177	
% Descent		0.013632	0.007179		0.009023		0.004365
% Cruise	0.028803	0.014506	0.026162	0.013837	0.0171263	-0.028792	-0.017477
% Heavy	0.015410				0.014640		
% Medium	0.015410	0.001758	0.000787	0.004030	0.017151	-0.000358	0.002816
% Light		0.051757	0.040354	0.015016			
% Morning	0.002275		0.003847	0.007199	0.006454		-0.003868
% Afternoon	0.009007	0.006839					-0.019847
% Night			0.006376	0.004424		0.019648	

Note: Shaded values do not satisfy the condition $p\text{-value} > 0.05$

Table 6. Summary of the models for each region.

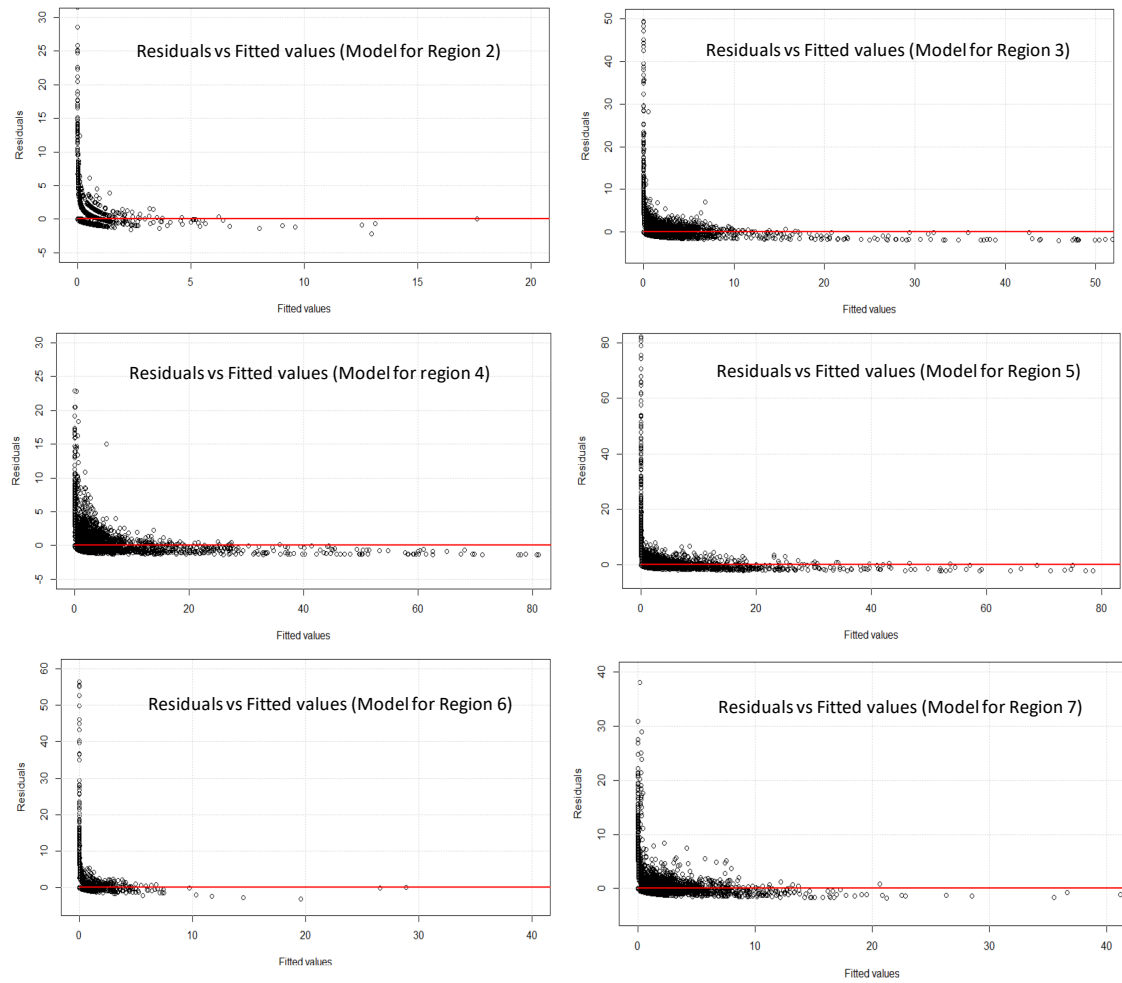


Figure 19. Residuals and fitted values of the models for Regions 2 – 7.

Table 6 shows that all the models are similar in terms of accuracy (mean residual value) and in the variables used. However, we can see that a given variable does not always affect the number of losses of separation in the same way.

- **Number of flights:** This variable is present in all models. Furthermore, in all regions it is the variable with the lowest individual AIC. As can be seen in Table 6, the coefficients of this variable are always positive indicating that in all regions the more flights there are, the more losses of separation. The coefficient is more or less constant with a value of between 0.01 and 0.02 in all regions except Region 2 where it has a value of 0.035. Therefore, this is the region where a variation in the number of flights has the greatest impact on the number of losses of separation. For each additional flight the number of losses of separation increases by 3.58%.
- **Ascent, Descent, Cruise:** Of these three variables the only one that is always present is % Cruise due to the correlation between them. In other words, as long as two are present, it is as if all three are being considered. As can be seen in the table, the values of these coefficients are reasonably constant (Ascent = 0.005-0.012, Descent = 0.005-0.014, Cruise = 0.013-0.029). The way that they affect the number of losses of separation is always the same: % Ascent and % Cruise always have a coefficient with a negative value, and % Descent always has a coefficient with a positive value. We can deduce from this that an aircraft with a descending flight attitude increases the risk of loss of separation. The safest flight attitude is cruise not only because its coefficient is negative, but also because it has the highest value.
- **Heavy, Medium, Light:** Like the previous variables, these are conditioned by the correlation between them. From the table we can deduce that, in general, the higher the percentage of Heavy or Medium aircraft, the greater the number of losses of separation. In Region 2, % Light has a positive coefficient while in Region 3 it has a negative coefficient. This means that in the latter, the greater the percentage of light aircraft, the fewer the losses of separation.
- **Morning, Afternoon, Night:** The data in the table shows that, as a rule, the higher the percentage of aircraft in the Afternoon schedule, the fewer losses of separation there are. The other two variables (Morning and Night) do not behave consistently. In Region 3, % Night has a negative coefficient while in Region 4 it has a similar value but is positive. This shows that there is no consistency in terms of which schedules are more likely to generate losses of separation. A priori it may mean that the regions are too large to demonstrate the impact of this variable. However, the variability shown suggests that by bringing the models down to the level of sector or control centre we may be able to identify the impact of the specific time schedule, and therefore of the sectorisation policies and allocation of human resources, on the occurrence of losses of separation.
- **Crossing Traffic:** Direct interpretation of the coefficients of this variable is complex due to its very nature. First, we must establish what positive and negative variations in the value mean. An increase in the value of this variable (assuming the rest are constant) means that there is an increase in the number of aircraft flying in the same direction within a given segment. In other words, there is a smaller number of aircraft flying in the opposite direction. All models except one (Region 2) yield negative coefficients, therefore, in these regions, for a given number of aircraft, the greater the number of aircraft operating in the same direction, the lower the number of losses of separation losses. In Region 2, as the coefficient is positive, the converse is true.

- Average FL: Similar to the previous case, the value of the coefficient for this variable is negative for all models except one (Region 6). This means that the higher the average flight level of the segment, the fewer the losses of separation. One of the reasons for this may be the correlation between Average FL and % Cruise. In Region 6, the lower the average flight level of the segment, the fewer the losses of separation. It is worth mentioning that in the case of the variable Average FL one unit corresponds to a value of 10, i.e. 1000 ft.
- Length: This variable is present in all models. The value of the coefficient varies between 0.006 and 0.021 and is always positive. The conclusion is that the greater the length of a segment, the more losses of separation there are.

7. Conclusions and future work.

The objective of this study is to develop models, capable of predicting the number of losses of separation between aircraft in a given segment of the airspace of a route, that are not solely based on the analysis of the trajectories of aircraft. The methodology used is based on extrapolating the concept of Safety Performance Functions, used to predict safety occurrences in ground transportation, to the aeronautical environment.

To achieve this, a methodology of work, analysis and modelling is developed to enable us develop functions, to predict the number of losses of separation in a segment of airspace, adapted and calibrated to reflect the specific characteristics of a given airspace region.

The work done demonstrates the interest in and feasibility of developing SPFs to analyse and predict occurrences in airspace. The results of the different models show that it is possible to model, quite accurately, the number of losses of separation using the variables considered. This is done using a Zero-inflated negative binomial distribution. This work demonstrates that, thanks to the methodology developed, not only can a regression model be generated but that also it may be used to analyse the effect of the variables on the predictions made. It has also been shown that not all the variables affect the prediction of losses of separation in a uniform manner. The study by regions demonstrates that, depending on the geographical area where the segment is located, there are variables that affect the predicted values to a greater or lesser extent, or even in the opposite way.

The potential of a study of these characteristics to predict losses of separation in air segments is clear. However, it is also worth mentioning that the methodology developed can be extrapolated to analyse safety in other airspace entities such as sectors, waypoints or even airports.

Increased knowledge about which characteristics are more relevant to the occurrence of losses of separation can lead to an improvement in safety. It can also reduce the workload of controllers by improving efficiency and optimisation.

With regard to this methodology, future work should focus on improving the following three areas:

1. Data. When generating a work methodology, the accuracy or veracity of the data is key. Once the working methodology has been established, it is important to always look for real data or, where this is not possible, to use highly reliable simulations or models.

2. Optimisation of the methodology. As seen in this study, when we work with large amounts of data small inefficiencies can have a significant negative impact on processing time. All code and algorithms must be refined until they are as efficient and effective as possible so that they do not consume more time than is strictly necessary. Processing power is another key factor. Sometimes, however optimal the algorithm, the amount of data or number of operations to be processed is too great for conventional or even high-performance equipment.

3. Regression models. In this paper only a few regression models are mentioned and the final model is made using just one of these. Further work is required on the ability of the different regression models to fit the data. It would also be interesting, as with SPFs, to test the use of Bayesian models to predict losses of separation. These models have, at times, proven to be more accurate than the rest of the models in predicting road accidents, particularly when the data contains an excess of zeros.

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