Predictive Maintenance Model of Refined Aircraft Tires Replacement

Timur Tyncherov⁠¹,³(✉) and Liubov Rozkova²,³

¹ S7 Engineering LLC Domodedovo Airport, Building 9, Moscow Region 142015, Russia
t.tyncherov@s7.ru
² S7 TechLab LTD, Petrovka Street, 7, Office 4a, Moscow 107031, Russia
³ Transport and Telecommunication Institute, Riga, Latvia
st61824@students.tsi.lv

Abstract. Development of new predictive maintenance models in aviation relies on traditional maintenance programs that cost-effectively ensure flight safety. Design individually oriented predictive maintenance programs for each group of units according to the specificity of systems, assemblies and structural elements of modern aircraft requires considering data of behaviour during aircraft operational life cycle (aircraft digital twin). This article describes the current practical approach and proposes a model of predictive maintenance together with airline warehouse stock optimization system and Maintenance Repair and Overhaul (MRO) organization capacity management with particular focus on tires. Analysis of parameters that can potentially affect aircraft nose wheel tires wear and selection of the most relevant factors to build a model for tire replacement forecast using flight data recorders are described in this study. The resulting model is used for the creation of automated production load management system for MRO organization facilities considering their ultimate capacity. The model determines optimal stock or buffer needed for wheel replacement and continuous aircraft fleet operation. The model gives the possibility to calculate the minimum necessary number of spare wheels in the warehouse to ensure continuous operation of a given number of aircraft and a given MRO capacity. As a result of this, I present the Analysis of method’s economic efficiency and evaluate losses associated with early wheel removal and spare wheels capacity.

Keywords: Aircraft predictive maintenance · MRO stock optimization · Capacity management · Regression analysis

1 Introduction

Current reality poses new challenges for civil aviation. This industry, which normally has moderate growth and is highly dependent on the economic situation in a particular country and the whole world, suffers enormous financial losses in a pandemic. COVID-19 has hit all sectors of civil aviation. The largest manufacturers of aviation equipment are forced to cut production plans radically, which leads to the dismissal of personnel. Suppliers of aviation equipment and spare parts suffer along the chain. Airlines around...
the world are suffering losses. A large number of aircraft are in long-term and expensive storage, awaiting market recovery. Passenger traffic is recovering very slowly, and carriers are forced to undercut prices, fighting for a passenger. Despite state support, low rates and insignificant demand for air transportation are forcing airlines to reduce their fleet and personnel and optimize costs. Following airlines and manufacturers, leasing companies also suffer. Demand for new aircraft has drastically decreased compared to pre-crisis levels. A large number of airlines terminate lease agreements ahead of schedule, and a significant number of aircraft are returned to lessors due to airline bankruptcy. Accordingly, in the current falling air transportation market, finding customers for further remarketing is extremely difficult.

Figure 1 shows how COVID-19, according to International Air Transport Association (IATA) reports [1], affected global Revenue Passenger Kilometers (RPK - it is calculated as the number of revenue passengers multiplied by total distance traveled). Yellow sector reflects growth forecast for PRK, indicating boundaries of the best and worst-case scenarios for development of the situation with the virus.

![Fig. 1. RPKs, trillions per year.](image)

The situation is also bad in the area of aircraft maintenance. A lot of aircrafts do not fly and are in long-term storage, and those that fly have extremely limited flight time. For aircraft in storage, manufacturers are modifying their maintenance programs to postpone technical regulations until parking ends. Accordingly, need for aircraft and component maintenance has also dropped significantly. In order to survive in such conditions maintenance, repair and overhaul organizations (MRO) are also forced to reduce costs. First of all, non-core assets and projects fall under reduction. For example, a staff of programmers and mathematicians dealing with Big data analysis and defect forecasting.

Such projects are considered as high risk and not justifying themselves from a financial point of view. For example, in article [2] authors critically consider the benefits of application without considering economic aspects. Airlines and MRO organizations are somewhat frustrated with predictive maintenance models. Everyone
understands that this is the future and that the potential of this technology is vast, but there is no hype anymore. Lack of quick results in the context of the global crisis is forcing companies to close such projects and reduce their competencies in this area. Instead, they turn to predictive maintenance solutions from major manufacturers (such as Airbus, Boeing, General Electric, and etc.). However, these solutions are not always right for a particular airline (for example, if it operates aircraft in special conditions).

Moreover, these solutions are mostly made for predicting defects in aircraft units. The preventive replacement of the unit, which should fail soon, will prevent possible flight schedule interruptions. However, MROs would be more interested in predicting defects discovered during basic maintenance. For example, aircraft structure defects, the repair of which is laborious and time-consuming. Discovery of defects that require complex repairs can lead to a delay in aircraft departure from maintenance. Lack of forecast for such defects forces MRO organizations to:

- reinsure themselves when planning the required resources to perform maintenance,
- shift risks to the airline, by including into contracts clauses on the possibility of not meeting the agreed terms of maintenance in case of defects that require “complex and laborious” repairs.

Both approaches have negative consequences. In the first case, we deal with not the optimal number of personnel and large warehouses with spare parts, just in case. In the second case, we have high reputational costs.

This article is aimed to demonstrate a low-cost, practical approach to solving problems of predicting defects (based on flight-recorded data) by the example of predicting the degree of wear of aircraft nose wheels. Nose wheels are so-called highly liquid spare parts, i.e. parts that are changed regularly enough. Procurement and logistics specialists are not interested in such parts. They are more interested in low-liquidity spare parts with long delivery times and predictable demand. For example, in the article [10] Mr Larin examines the problem of forecasting the need for low-turnover spare parts at the time of aircraft service.

However, in the overall ranking, cost of tire replacement is in the first place (i.e. for a fleet of one hundred aircraft, the total cost of replacing tires per year exceeds those for other spare parts). Thus, the forecast of high liquidity spare parts can provide significant benefit if we consider its’ benefit as a combination of three factors. The first factor is to prevent flight delays that could result in wheel wear detection before departure. The second factor is the optimization of spare wheel stock, which is necessary to maintain the duration of flights. The third factor is an optimization of a load of Wheel Service Workshop (which makes repairs), since planned wheel replacement that is close to wearing limits can smooth out peaks in workshop load and optimize a number of its personnel.

2 Wheels and Tires

As part of this research, we will consider only single-aisle nose landing gear (or in other terminology narrow-body) of the aircraft. These aircraft are widespread and demanded aircraft such as Boeing 737 and Airbus A320 families. Solving the problem
of forecast refinement using flight data analysis is more complicated for nose wheels than for basic ones. Since the influence of factors such as crosswind or aircraft landing weight on wear is not that significant. That is why the solution to the problem for nose wheels was chosen as a proof of the concept.

To build an adjusted forecast of wear, we will consider only the aircraft landing stage. More precisely, we will investigate the stage of touching the ground with the wheels of the nose landing gear and run until the release of the strip. As on landing, tires undergo severe overloads and, accordingly, wear out to the maximum. Conclusions of study [3] prove it.

Typically, single-aisle aircraft landing gear system has two main landing gear and nose landing gear. The nose landing gear has a steering system and is not equipped with brakes. Radial or conventional type tires are installed on two wheels of the gear. The steering system is limited as a function of the aircraft speed and the origin of the orders (pilot or autopilot). After takeoff, nose wheels are automatically centred under the action of cams in the shock absorber. That means that during landing nose wheels have the same direction as the lateral axis of the aircraft. Discrete logic signals are given to applicable systems when:

- the NLG shock absorber is compressed,
- the NLG shock absorber is not compressed.

Replaced wheels are sent to wheels shop for service where they are disassembled and inspected. Tires on the wheels are replaced. Tires are either autoclaved or recycled.

Tire damage or wear may be the reason for removal. Damage such as Flat Spots, Chevron Cutting, Aggressive Wear, Foreign Object Damage (FOD) or Tread Cuts, Tread Chipping, and Chunking, Rib Undercutting, Open Tread Splice, Stripped Rib, Side Damage and other damage that does not belong to Normal Wear [4] are not considered in this study. In the course of analysis records about the reason for wheels removal, for statistics, we only considered wheels for which the reason for removing was wear.

The exact number of landings before removal for each wheel depends on factors such as weather, hard landings, crosswind landings, anti-skid action, and rough or damaged strip surfaces. All these factors can affect the condition of the rubber. Furthermore, even wheels included in the same set on the same aircraft may differ.

### 3 Tire Wear Prediction Methods Review (Current State)

Normally aircraft tires are replaced on condition. Aviation technicians and pilots inspect the wheels before each flight and replace the wheel if damage or unacceptable wear is found. Wear limits are usually indicated either by documentation of the aircraft manufacturer or tire manufacturer. The grooves molded in the tread are used as wear indicators. Tires are replaced when the tread is worn to the base of a groove.

The authors of the work [2] consider application of the neural network to predict the failure (complete wear) of the tire of the De Havilland Dach-8 aircraft. Neural networks is compared to a linear-regression prediction method. Such prediction is more accurate in case of tire wear analysis, but in this study I made the prediction only on
basis of flying time (Flight Cycles). That is, individual reasons for increased wear of each wheel are not considered separately. And the goal of our project is to predict removal of a particular wheel due to tire wear.

In [3], authors carefully examine process of flat spot (non-uniform wear) formation, its dependence from Vertical Speed and yaw angles of the aircraft. Also influence of formed flat spot on further wear of a wheel. Data for analysis was obtained by conducting a series of experiments on a test bench. The authors built digital twin tires. A Monte Carlo simulation technique along with a Cotter sensitivity analysis was used to complete digital twin model. The model was then used to predict Probability of Failure.

Effect of temperature and Slip angle on wear rate of aircraft tires is discussed in [4]. The authors carried out experimental studies examining degree of tire wear depending on different temperatures and Slip angle. Main conclusion of this work is that the main factor affecting tire wear is Slip angle, i.e. aircraft drift due to crosswind increases tire wear.

During work on this project, we learned that one of the airlines, together with a major tire manufacturer, had launched a project to predict tire wear. According to press releases published by the companies [5], it is planned to use flight data of the airline and tire insights and digital tire wear prediction technologies from manufacturer to determine optimal time to replace tires. The work is aligned with what we are doing with the only difference that in our case the manufacturer is not involved. The accuracy of predictions based on knowledge of tire manufacturer will potentially be higher, but one of the goals of this work was to maintain low costs for the project as a whole. That would not have been possible if the project had been in cooperation with a large corporation, since only costs for the lawyers who draw up a contract would exceed the entire budget of the project.

4 Refined Maintenance Model of Aircraft Tires Replacement

Data of chosen for study airline shows that average lifetime of a nose wheel with a part number on a single aisle aircraft is 267 flight cycles. This average time does not include outliers that occur when tire is damaged. Such outliers can occur on the first day of a new tire’s operation and on the last. But they are sporadic and therefore statistically insignificant. The task is to make a wheel wear model for improved prediction of removal.

Each time an aircraft lands different forces and moments affect on the wheels. These forces and moments affect intensity of tire wear and depends on many factors of airplane-environment system. Such as weather (wind, precipitation), aircraft mass, forward and vertical speeds, flight pass vector, braking intensity, and so on. Aircraft’s Flight Data Recording (FDR) system records over 1,000 parameters at any given time. Accordingly, it is necessary to select those parameters that have maximum effect on tire wear, in other words, correlate.

After analysis of all information recorded by the FDR system of the aircraft of single aisle family, a set of information units was chosen that should hypothetically
correlate with tire wear. The following Table 1 gives a list of parameters that were chosen and their short description.

For analysis we have chosen fleet from a sister ship (identical configuration) aircraft of the same operator. We have made analysis of the history of operation of 84 wheels from the moment of installation to the moment of removal thereof. Data, according to the rules of Machine learning, is divided into two sets: training and validation. A linear regression model [6] was used to predict wear. Most accurate (according to mean absolute value error score) model was chosen on cross-validation on the training set. The final score was calculated on the validation dataset.

For detailed description of the process of data preparation and modeling, the authors wrote an individual article [11]. Below we present only the final results.

Parameters for the model were selected among correlated explanatory variables with the target value (remaining cycles to wheel removal). Cross correlated explanatory variables with smaller correlation were not consider. The final parameters selected for modelling are presented in Table 2. The description column contains the physical description of the parameter. The Period column contains the number of seconds after the aircraft landed, the data of which was used to calculate the percentile. The Percentile column contains the number of the percentile with which the explanatory

| Parameter | Parameter description |
|-----------|-----------------------|
| Body lateral acceleration | Acceleration parameter group |
| Lateral acceleration | |
| Longitudinal acceleration | |
| Normal acceleration | |
| Roll angle | |
| Ground Speed | Ground speed is the horizontal speed of an aircraft relative to the ground |
| Flight path angle | Flight path angle $\gamma$ is the angle between horizontal and velocity vector, which describes whether aircraft is climbing or descending |
| A/C(aircraft) weight | Aircraft weight during landing |
| Rudder pedal position | These parameters show pilot or autopilot input on rudder or nose wheel |
| NWS (nose wheel steering) F/O (first officer) order | |
| NWS Capt order | |
| NWS system order angle | |
| NWS wheel angle | |
| Right brake pedal angle | Ununiform exposure on brake pedals causes may causes skidding of nose wheel |
| Left brake pedal angle | |
| Drift angle | Difference between heading of an aircraft and its track (due to wind for example) |
variable was obtained. The correlation and the p-value columns contain the Pearson correlation and its level of the confidence interval, respectively.

**Table 2.** Variables correlation with total cycles for wheel before removal

| Description                        | Period, seconds | Percentile, % | Correlation | p-value     |
|------------------------------------|-----------------|---------------|-------------|-------------|
| Body lateral acceleration          | 210             | 75            | 0.54        | 2.34 \cdot 10^{-7} |
| NWS Capt order                     | 80              | 5             | 0.53        | 4.28 \cdot 10^{-7} |
| Roll angle                         | 80              | 70            | 0.45        | 2.8 \cdot 10^{-5}  |
| NWS system order angle             | 200             | 5             | 0.41        | 0.0001      |

Linear regression model has the following form:

\[ y = \text{Constant} + \sum_{i=1}^{5} X_i \beta_i + \varepsilon, \]  

where \( X_i \) are features made from flight data parameters with appropriate, \( \beta_i \) - regression model coefficients (Cycles from installation – number of flight cycles since installation on the aircraft).

For prediction of wheel tire wearing it recalculates rest of tire life after each landing with coefficients from Table 3. The coefficients were calculated using python programming language.

Consider the resulting coefficients for linear regression. For the seventy-fifth percentile of Body lateral acceleration, a regression coefficient of \(-7.16\) was obtained, which shows that the smaller the given value, and therefore the narrower the distribution of the random variable itself, the greater the prediction. From here on, it should be must be kept in mind that all explanatory variables were normalized in a standard way.

**Table 3.** Coefficients for evaluated regression.

| Description                        | Period, seconds | Percentile, % | Feature id                                   | Coefficient value |
|------------------------------------|-----------------|---------------|---------------------------------------------|-------------------|
| Intercept term                     | –               | –             | –                                           | 167.18            |
| Body lateral acceleration          | 210             | 75            | D29a07_abs_sec_210_q_0.75                    | -7.16             |
| NWS system order angle             | 200             | 60            | D13a03_abs_sec_200_q_0.6                     | -4.72             |
| NWS Capt order                     | 80              | 5             | D13a01_sec_80_q_0.05                         | 6.56              |
| Roll angle                         | 80              | 70            | D29a05_abs_sec_80_q_0.7                      | -3.77             |
A similar situation is observed with features obtained from NWS Captain order and NWS system order angle.

Only one variable entered the regression with a positive coefficient. This variable is the fifth percentile of the NWS Capt order. Considering that the nose wheel steering (NWS) can have both positive and negative signs turn, it turns out that the narrower the distribution in the negative region, the longer the wheel service life. We could not find references to similar results in the reviewed studies; this phenomenon will be studied deeply in subsequent studies.

The accuracy of resulting model is comparable to forecast based on average is 267 flight cycle (FC). Actual wheel wear values in the fleet differ from the average by ±30 FC. During the prediction taking into account FDR parameters, it is possible to predict actual value with an accuracy of ±15 FC. It proves that variables were chosen correctly.

We will evaluate the value of the result obtained by assessing the possible financial benefit due to cost savings.

Cost Optimization
There are two most popular maintenance programs (see Table 4) for tire replacement on the aircraft.

The first approach is when aircraft tires are inspected by engineering personnel and crews after and before each flight. If unacceptable wear is found, tires are replaced. This program has several disadvantages and advantages. The main advantage is maximum use of wheel resource since the wheel is used until it is completely worn out. The disadvantage of such a program is a need to maintain a large stock of spare wheels to compensate for peak replacements. Figure 2 shows the statistics of the receipt of wheels for repair in a wheel shop. These wheels were removed from a fleet of 70 aircraft of one airline. Average repair time for one wheel may be considered as three

| Tires maintenance program | Pros                                    | Cons                                             |
|---------------------------|-----------------------------------------|--------------------------------------------------|
| On-condition              | • Maximum tire flight cycles resource usage | • Big home based stock                           |
|                           |                                         | • AOG high probability                           |
|                           |                                         | • Uneven workload on wheel repair shop (staff overtime) |
| Soft time                 | • Protection from AOG                   | • Big home based stock                           |
|                           |                                         | • Incomplete usage of the wheel resource         |
|                           |                                         | • Uneven workload on wheel repair shop (staff overtime) |
| Prediction ±15 FC accuracy| • Optimal home base stock               | • Incomplete usage of the wheel resource (but less than 15 FC) |
|                           | • Planned work of wheel repair shop without peaks |                                           |
|                           | • Protection from AOG                   |                                                 |
days. Assuming that wheel shop has no restrictions on simultaneous maintenance of wheels due to overtime of staff, we get that maximum number of wheels removed within three days is 15 (data obtained via analysis of wheel shop statistics). That is, to ensure operational activities of 70 aircraft fleet, it is necessary to have a warehouse of at least 15 wheels. According to IATA research, cost of maintenance of a warehouse reaches 30% of the cost of goods.

The second one is – Soft time. This is a wheel change according to operating time, which guarantees removal of a wheel before reaching wear limits. According to this program a company is protected from AOG, but an increased tire consumption is likely to happen. Since, according to available statistics, actual wear is ±30 FC from the average, then for soft time lower limit is selected to ensure safety: $267 - 30 = 237$ FC. That is, at least 11% of wheel’s life time is not generated. At the same time, home based stock must be kept at the same level to parry peak removal of wheels.

Wheel wear prediction combines the best features of both programs. Since the accuracy is ±15 FC, approximately 6% will not be generated (if we take average as starting point). This will increase tire utilization. Additionally, by predicting peak period of wheel removal, by issuing a task for early removal, you can optimize wheel shop loading, reduce overtime costs and, as a result, reduce home based stock, which is a buffer.

5 Conclusion

The obtained results prove the correctness of the theory. The simplified digital twin of nose wheel tire lifecycle with the use of flight information allows getting the prediction accuracy that is twice the accuracy of the average prediction. Results of model work are using in the real production process.
Although the results obtained significantly increase the efficiency of planning nose wheel replacements, further improvements in forecast model are planned. A complete digital twin of the aeroplane-environment system will be modelled. Actual (not calculated by aircraft’s inertial system) data on the direction and strength of the wind will be entered into forecast model. Precipitation and coefficient of adhesion data on the runway (these data can be taken from actual weather reports at METAR airport). The model will also take into account a specific airfield and runway. As different runways have different surface conditions and affect tire wear in different ways.

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