ISSN 1648-7788 / eISSN 1822-4180

AVIATION

2024
Volume 28
Issue 1
Pages 9–15
https://doi.org/10.3846/aviation.2024.20988

A MATHEMATICAL MODEL FOR IDENTIFYING MILITARY TRAINING FLIGHTS

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Article History:
- received 28 November 2023
- accepted 11 January 2024

Abstract. The main tasks of the Training Air Base concern the practical training of cadets in piloting techniques as well as maintaining and improving the piloting skills of the instructors. It is essential to maintain the infrastructure of the airfield and the Base as a whole ready for operation. This allows for fulfilling the fundamental mission of such military units, which is to provide effective operations for the defence of the state.

Therefore, measures to support and improve the operation of such military facilities are extremely important and also became the genesis of this article. It analyses and evaluates the number of flights carried out over seven years (2016–2022) at the studied training base using mathematical modelling, allowing to assess the variability of the studied series. The phase trends method was used for this purpose, preceded by a seasonality study. It allowed the identification of periods in which the number of flights performed varies significantly. Such knowledge enables better regulation of the airport's operation, adjustment of activities to the needs, and the determination of further directions for airport development and the justification of potential investments. An additional value of the article is the presentation of a mathematical modelling method specifically designed for seasonal time series, along with their diagnostics. It also provides an opportunity for other institutions to carry out tasks while upholding the highest standards.

Keywords: military training flights, seasonality, phase trends method, cadet training, military airport.

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1. Introduction

The ability to perform flights depends on numerous factors, with safety being a key element of air operations. This is pointed out by numerous authors of studies in the field of aviation, emphasizing the necessity of implementing all solutions that can enhance flight safety and mitigate risks (Bauranov & Rakas, 2021). Conducting analyses that enable flight management in a way that minimizes risks before they lead to incidents or accidents is particularly important (Ellis et al., 2021). The Federal Aviation Administration also identifies maintaining safety as an Overarching Principle (Federal Aviation Administration, 2020). Meteorological conditions and proper adaptation of tasks to occurring atmospheric phenomena, such as fog, cumulonimbus clouds, hail, rain, and snowfall significantly impact flight safety. This is emphasized in numerous publications, where authors point out the importance of avoiding areas with turbulence and those affected by adverse weather conditions for flight. Another equally significant factor influencing flight operations is the state of maintenance of aviation equipment in a broad sense (aircraft, navigational aids, radars) and elements of airport infrastructure. In military aviation, the number of available aircraft is crucial, determining both the quantity and types of air operations conducted. Maintaining airplanes and helicopters in proper technical condition reduces the risk of failures, which not only disrupt the tasks of the damaged aircraft but can also affect other ongoing flights. Technological advancements enable the use of increasingly advanced navigational methods, enhancing the ability to fly in conditions with limited visibility or within clouds. Modern systems facilitate safe landing at airfields, with continuous monitoring by air traffic services, thereby enabling an increasing number of users to fly.

Therefore, many factors influence the execution of aviation tasks, making the examination of this variability over time a crucial issue for the analysis and assessment of airport functioning. It is, however, a challenging task, with many authors considering it a major challenge (Kanavos et al., 2021). Mathematical methods are well-suited for this purpose, enabling the identification of time series and the construction of a flight model. This model can be instrumental in providing crucial information describing the airport's operations and development. The aviation industry employs mathematical modelling at various levels, encompassing both operational management and strategic planning (Banerjee et al., 2020). This facilitates sustainable airport development planning and the formulation of strategies for the sustainable development of airports (Wang & Song, 2020). Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports. Journal of Air Transport Management, 89, 101925. By analysing the number of flight operations over the years, it becomes possible to monitor the decrease or increase in traffic at the airport. Consequently, it is feasible to determine whether investments in airport infrastructure, modern equipment, and an increased number of ground aviation staff are justified. This staff includes personnel responsible for maintaining cleanliness of runways and taxiways, aircraft maintenance technicians, as well as ground navigation aids and air traffic controllers. Moreover, assessing air operations on a monthly basis may encourage efforts to distribute them more evenly throughout the year.

Flight analysis is a prevalent topic in world literature, with a particular focus on flight safety, constituting the primary theme of most publications. Authors delve into the analysis of human factor (Kelly & Efthymiou, 2019; Amalberti & Wioland, 2020), the potential for detecting flight anomalies (Sheridan et al., 2020; Wei et al., 2023; Kosacki & Tomczyk, 2022), diagnosing faults (Su et al., 2023), and identifying defects in both manned and unmanned aircraft (Chen et al., 2020; Czyż et al., 2023; Leško et al., 2023). Many publications also address ecological concerns and the minimization of negative impacts on the natural environment, even during the aircraft design stage (Parolin et al., 2021). In this context, decarbonisation of air transport (Klöwer et al., 2020; Chen et al., 2020; Andrych-Zalewska et al., 2023) and the reduction of fuel consumption during flight (Soltani et al., 2020; Ziółkowski et al., 2022) are extensively analysed. Selected publications focus on the assessment of aircraft delays (Yu et al., 2019; Gui et al., 2019). Authors emphasize the imbalance between demand and air traffic capacity, particularly concerning the largest airports (Lambelho et al., 2020). During Covid-19, numerous publications focused on the interaction of the pandemic with air transport, particularly in relation to the spread of the disease (Pavli et al., 2020) and flight risks (Khatib et al., 2020). A separate strand in the literature involves research on assessing customer satisfaction and contentment (Kumar & Zymbler, 2019; Han et al., 2019), primarily aimed at building the strength of the brand and customer attachment to specific choices. However, despite the multitude of studies on flight analysis and their evaluation in various aspects, they concern primarily civil and commercial flights (Yu et al., 2019; Mínguez Barroso & Muñoz-Marrón, 2023). In the military context, there are fewer such studies. The primary focus of the analyses is on the study of military pilots and their reactions to participating in combat flights (Villafaina et al., 2021) and the associated risks (Shaw et al., 2021).

A limited number of articles addressing the specificity of military flights, especially those conducted as part of pilot training, have opted to present these considerations. Their objective was to analyse and evaluate training flights conducted in the largest centre in Poland, which trains candidates for military pilots. The substantial variability of observations in the time series prompted the selection of a mathematical model enabling such an analysis. Therefore, an additional advantage of this publication is the presentation of a method dedicated to observations characterized by significant seasonality (Borucka, 2023). The use of the phase trends method allowed for the identification of a time series taking into account this feature of the series.

2. Characteristics of the research subject and phase trends method

The study covered flights performed in the years 2016–2022 at the airfield in Dęblin (Poland), operated by the 41st Training Air Base. The main task of the base is aviation training for cadets of the Eaglet School, using M-346 "Bielik" aircraft as well as SW-4 "Puszczyk" and Mi-2 helicopters. The flight activity at the Dęblin airfield is additionally influenced by the operations of the Military University of Aviation, utilizing various aircraft types, such as Diamond 20, Diamond 40, Diamond 42 planes as well as Guimbal Cabri G2 and Robinson R44 helicopters. Furthermore, the Eaglets Aero Club at the Dęblin airport operates various types of aircraft, such as Cessna 150, Cessna 172, and Diamond 20.

Let $(\Omega, \mathcal{F}, P)$ be a probabilistic space, R – the set of real numbers and N – the set of natural numbers. The evolution over time of any object with properties described by a set of one-dimensional random variables $X(t)_{t\in T}$, defined on the same probabilistic space $(\Omega, \mathcal{F}, P)$, with values $x(t)$ z depending on the physical time t is called a stochastic process (Liu & Xiao, 2022; Kozłowski et al., 2023). The implementation of a stochastic process, which for $t = 1, 2, 3, \dots$ is a sequence of $\{x_t\}_{t\in N}$ subsequent observations $x_1, x_2, x_3 \dots$ is called a time series, i.e. for each $t \in N$ a random variable $x_t : \Omega \to R$.

The analysis of time series of aircraft flights aims to check whether this phenomenon follows identifiable regularities. This involves isolating the systematic component and random noise, i.e. the so-called interference. The development of the phenomenon over time is most often influenced by (Borucka & Sobecki, 2023):

- trend (long-term, systematic changes),
- seasonal fluctuations (regular deviations from the development trend associated with repeated periods),
- cyclical fluctuations (related to the business cycle)
- random fluctuations (irregular changes).

Identification of the above factors enables the selection of an appropriate model describing the phenomenon under study.

If seasonal fluctuations occur in the time series $\{x_t\}_{t\in N}$, the method used to identify such a component is the analysis of phase trends (Lyu et al., 2021). This involves the separation and identification of m-subseries separated from the original time series that correspond to different phases of periodic fluctuations. The least squares method is used for this purpose.

If the time series $\{x_t\}_{1 \le t \le N}$ has m phases and $N = Tm$ it can be divided into m subseries $\{x_k^1\}_{1 \le k \le T}$, $\{x_k^2\}_{1 \le k \le T}$, …, $\{x_k^m\}_{1 \le k \le T}$ where (Kozłowski, 2015):

$$\{x_k^1\}_{1 \le k \le T} = \left\{x_1, x_{m+1}, x_{2m+1}, \ldots, x_{(T-1)m+1}\right\}; \tag{1}$$

$$\{x_k^2\}_{1 \le k \le T} = \left\{x_2, x_{m+2}, x_{2m+2}, \ldots, x_{(T-1)m+2}\right\}; \tag{2}$$

$$\{x_k^m\}_{1 \le k \le T} = \left\{x_m, x_{2m}, x_{3m}, \ldots, x_{Tm}\right\}. \tag{3}$$

For each of the subseries defined in this way, for $1 \le k \le T$ it is possible to determine phase trend models of the form (Kozłowski, 2015):

$$x_k^1 = f_1\left(k, \Theta_1\right) + \varepsilon_k^1; \tag{4}$$

$$x_k^2 = f_2\left(k, \Theta_2\right) + \varepsilon_k^2; \tag{5}$$

$$x_k^m = f_m\left(k, \Theta_m\right) + \varepsilon_k^m. \tag{6}$$

Deterministic functions $f_i\left(t, \Theta_1\right)$ for $i = 1, 2, \ldots, m$ determine the internal dynamics of the subseries $\{x_k^i\}_{1 \le k \le T}$ while $\varepsilon_{k\,1 \le k \le T}^m$ constitute uncorrelated random variables with a normal distribution $N\left(0, \sigma_i^2\right)$. For such a model, the values of the parameters, $\Theta_1, \Theta_2, \ldots, \Theta_m$ are estimated using the least squares method (Zhang & Zhao, 2023).

Following identification, the time series $\{x_t\}_{t \in N}$ has the form (Kozłowski, 2015):

$$x_t = \begin{cases} f_1\left(\left[\frac{t}{m}\right] + 1, \hat{\Theta}_1\right) + \varepsilon^1_{\left[\frac{t}{m}\right]+1}, & \text{when } mod\left(t, m\right) = 1 \\ f_2\left(\left[\frac{t}{m}\right] + 1, \hat{\Theta}_2\right) + \varepsilon^2_{\left[\frac{t}{m}\right]+1}, & \text{when } mod\left(t, m\right) = 2 \\ f_{m-1}\left(\left[\frac{t}{m}\right] + 1, \hat{\Theta}_{m-1}\right) + \varepsilon^{m-1}_{\left[\frac{t}{m}\right]+1}, & \text{when } mod\left(t, m\right) = m - 1 \\ f_m\left(\left[\frac{t}{m}\right] + \hat{\Theta}_m\right) + \varepsilon^m_{\left[\frac{t}{m}\right]}, & \text{when } mod\left(t, m\right) = 0 \end{cases}, \tag{7}$$

where $\left[\frac{t}{m}\right]$ denotes the integer part of dividing t by m, and $mod(t,m)$ denotes the remainder of dividing t by m.

3. Identification of model parameters

The analysed time series of flights is presented in Figure 1. It can be seen that flights are subject to systematic changes based on the month in which they take place.

Strong monthly seasonality is confirmed by Figure 2.

The chart above shows that the fewest flight operations occur out in winter months, namely December and January. This is attributed, among other factors, to the 41st Training Air Base not conducting training for cadets of the Military University of Aviation during this period, as nearly entire annual flying plan is completed, and aircraft are serviced. From mid-February, a gradual increase in flight operations is observed due to the resumption of instructors' currency and shift in weather conditions to more favourable ones, such as lengthening days and less frequent snowfall, the latter significantly limiting flight operations. At the turn of March and April, cadet internships begin, leading to a gradual increase in the number of flight operations, reaching a maximum in August. Subsequently, the number of operations performed decreases again, especially between October and December, as evidenced by the end of the cadet apprenticeship period and deteriorating weather conditions in autumn and winter, including fog and precipitation, along with shortening days. Considering the number of flight operations performed in the 41st Training Air Base over the years, a gradual increase is observed, resulting from the growing number of available

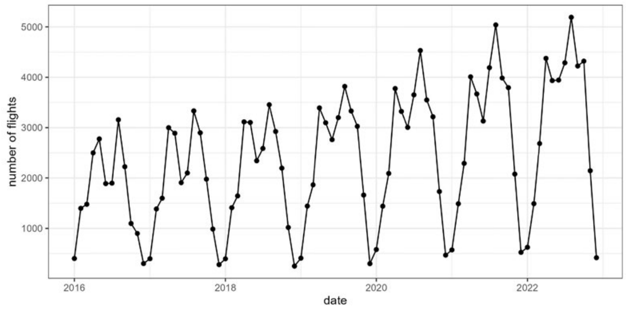

Figure 1. The studied time series – training flights in 2016–2022

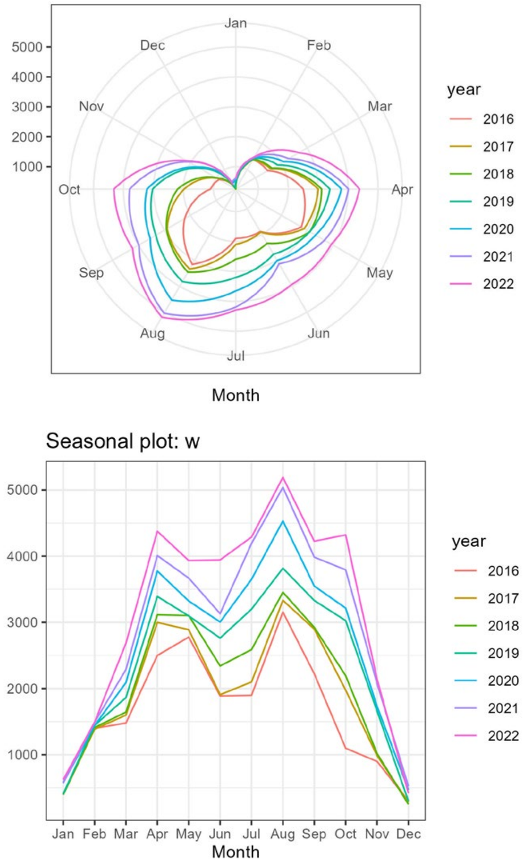

Figure 2. Periodicity of the tested series

aircraft and the annual rise in recruitment at the Military University of Aviation in the faculty of piloting.

The observed seasonality led to dividing the analysed time series $\{x_k\}_{1\le t\le 84}$ into 12 sub-sequences corresponding to individual months, representing different phases in the analysed series. The results of such fitting are presented in Figure 3.

Figure 3 shows that a linear trend was determined for each month (sub-series), therefore the following was assumed:

$$x_t = \begin{cases} x_k^1 = \alpha_o^1 + \alpha_1^1 k + \varepsilon_k^1 \\ x_k^1 = \alpha_o^2 + \alpha_1^2 k + \varepsilon_k^2 \\ x_k^1 = \alpha_o^3 + \alpha_1^3 k + \varepsilon_k^3 \\ x_k^1 = \alpha_o^4 + \alpha_1^4 k + \varepsilon_k^4 \\ x_k^1 = \alpha_o^5 + \alpha_1^5 k + \varepsilon_k^5 \\ x_k^1 = \alpha_o^6 + \alpha_1^6 k + \varepsilon_k^6 \\ x_k^1 = \alpha_o^7 + \alpha_1^7 k + \varepsilon_k^7 \\ x_k^1 = \alpha_o^8 + \alpha_1^8 k + \varepsilon_k^8 \\ x_k^1 = \alpha_o^9 + \alpha_1^9 k + \varepsilon_k^9 \\ x_k^1 = \alpha_o^{10} + \alpha_1^{10} k + \varepsilon_k^{10} \\ x_k^1 = \alpha_o^{11} + \alpha_1^{11} k + \varepsilon_k^{11} \\ x_k^1 = \alpha_o^{12} + \alpha_1^{12} k + \varepsilon_k^{12} \end{cases} . \qquad (8)$$

For $1 \le k \le 7$,

whereas $\varepsilon^i_{k1\le k\le 7}$ for $i = 1,\ldots,12$ represent sequences of uncorrelated random variables with a normal distribution $N\left(0,\sigma_i^2\right)$.

Using the least squares method, the equation parameters were determined for each month according to Equation (8), which, along with the estimation error, are presented in Table 1.

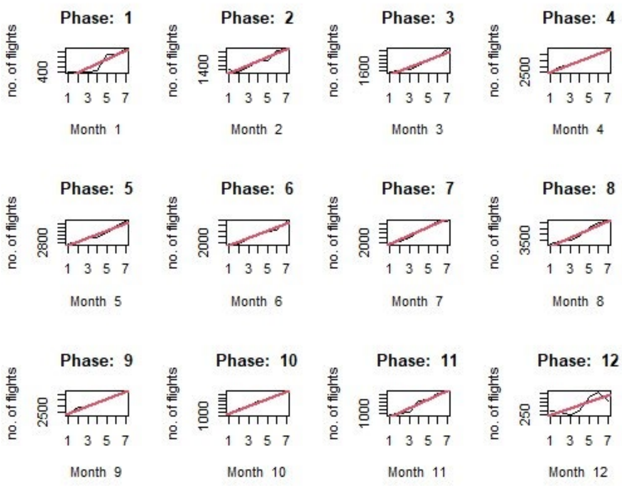

Figure 3. Fitting phase trends to individual subseries (months)

Table 1. Model coefficients estimated using LSM

Month/phase number	a_0	a_1	SE
1	310.86	42.79	50.57
2	1363.43	18.39	14.13
3	1172.29	194.43	111.67
4	2265.29	296.71	80.07
5	2506.29	187.32	112.02
6	1385.71	331.32	184.52
7	1356.00	443.61	148.95
8	2560.86	378.32	210.57
9	2047.00	314.43	127.89
10	757.00	511.57	166.12
11	555.86	236.68	151.10
12	212.29	37.57	74.31

Following the identification of parameters, the time series $\{x_k\}_{1\le t\le 84}$ is expressed as:

$$x_t = \begin{cases} 310.86 + 42.79\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^1_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=1 \\ 1363 + 4318.39\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^2_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=2 \\ 1172.29 + 194.43\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^3_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=3 \\ 2265.29 + 296.71\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^4_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=4 \\ 2506.29 + 187.32\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^5_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=5 \\ 1385.71 + 331.32\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^6_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=6 \\ 1356.00 + 443.61\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^7_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=7 \\ 2560.86 + 378.32\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^8_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=8 \\ 2047 + 314.43\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^9_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=9 \\ 757 + 511.57\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^{10}_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=10 \\ 555.86 + 236.68\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^{11}_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=11 \\ 212.29 + 37.57\left(\left[\frac{t}{12}\right]+1\right) + \varepsilon^{12}_{\left[\frac{t}{12}\right]+1}, \text{ when } mod(t,12)=0 \end{cases},$$

where:

$\varepsilon_t^1 \sim N\left(0,50.57^2\right)$, $\varepsilon_t^2 \sim N\left(0,14.13^2\right)$, $\varepsilon_t^3 \sim N\left(0,111.67^2\right)$, $\varepsilon_t^4 \sim N\left(0,80.07^2\right)$, $\varepsilon_t^5 \sim N\left(0,112.02^2\right)$, $\varepsilon_t^6 \sim N\left(0,184.52^2\right)$,

$\varepsilon_t^7 \sim N\left(0,148.95^2\right)$, $\varepsilon_t^8 \sim N\left(0,210.57^2\right)$, $\varepsilon_t^9 \sim N\left(0,127.89^2\right)$, $\varepsilon_t^{10} \sim N\left(0,166.12^2\right)$, $\varepsilon_t^{11} \sim N\left(0,151.10^2\right)$, $\varepsilon_t^{12} \sim N\left(0,74.31^2\right)$.

4. Discussion of results

To evaluate the proposed phase trends model, the coefficient of determination was calculated for each identified phase. The results are presented in Table 2.

This allows for the conclusion that the model fit is exceptionally well. For each sub-series, the calculated coefficient of determination is remarkably high. This is also confirmed by Figure 3, where time series (represented by the black line) depicting successive phases in the studied series $\{x_k\}_{1\le t\le 84}$ are shown, while the red lines represent trend lines determined for each sub-series. The trend lines for most sub-series practically overlap with the empirical data, indicating a very good fit. Sub-series identification is more evident in Figure 4 and Figure 5, which present sample graphs for phases 4 and 7. For April (phase 4), the model, in consecutive years $k = 8,9,10,\dots$, corresponding to periods $t = 100,112,124,\dots$ takes the form (Figure 4):

$$x_{12k+4} = 2265.29 + 269.71k + \varepsilon_k^4,$$

where $\left\{\varepsilon_k^4\right\}_{k\ge 8}$ is a sequence of random variables with a normal distribution $N\left(0,80.07^2\right)$.

On the other hand, for July (phase 7), in consecutive years $k = 8,9,10,\dots$, corresponding to periods $t = 103,115,127,\dots$ the model takes the form (Figure 5):

$$x_{12k+7} = 1356 + 443.61k + \varepsilon_k^7,$$

where $\left\{\varepsilon_k^7\right\}_{k\ge 8}$ is a sequence of random variables with normal distribution $N\left(0,148.95^2\right)$.

Thus, the presented model can be considered reliable and applicable to the studied structures, not only for the identification of time series of flights but also for their assessment and forecasting of future values. Additionally,

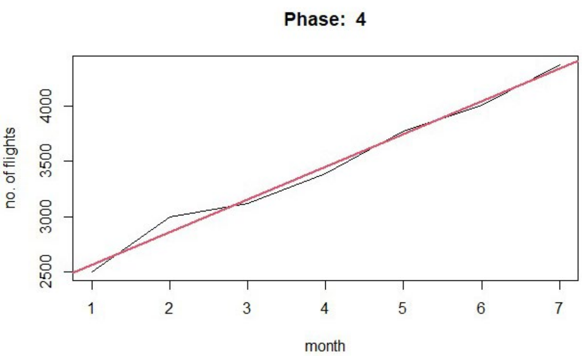

Figure 4. Trend model fit for phase 4 (April)

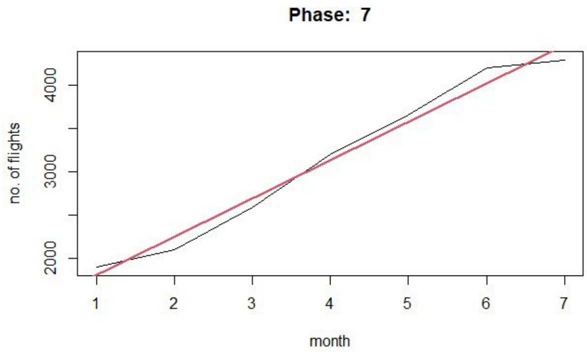

Figure 5. Trend model fit for phase 7 (July)

the computed values of the model coefficients allow for the evaluation of the number of flights and their changes over time for individual months. A clear increase is evident in each of them. For example, for the months analysed above, i.e., April and July, the increase is over 296.71 flights for phase 4 and over 443.61 flights for phase 7, respectively. Based on the model identification for each month, it is possible to estimate not only the expected values of the number of flights in subsequent periods but also confidence intervals regarding the number of flights for each month.

The application of the model proposed in the article will, therefore, enable a better assessment of flights performed in each month, aligning available human and material resources with the tasks performed, and improving training schedule management. The proposed model can provide excellent support for airport processes, being simple to interpret and apply. Its versatility also allows for utilization in other systems where activities – operations are characterized by clear seasonality.

5. Conclusions

Flight analysis and knowledge about their seasonality, as well as information about the upward trend, are important from the point of view of both the training of cadets and the introduction of solutions allowing for a safe increase in the number of operations at the Dęblin airfield. The information contained in the analysis can be used by staff responsible for planning flights to – if possible – optimally distribute them throughout the year. Moreover, the results of the analysis indicate the need for continuous development of the airfield, both in terms of equipment and available infrastructure, as well as an increase in the number of aviation personnel and their appropriate training.

The proposed model well reflected the seasonality diagnosed in the series. The selected phase trend analysis method worked well in this case, providing reliable results.

Table 2. The value of the coefficient of determination R^2 for each sub-series

Month/phase number	1	2	3	4	5	6	7	8	9	10	11	12
R^2	80.04	90.47	94.44	98.72	94	94.75	98.03	94.76	97.13	98.15	93.22	58.87

As part of further research, models will be constructed to also analyse other factors affecting the number of military flights, taking into account the impact of, for example, meteorological conditions, economic factors and the geopolitical situation. In this article, in accordance with the authors' assumption, only the time factor was analysed.

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