TRANSPORT PROBLEMS 2017 Volume 12 Issue 3
PROBLEMY TRANSPORTU DOI: 10.20858/tp.2017.12.3.5

Keywords: aerospace performance factor; safety evaluation tools; safety performance index; signal analysis; stochastic control

Andrej LALIŠ
Czech Technical University in Prague, Faculty of Transportation Sciences
Horská 3, Prague 2, 128 03, Czech Republic
Corresponding author. E-mail: lalisand@fd.cvut.cz

TIME-SERIES ANALYSIS AND MODELLING TO PREDICT AVIATION SAFETY PERFORMANCE INDEX

Summary. Safety performance index is a tool with the potential to grasp the intangible domain of aviation safety, based on quantification of meaningful aviation safety system properties. The tool itself was developed in the form of Aerospace Performance Factor and is already available for the aviation industry. However, the tool turned out to be rather unsuccessful as its potential was not fully recognised by the industry. This paper introduces performed analysis on the potential and it outlines new features, utilising time-series analysis, which can improve both the recognition of the index by the industry as well as the motivations to further research and develop methodologies to evaluate overall aviation safety performance using its quantified system properties. This paper discusses not only the features but also their embedding into the existing approach for the development of aviation safety, highlighting possible deficiencies to overcome and relating the scientific work already performed in the domain. Various types of appropriate time-series methodologies are addressed and key specifications of their use with respect to the discussed issue concerning safety performance index are stated.

1. INTRODUCTION

Aviation safety is one of the most studied domains today. Technology used by airplanes and airports reached a very high level of safety and reliability; nevertheless, accidents and serious incidents still happen. Even though the frequency is very low – only 4 fatal accidents in almost 38 million flights per year 2015 [1] – there still exists significant political commitment [2] to improve this performance. Recent commercial aviation incidents and accidents are, however, becoming more and more complex issues [3], which makes this commitment quite a challenge. For various reasons, traditional methods for preventing them do not work sufficiently any more. As an instance, the otherwise very successful Reason's model is rather ineffective against the background of today's aviation safety issues [4], primarily due to the industry complexity, in which not only its components but also complex interactions between them matter. Surely, the model can still be used for understanding particular issues in terms of proximity events, but to truly achieve the goal of any further and stable aviation safety improvement, the solutions are still to be researched today. It is the complexity that makes today's accidents difficult to prevent.

To a certain extent, it is questionable how much the existing level of safety in aviation can still be improved, but given the present status and goals in the domain of aviation safety [2] and system theory and safety engineering knowledge [4], further improvements appear manageable. Because the industry is a socio-technical system in its very nature, solutions must first be capable of handling the intangibility induced by the presence of humans both in the operations as well as high in the management and organisational structure. Even though humans as individuals are still the subject of research in aviation [5, 6], neither the human factor nor the technology itself is recognised as the core issue [7]. The industry demands more systemic solutions to handle the high complexity of its internal and external interactions.

To date, these interactions are handled by human controllers, whether it is regulation or management of the respective aviation organisation. Decades of industry globalisation and commercial flying established rules and regulations for the best practice to handle the most common emerging issues [8, 9], but a gap still exists as far as the flawed interactions of recent accidents are concerned. Not only are they complex and difficult to effectively prevent, but they suggest that there are some background issues that are hardly manageable because of commercial privacy or many different motivations and goals of the humans involved. The interface between aviation components in many cases lies between two or more separate organisations that often compete on the market and are unwilling to share safety information to the extent that would allow completing the full picture of what happened, which is also recognised in recent surveys indicated by lower reporting activity [10].

One of the possible solutions to this rigour is to research, develop and implement tools, which would be based on quantification of system properties, which are reasonably quantifiable while still intangible. Some such attempts already exist: key safety performance indicators and safety performance measurement are the examples of efforts to quantify intangible safety. These efforts are limited and still fragmented, however, as no effective aviation safety performance framework exists.

Tools capable of effective quantification of respective system properties are to be complemented by system theory-based knowledge and best practice. This way, current safety management can be shifted to a brand-new level, exploiting the capabilities of today's mathematics and safety engineering. Undoubtedly, the solutions to be researched have serious potential to surpass existing safety management in both effectiveness and complexity and it arguably needs to be decomposed into two main separate parts: the quantification of system properties and system theory-based safety engineering. This paper will provide an overview of the approach to solutions being developed to quantify aviation safety system properties within an on-going junior research project.

2. PERFORMANCE INDEX

Safety performance indicators can be subjected to deeper analysis and aggregated into safety performance, sometimes referred to as safety performance index. This index serves as a tool providing an integrated view on safety data and assessing how well the actual safety management is performing within the respective organisation or industry, depending on the type of indicators being aggregated [11]. It has the potential to influence safety management's decisions as it points safety managers to the most influencing issues in terms of the overall level of safety at any time, prioritising their work towards areas of higher concern.

In the domain of aviation safety, the way to obtain a safety performance index was defined as Aerospace Performance Factor (APF). The APF is based on hierarchically structured safety performance indicators, weighed by their pair-wise comparison by subject-matter experts. The core equation to obtain the APF is as follows [12]:

$$APF = \frac{\sum_{i=1}^{k} W_i \cdot N_i}{appropriate\ denominator} \tag{1}$$

where 'W' is weight of respective safety performance indicator, 'N' is the number of indicator observations and 'k' refers to total number of safety performance indicators in the system. The appropriate denominator may depend on the type of aviation organisation and, for example, hours flown or sectors flown in the time interval of interest can be used here [13]. Safety performance indicators used by EUROCONTROL to calculate the APF were defined based on ESARR2 requirements (see Fig. 1) and are specified for Air Navigation Service Providers.

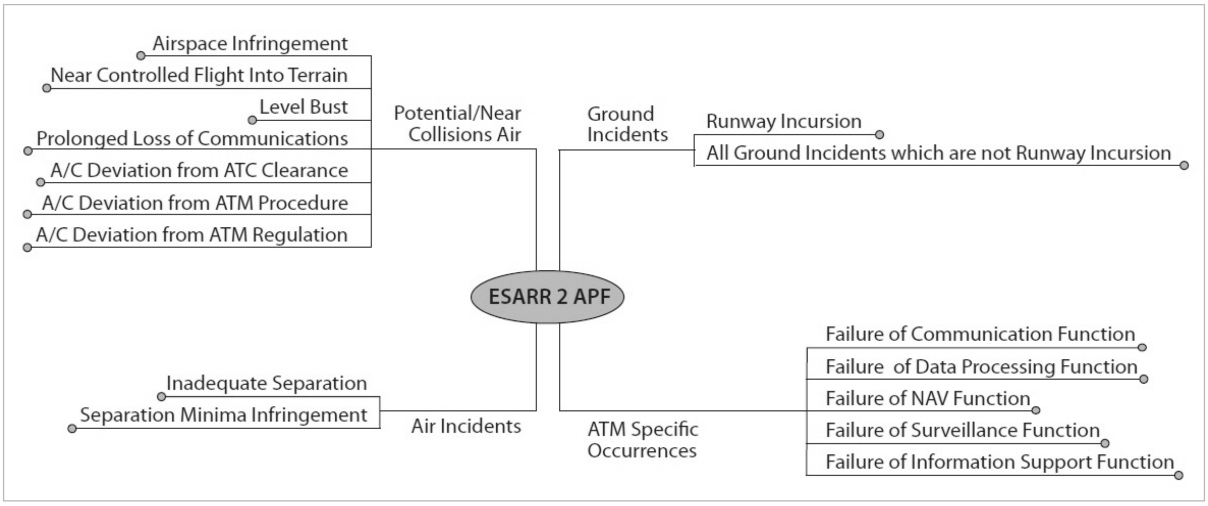

Fig. 1. APF safety performance indicators [12]

These indicators comprise just the tip of the aviation safety iceberg, but to outline the methodology, they are sufficient. Monthly quantified APF for the time interval from January 2006 to December 2008 using the safety performance indicators from Fig. 1 is depicted in Fig. 2. The APF is shown in black colour, its constituents (four main groups of indicators) in grey and the red line is a simple linear regression analysis to indicate the trend. In this case, the APF refers to the achieved level of safety for the European Air Traffic Management (ATM) system, providing safety management with overall safety performance supervision. The safety management concerned may subject the achieved APF to analysis and see which of its constituents has contributed most to influence the APF.

From the perspective of resolving issues outlined in the previous chapter, the APF or safety performance index offers a tool to quantify system properties, but it heavily depends on the selection of safety performance indicators to be aggregated. Omission of any ‘symptoms’ to be captured by the indicators may lead to serious incapability of the index to perform as intended. This problem is amplified by the fact that the aviation industry is highly dynamic and these indicators need to be constantly revised. Another issue is the quality of safety data, which originate from different sources whether within an organisation or between two or more aviation stakeholders. These sources frequently overlap and when it comes to classification or description of the issue, it is not rare that they draw a slightly different picture. Certainly, this is also caused by the absence of an effective framework for aviation safety data classification, but there are already efforts spent to resolve this issue [14].

Despite the methodology being already available in year 2009, so far, the application of this tool for commercial aviation has been very limited. Both issues described above contributed to the lack of its application, but the potential for future extension and application still exists. It can be recognised, especially, in the context of today’s industry-wide efforts [2] to develop safety management to the stage at which tools to quantify system properties will find more extensive application within future risk management of advanced safety management systems. Important to note is that despite the present situation in aviation, the APF methodology affected the definition of safety performance indicators adding some requirements for their form and structure.

3. NEED TO PREDICT

There is some unexploited potential of the APF itself, which could expedite deployment of the solutions being researched today. The potential is recognised with regard to predictive analysis of the signal obtained from APF measurement in time (see Fig. 2).

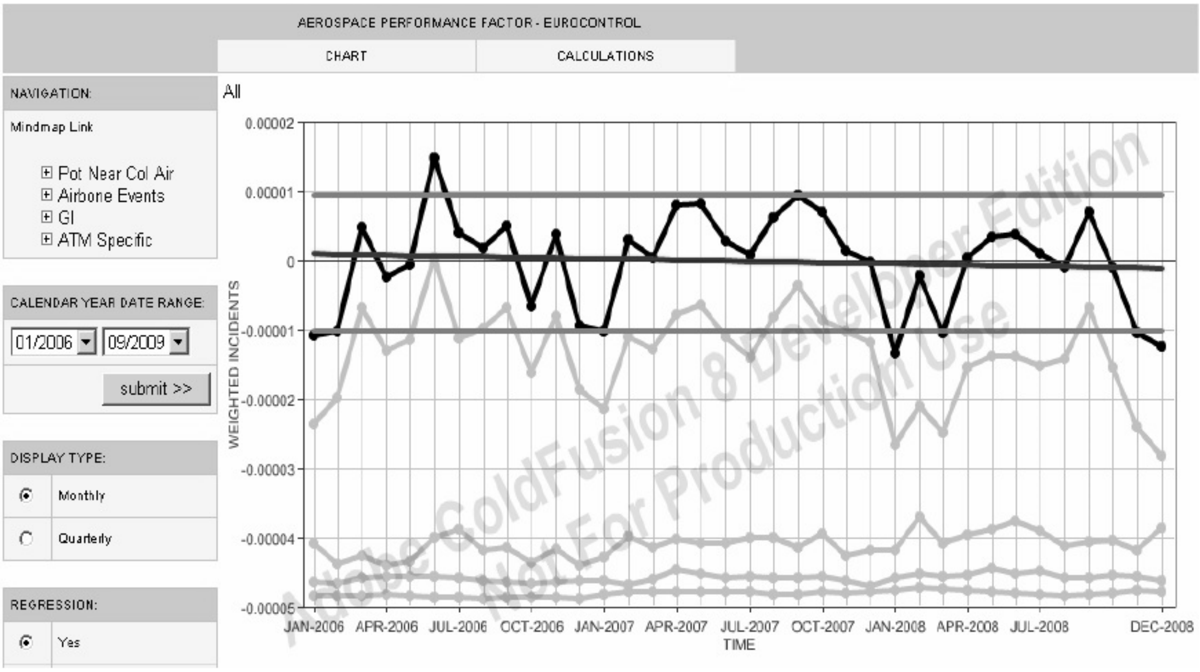

Fig. 2. APF measured from 2006 to 2008 [13]

The safety management's decision process on whether to take some actions can be facilitated by providing the management with predictions. If the management would know, given the past APF values, what will most likely happen next, it would be much easier to see at least how important it is to intervene in the system. The issue was already formulated and addressed to a certain extent in other scientific work [15]; however, the approach was specific for an Italian environment and did not account for other possible solutions to the problem. Similar demand for effective prognoses exists in economy, in which central banks monitor inflation rates or GDP growth and, based on their short-time predictions, they safeguard the stability of their controlled part of the economy, with there are already being quite advanced solutions in place nowadays [16].

The depicted APF in Fig. 2 resembles a similar kind of signal as we can observe in econometrics, which may be processed by time-series analysis in order to analyse it for further dependencies. The APF in Fig. 2 does not seem to bear any significant trends but, rather, a stable behaviour, which is also confirmed by the red linear regression. However, it may contain some dependencies when decomposed into its elements, such as seasonality, which could be discovered by robust time-series analysis. Likewise, other external variables may influence the APF. Definition of the approach to this type of analysis (predictions) and its appropriate embedding into the concepts of future safety management has the recognised potential of expediting safety management development and introducing new features to be implemented with regard to safety performance and its indicators.

4. TIME-SERIES ANALYSIS

Unlike the research already performed to predict safety performance [15], this paper promotes robust exploitation of time-series analysis. The reason is that, with respect to this, the Italian case was rather limited by its use of maximum likelihood estimation (MLE) and autoregressive and moving average models to predict safety occurrences filtered by the Pareto principle, such as Traffic Collision Avoidance System (TCAS) related issues. The problem is that the idea of predicting future events as a core solution for safety performance predictions, even as an estimation, leads to serious bias by its nature. The solution to this problem appears to be the prediction of the APF (safety performance index) instead, with optional utilisation of external and internal explanatory variables. There are several methods that allow predictions of univariate time-series, such as the APF, to various extents [17]:

- linear trend and mean (constant) model
- random walk models
- averaging and smoothing models
- linear regression models
- autoregressive and moving average models (ARMA) and their variations

The decision of which one to choose depends on many qualitative properties of the time-series analysed, such as trend patterns, correlations among variables, seasonality, etc. In theory, the elementary decision process to follow was already defined decades ago [18].

The main characteristic of the APF signal from Fig. 2 is the clear presence of a seasonal element as measured on a monthly basis. It is also underlined by the fact that, in aviation, the demand is variable and dependent on the season of the year, influencing the denominator in the APF equation. Similarly, the signal is influenced by growth or shocks in the global economy but there are other external explanatory variables influencing the numerator of that equation too, such as effectiveness of safety management, safety culture and others that aviation safety is directly related to. Further, the signal will most likely be influenced in a dynamic way, i.e., a perturbation will resonate the sample, suggesting internal dependencies. In addition, some of the external variables may be correlated.

According to all these presumptions, our needs fit best in the last two models to further assess the APF–linear regression model capturing seasonality and explanatory variables, and in the autoregressive and moving average model of the same capabilities.

5. LINEAR REGRESSION MODELS

Linear regression models are typically based on ordinary least squares (OLS) and they obey the following form [19]:

$$y_t = c + X_t \beta + u_t \tag{2}$$

where y_t is the response series, c is the regression model intercept, X_t is the matrix of concatenated predictor data values, i.e., observation of each predictor series, β is the regression coefficient and u_t is the disturbance or noise. Time runs discretely here, i.e., $t \in \mathbb{N}$. Applied on the safety performance index, the index itself will be the response whereas the predictor will capture all the explanatory variables. Parameters β and c are calculated coefficients from both predictor and response series data.

The model requires all variables to be scalars that may cause difficulties as far as 'soft' variables are concerned. Fortunately, it is not necessary to include all the variables that affect the index; thus, only those that are easy to quantify should be included as a starting point. As soon as the model provides meaningful output, adding new explanatory variables shall progressively reduce the noise and make the predictions more accurate. The same is valid for all other estimations the model is capable of providing, i.e., the estimation of explanatory variables affect the index captured in parameter β.

6. ARMA MODELS

These models are typically based on MLE and they obey the following form (in lag (L) operator notation) [20]:

$$H(L)y_t = c + X_t \beta + N(L)\varepsilon_t \tag{3}$$

where

$$\begin{aligned} H(L)y_t &= \varphi(L)(1 - L)^D \varphi(L)(1 - L^S) \\ &= 1 - \eta_1 L - \eta_1 L^2 - \cdots - \eta_P L^P \end{aligned} \tag{4}$$

is degree P lag operator polynomial capturing the effect of both seasonal and non-seasonal autoregressive (AR) polynomials, and

$$N(L) = \theta(L)\Theta(L) = 1 - \upsilon_1 L - \upsilon_2 L^2 - \cdots \upsilon_Q L^Q \quad (5)$$

is degree Q lag operator polynomial capturing the effect of both seasonal and non-seasonal moving average polynomial (MA), ε_t is a white noise innovation process and other variables are equivalent to those in the linear regression model described above.

The model itself offers one important difference compared with the linear regression model: it has the moving average component that accounts for historical values of disturbances in the form of white noise innovation process ε_t. In simple terms, the model recognises dependence among variables and both present and historical values of disturbance. Although this feature seems to have the capability to capture interesting and valuable characteristics of the system, a problem may arise when it comes to the principle for quantification of the actual disturbance:

$$\varepsilon_t = y_t - \overline{y}_t \quad (6)$$

where $\overline{y}_t$ is the predicted value of the response series at time t-1. Because there is no better way to estimate the disturbance, it is questionable whether the moving average component would not actually bias the model and reduce its performance. The response series in the form of safety performance or APF is just an estimation of this system-wide property and, assuming that its measurement is not biased, may add additional noise to the ARMA model. However, the actual performance is to be assessed on real data in order to distinguish between the ARMA and linear regression models or, in other words, between OLS and MLE application.

7. MODEL COMPARISON

The selection of either the ARMA or the linear regression model depends on the data and system to which these time-series analysis models are to be applied. Because the required aviation safety data are difficult to obtain because of their confidential nature and potential for causing damage to brand recognition, the performance of each of these models can be assessed unbiasedly using synthesised data. Such data, however, would never be able to simulate the real environment entirely and, thus, both models to be subjected to performance analysis have strong potential to perform similarly when using artificial data. The optimal solution would be for aviation organisations to decide to try these methods to analyse quantified system properties of their own discretion in order to discover their true potential.

As per the analysis outlined in this paper, and according to the theory, the safe bet appears to be the selection of the linear regression model, because of its simplicity. ARMA models are more complex and may perform better, but one should be cautious about apparent shortcomings with the disturbance calculation and, therefore, favour autoregressive elements with possible distributed lags rather than moving average components.

Finally, it is important to mention the integration of the predictions with other properties of the aviation safety system. One should bear in mind all the traps of predicting a biased signal when key ‘symptoms’ are not captured in the quantification process or when reluctance to build the full picture of what happened exists. This is the case when moving average model components are inevitable and when serious bias is the risk. This problem may be partly solved by breaking down the safety performance into its subcomponents (clusters of indicators) and applying predictions on these elements, or trying to resolve these issues with the latest safety engineering practice, i.e., by thorough system analysis.

In all cases, application of either of these two types of models determines the form of input, i.e., it lays down new requirements for safety performance indicators. As all predictor variables are to be scalars, the same is true for safety performance indicators. Although for some this means no change, other indicators such as effectiveness of safety management or safety culture need to be transformed into reasonable form for processing. The indicators can be transformed in many ways but, at this stage, it is difficult to identify the best transformation. Thorough analysis of the model performance using real data and various indicator transformations can determine it.

8. CONCLUSIONS

This paper summarised the options for applying robust time-series analysis for the purpose of safety performance index prediction. The ambition was to shift the existing ideas and approach to explore new ways for achieving future predictive risk management, namely by exploiting both mathematical capabilities and recent safety engineering practice and principles.

Apparent limitations lie with practical verification of the analysis performed. This is due to the limitations imposed by aviation safety data confidentiality and general reluctance to share the data between aviation organisations. On the other hand, the paper provides some insight for future research, which may identify ways to overcome the data confidentiality issue. As an alternative, synthetic data may be used to fill the gaps in the available data to estimate the potential of the proposed solution. The greatest potential for future research is recognised in application of systemic solutions with employment of explanatory variables for the purpose of safety performance index predictions.

Acknowledgement

This paper was supported by the Grant Agency of the Czech Technical University in Prague, grant No. SGS16/188/OHK2/2T/16.

References

1. IATA, 2016. *Safety Fact Sheet*. International Air Transport Association. Montreal. Canada. Available at: https://www.iata.org/pressroom/facts_figures/fact_sheets/Documents/fact-sheet-safety.pdf
2. ICAO, 2013. *2014 - 2016 Global Aviation Safety Plan: Doc 10004*. International Civil Aviation Organization, Montréal, Quebec, Canada. ISBN 978-92-9249-355-4.
3. Vittek, P. & Lališ, A. & Stojić, S. & Plos, V. 2016. Runway incursion and methods for safety performance measurement. In: *Production Management and Engineering Sciences. Proceedings of the International Conference on Engineering Science and Production Management (ESPM 2015).* Tatranská Štrba, High Tatras Mountains. Slovak Republic. 16th-17th April 2015. Bratislava: University of Economics in Bratislava. P. 321-326. ISBN 978-1-138-02856-2.
4. Leveson, N. Engineering a safer world: systems thinking applied to safety. Cambridge, MA: MIT Press. *Engineering systems*. 2011. ISBN 978-0-262-01662-9.
5. Novák, L. & Němec, V. & Soušek, R. Effect of Normobaric Hypoxia on Psychomotor Pilot Performance. In*: The 18th World Multi-Conference on Systemics*. Cybernetics and Informatics. Orlando, Florida: International Institute of Informatics and Systemics. 2014. Vol. II. P. 246-250. ISBN 978-1-941763-05-6.
6. Regula, M. & Socha, V. & Kutílek, P. & Socha, L. & Hánaková, L. & Szabo, S. Study of heart rate as the main stress indicator in aircraft pilots. In*: 16th Mechatronika 2014*. Brno: Brno University of Technology. 2014. P. 639-643. ISBN 978-80-214-4816-2.
7. ICAO, 2013. *Safety Management Manual (SMM): Doc 9859. 3rd edition*. International Civil Aviation Organization. Montréal. ISBN 978-92-9249-214-4.
8. Kraus, J. & Vittek, P. & Plos, V. Comprehensive emergency management for airport operator documentation. In: *Production Management and Engineering Sciences: Proceedings of the International Conference on Engineering Science and Production Management (ESPM 2015).* Tatranská Štrba, High Tatras Mountains, Slovak Republic. 2016. Bratislava: University of Economics in Bratislava. P. 139-144. ISBN 978-1-138-02856-2.
9. Fuchs, P. & Němec, V. & Soušek, R. & Szabo, S. & Šustr, M. & Viskup, P. The Assessment of Critica Infrastructure in the Czech Republic. *In Proceedings of 19th International Scientific Conference Transport Means*. Kaunas: Technologija. 2015. P. 418-424. ISSN 1822-296X.

10. Post, W. *ECCAIRS Survey*. Presentation at [ECCAIRS Steering Committee Meeting, Brussels, 26-27 October 2015]. Joint Research Centre. Brussels, Belgium. Available at: http://eccairsportal.jrc.ec.europa.eu/index.php/Documents/39/0/.
11. TRADE. *A Handbook of Techniques and Tools: How to Measure Performance*. 1995. U.S. Training Resources and Data Exchange Department of Energy, Washington, DC. Available at: Internet: http://www.orau.gov/pbm/handbook/handbook_all.pdf
12. EUROCONTROL. *The Aerospace Performance Factor (APF): Developing the EUROCONTROL ESARR 2 APF*. 2009. European Organisation for the Safety of Air Navigation Brussels, Belgium. Available at: http://aloftaviationconsulting.com/publications/ECTL_APF_Implementation_Plan.pdf.
13. Lintner, T.M. & Smith, S.D. & Licu, A. & Cioponea, R. & Stewart, S. & Majumdar, A. & Dupuy, M.D. *The measurement of system-wide safety performance in aviation: Three case studies in the development of the aerospace performance factor (APF)*. 2009. Available at: https://www.eurocontrol.int/eec/gallery/content/public/document/other/conference/2009/safety_r_and_d_Munich/day_1/Tony-Licu-(EUROCONTROL)-Steve-Smith-(FAA)-Paper.pdf
14. EASA, 2015. *ECCAIRS Taxonomy and NoA Update. Presentation at [ECCAIRS Steering Committee Meeting, Brussels, 27th October 2015]*. European Aviation Safety Agency, Brussels, Belgium. Available at: http://eccairsportal.jrc.ec.europa.eu/index.php/Documents/39/0/.
15. Di Gravio, G. & Mancini, M. & Patriarca, R. & Costantino, F. Overall safety performance of Air Traffic Management system: Forecasting and monitoring. *Safety Science*. 2014. Vol. 72. P. 351-362.
16. Rochelle, M.E. & Gurkaynak, R.S. How Useful are Estimated DSGE Model Forecasts for Central Bankers? *Brooking papers on Economic Activity, Economic Studies Program. The Brooklins Institution*. 2010. Vol. 41 (2 (Fall)). P. 209 -259.
17. Nau, R.F. *Statistical forecasting: notes on regression and time series analysis* [*online*]. Duke University: Fuqua School of Business. Durham. 2016. Available at: http://people.duke.edu/~rnau/411home.htm.
18. Chambers, J.C. & Mullick, S.K. & Smith, D.D. How to choose the right forecasting technique. *Harvard Business Review*. 1971. Vol. 49. No. 4. P. 45-74.
19. Kutner, M.H. & Nachtsheim, Ch.J. & Neter, J. & Wasserman, W. *Applied Linear Statistical Models: 5th Edition*. Irwin, The McGraw-Hill Companies. 2005. ISBN 0-07-238688-6.
20. Box, G.E.P. & Jenkins, G.M. & Reinsel, G.C., 1994. *Time Series Analysis: Forecasting and Control. 3rd ed. Englewood Cliffs*. NJ: Prentice Hall. 1994.

Received 23.03.2016; accepted in revised form 08.09.2017