Research Article

An Overview of Forecasting Studies Applied in Different Areas of The Aviation Industry Between 2020 and 2024

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Abstract

The aviation industry is dynamic due to many uncertain processes such as meteorological conditions, economy, wars, pandemics and aircraft failures. This situation makes decision-making processes difficult and decision makers need forecasting techniques to solve this problem. In this way, operational efficiency, line, hangar and flight safety can be maximized while flight and maintenance related costs can be minimized. Issues such as Air Traffic Control, breakdown and maintenance processes, the development of the number of passengers and aircraft in the coming years, accident risks, harmful gas emissions over the years and the need for personnel and aircraft are the application areas of forecasting techniques in aviation. In this context, forecasting methods also serve as a cornerstone for sustainable aviation. In this article, forecasting studies carried out in different categories in the aviation sector between 2020-2024 are systematically analyzed in terms of problems and methods applied. Results of the research, Machine learning, deep learning, data mining, statistical techniques and data mining have been found to be used extensively in solving problems. In addition, researchers have conducted intensive studies on the effects of the pandemic period and the recovery of the sector and focused on CO2 emissions. The benefits of using these methods for companies and decision makers are presented in the studies. This paper aims to provide a critical indication of the future of air transportation by systematically reviewing forecasting studies over the years. The review reveals the importance of forecasting in aviation and contributes positively to the creation of a sustainable, safe and efficient transportation sector.

Keywords: *Forecasting, Aviation Sector, Artificial Intelligence, Optimization, Sustainability.*

1. Introduction

Forecasting is the process of making predictions about possible future outcomes or outputs based on data obtained in the past and present through applications, sensors or observations. With the advances in science and technology, rapid solutions can be obtained from large data stacks with statistical analysis and artificial intelligence-based methods. Forecasting, which has a wide range of applications, has a strategic importance in reducing costs, using resources efficiently and developing policies for the future in sectors with high complexity, uncertainty and dynamism.

Airline transportation is a sector where forecasting methods are frequently used. Bad weather conditions, air traffic density, passenger numbers, breakdowns and other technical reasons are the main reasons for using forecasting methods in this sector. Forecasting these factors with high accuracy will increase operational safety, process efficiency and expected profit, while minimizing costs.

Forecasting applications in aviation cover a wide range of areas. Fleet assignment, flight scheduling, aircraft routing, personnel requirements, personnel scheduling, aircraft landing and take-off times, air traffic management and harmful gas emissions are some of the main ones. In addition, forecasting the number of aircraft and passengers, detecting malfunctions, deciding on new flight destinations and pricing tickets are other application areas of forecasting. Finally, forecasting techniques are needed for long-term strategic decisions such as opening new airports, increasing airport capacity and expanding the aircraft fleet.

Forecasting provides information on the future conjuncture of the aviation industry and enables the necessary measures to be taken at the right time by analyzing the uncertainties accurately. Thanks to forecasting studies, the current state of the system can be analyzed and possible aspects that may fail or may fail can be identified.

In this article, studies on forecasting applications in the aviation industry between 2020 and 2024 are systematically analyzed. It is tried to share the current methods used and the directions of forecasting in aviation with the researchers. In the next section, information on studies on forecasting in aviation is presented.

2. Materials and Methods

The work on aviation forecasting between 2020 and 2024 is summarized below.

Yang, H., and O'Connell constructed a forecasting model using the ARIMA method to estimate the magnitude of carbon emission from the development of the Shanghai aviation industry over the years and to determine the environmental impact of this situation. As a result of the analysis for a five-year period, it was determined that the CO2 emission in June-2021 DE will reach approximately 37 million tons. They also developed several strategies to reduce carbon emissions based on these results [1].Liao et al.

estimated the systemic factors in the aviation industry using the GBN technique. The model predicted future economic indicators with high accuracy and was found to be better than other techniques [2]. Chung et al. conducted a review study on the application of DM in the aviation industry. The study focused on data analysis, network planning, future predictions and machine learning and made suggestions for future studies [3]. Ryley et al. assessed the impact of climate change on the aviation sector based on papers in the literature and suggested various approaches and policies to mitigate this impact [4]. Liu et al. evaluated the pandemic impact on airline transportation in China from an economic perspective using GARCH model and text mining techniques. Focusing on the volatility of stocks, the study observed the volatile volatilities in airport and logistics stocks due to the pandemic [5].

Jin et al. developed a hybrid approach based on VMD-ARMA/KELM-KELM methods and reported that it solves the problem of highly dynamic passenger demand forecasting with high accuracy and gives better results than existing methods [6]. Dou, conducted a survey on the benefits of using big data technology in aviation and the methods used in this context. He stated that the multilayer network analysis technique will contribute to performance improvement [7]. Kanavos et al. used ARIMA, SARIMA and DLNN methods in the problem of forecasting the number of passengers in the aviation industry [8]. Dahooie et al. evaluated technology forecasting methodologies to be used in the aviation sector using SWARA and MUTLIMOORA methods from multi-criteria decision making techniques and conducted an application study in Iran Aviation Industries Organization (IAIO) [9]. Baisariyev et al., aimed to predict the demand for spare parts using information obtained from airline transportation with the Bootstrap method and stated that the method was more effective compared to other techniques as a result of the application study [10].

Sun and Geng developed a hybrid forecasting technique based on the IOWA method to predict accident risk in the aviation industry. The application results indicate that the hybrid method performs forecasts with higher accuracy than single models [11]. Verma and Kumar focused on the safety problem in the aviation industry and used data mining, ensemble techniques, time series and artificial neural network models to predict aviation accidents. In addition, they have shown that hybrid methods will produce more successful results in prediction models [12]. Sahin et al. focused on uncertain demands in the aviation industry and used 5 different methods, namely Croston, Exp.Smoothing, Naïve, Syntetos and Grand Total, to solve the problem. He stated that Exp.Smoothing in Intermittent data, Naïve in Erratic data and Croston method in Lumpy data type are the most successful methods [13]. Zheqi et al. tried to predict the aviation safety problem with deterministic forecasting models with high confidence intervals [14]. Romani et al. used ARIMA and MLP techniques to improve flight performance in the aviation sector in Indonesia after the pandemic and found that MLP gave better results [15].

Gole et al., pandemic sonrası pandemic sonrası havacılık endüstrisinde yaşanan mali ve teknik problemleri incelemiş ve problemin çözümü için çeşitli önerilerde bulunmuştur [16]. Gudmundsson et al. evaluated the impact of the pandemic on airline transportation from an economic perspective and estimated how long it would take the industry to return to pre-pandemic conditions. Using the ARIMAX method, the authors suggest that the recovery process will take 2.5 years on average for passenger demand. For cargo transportation, this period may be shorter [17]. Ovdiienko et al. analyzed the impact of the pandemic on CO2 emissions and stated that the focus should be on carbon pricing strategies to reduce emissions [18]. Cui et al., used MCS technique for spare parts demand in the aviation industry and considered stochastic situations. The study aims to provide a more reliable control of inventory levels [19]. Khafidli and Choiruddin estimated the impact of the pandemic on air traffic using the LSTM method [20].

Hanson et al. examined the effect of income level on ridership under different economic indicators and investigated the effect of elasticity on post-crisis recovery [21]. Jiang et al. estimated passenger satisfaction in airline transportation with data mining techniques and examined the factors affecting satisfaction. As a result of the application study, they stated that RF performed better classification performance than other methods [22]. Kitsou et al., Kitsou et al. used time series analysis to forecast international passenger numbers in Greece after the pandemic [23]. Demir estimated the CO2 emissions in the United Kingdom for the period up to 2029 based on the number of airplanes and passengers. He used time series analysis and genetic algorithm as forecasting methods and considered domestic and international flights [24]. Ayaydin and Akcayol, DRNN, LSTM and RF techniques were used to predict flight delays and it was found that LSTM predicted flight delays with an accuracy level of 96.5% [25]

Flores et al. focused on aviation safety and conducted a forecasting study on the risk management problem. They considered the factors affecting risks in the problem and used GLARMA, INGARCH and DLM techniques for forecasting [26]. Zachariah et al. conducted a survey study on the methods used in the demand forecasting problem in the aviation industry. The study discusses the advantages and shortcomings of the methods, identifies the problems encountered in forecasting and provides suggestions for future work for researchers [27]. Li et al. focused on green aviation and conducted a forecasting study to reduce carbon emissions. They developed a “decomposition forecasting” approach and applied it to domestic and international flight data [28]. Yang et al. used BPNN and MCS to estimate carbon emissions in air transportation. In the study where the uncertainty constraint is considered, recommendations are made for emission reduction [29]. Bain et al. conducted a survey study on estimating the amount of radiation to which flight crew and passengers are exposed during flight [30].

Filelis-Papadopoulos et al., developed NNAART for CO2 emission estimation under uncertainty and compared the proposed method with machine learning techniques. They performed an application study on a dataset obtained from approximately 30000 flight data and found that they achieved higher results in shorter times [31]. Zhong et al. developed a hybrid forecasting model (DCEF) using EMD, ARIMA and TSDV methods together. They used the proposed method for forecasting carbon emissions and reported good quality results compared to other models. [32]. Anupam and Lawal used the NARX technique to forecast passenger traffic and conducted an application study on Norway. It evaluated the passenger flow under dynamism and non-linearity constraints. As a result of the application study, they stated that they obtained more successful results than LSTM [33]. Gür focused on share price forecasting with SVM, XGBoost and LSTM and conducted an application study on Turkish Airlines. As a result of the study, he stated that LSTM performs better prediction [34]. Setiyawan et al., focused on forecasting post-pandemic fuel demand with ARIMA method and aimed to use the results in inventory operations. The application study is based on Jakarta Airport [35].

Kilic et al., predicted the performance of turbojet engines under flight dynamics using the LSTM method [36]. Raj et al., focused on the estimation of meteorological parameters with the Hybrid Iterative Input Selection - Long Short-Term Memory (IIS-LSTM) method and conducted an application study at Nadi and Nausori International Airports in Fiji. The results of the study indicate that the hybrid method provides quality forecasts [37]. Gu et al. solved the passenger traffic forecasting problem with the BPNN and SARIMA based on MRE, MSE and RMSE indicators and conducted an application study in Chinese Civil Airline transportation. In the paper, they considered the pandemic period [38]. Chen and Ai, in their study on Chinese Civil Aviation, estimated carbon emissions with simulation and SD model and developed scenarios and strategies to reduce emissions with simulation studies [39]. Wang et al. CNN-Transformer to predict meteorological conditions for a short time period and performed an application study at Wuhan Tianhe Airport [40].

3. Systematic Evaluation of Forecasting Studies

In this section, the methods used to solve aviation forecasting problems and the specific characteristics of the problems are presented in a systematic way. Table 1 presents the labels of the solution methodologies and Figure 1 presents the usage statistics of the methodologies based on the reviewed papers. Table 2 gives the general titles of the topics covered in the papers and Figure 2 gives information on the extent to which these topics are covered in the studies.

Table 1: Solution method index

Method	Method Index	Abbreviation	Method	Method Index	Abbreviation
Autoregressive Integrated Moving Average	1	ARIMA	**Deep Learning Neural Networks**	11	DLNN
Gray Bayesian Network	2	GBN	**Step-wise Weight Assessment Ratio Analysis**	12	SWARA
Survey	3	---	**MUTLIMOORA**	13	---
Generalized Autoregressive Conditional Heteroskedasticity	4	GARCH	**Bootstrap**	14	---
Text Mining	5	TM	**Induced Ordered Weighted Averaging**	15	IOWA
Variational Mode Decomposition	6	VMD	**Data Mining**	16	DM
Autoregressive Moving Average Model	7	ARMA	**Community Techniques**	17	CM
Kernel Extreme Learning Machine	8	KELM	**Time Series**	18	TM
Hybrid Model	9	HM	**Artificial Neural Network**	19	ANN
Seasonal Autoregressive Integrated Moving Average	10	SARIMA	**Croston**	20	---
Method	**Method Index**	**Abbreviation**	**Method**	**Method Index**	**Abbreviation**
Exp.Smoothing,	21	ES	**Integer-valued GARCH**	34	INGARCH
Naïve	22	---	**Dynamic Linear Model (DLM)**	35	DLM
Grand Total	23	GT	**Decomposition Approach**	36	DA
Syntetos	24	---	**Back Propagation Neural Network**	37	BPNN
Deterministic Forecasting Models	25	DFM	**The Non-Negative Adaptive Auto-Regression method with Thresholding**	38	NNAART
Multilayer Perceptron	26	MLP	**Empirical Mode Decomposition**	39	EMD
Autoregressive Integrated Moving Average with Exogenous Variables	27	ARIMAX	**Truncated singular value decomposition**	40	TSDV
Monte Carlo Simulation	28	MCS	**(Nonlinear Autoregressive with Exogenous Input)**	41	NARX
Long Short-Term Memory	29	LSTM	**Support Vector Machine**	42	SVM
Random Forest	30	RF	**XGBoost**	43	Extreme Gradient Boosting
Genetic Algorithm	31	GA	**System Dynamic**	44	SD
Recurrent Neural Network	32	DRNN	**Convolutional Neural Network-Transformer**	45	CNN-Transformer
Generalized Linear ARMA	33	GLARMA			

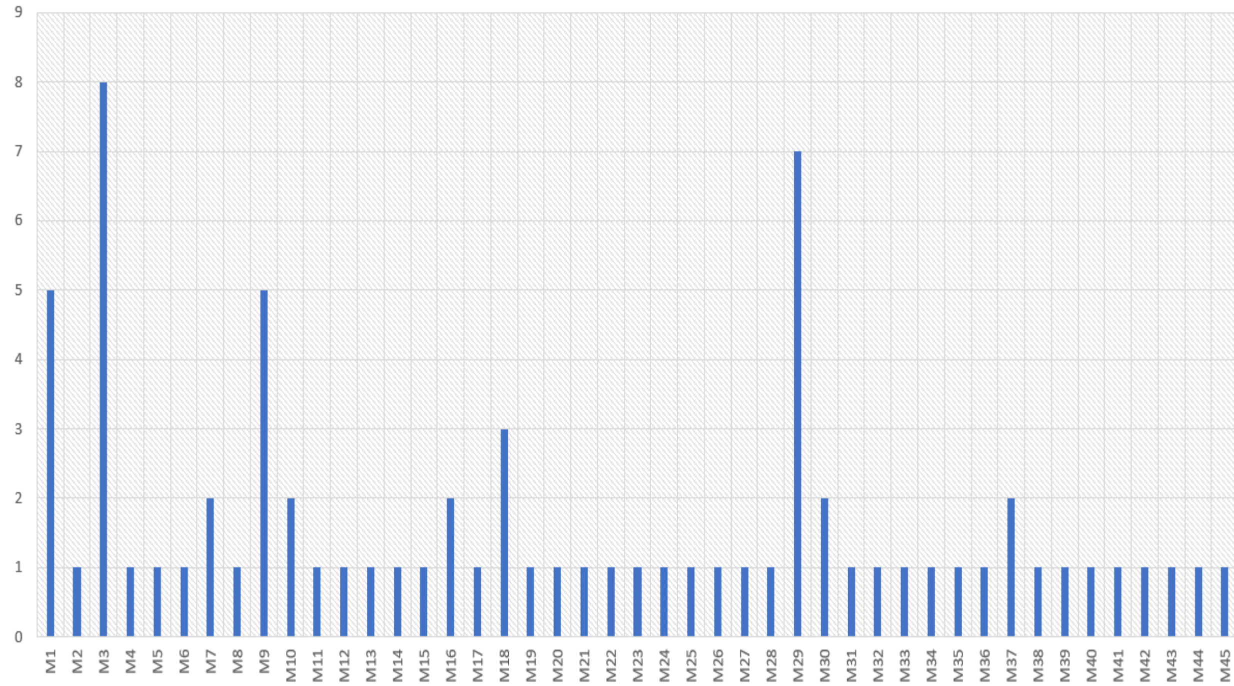


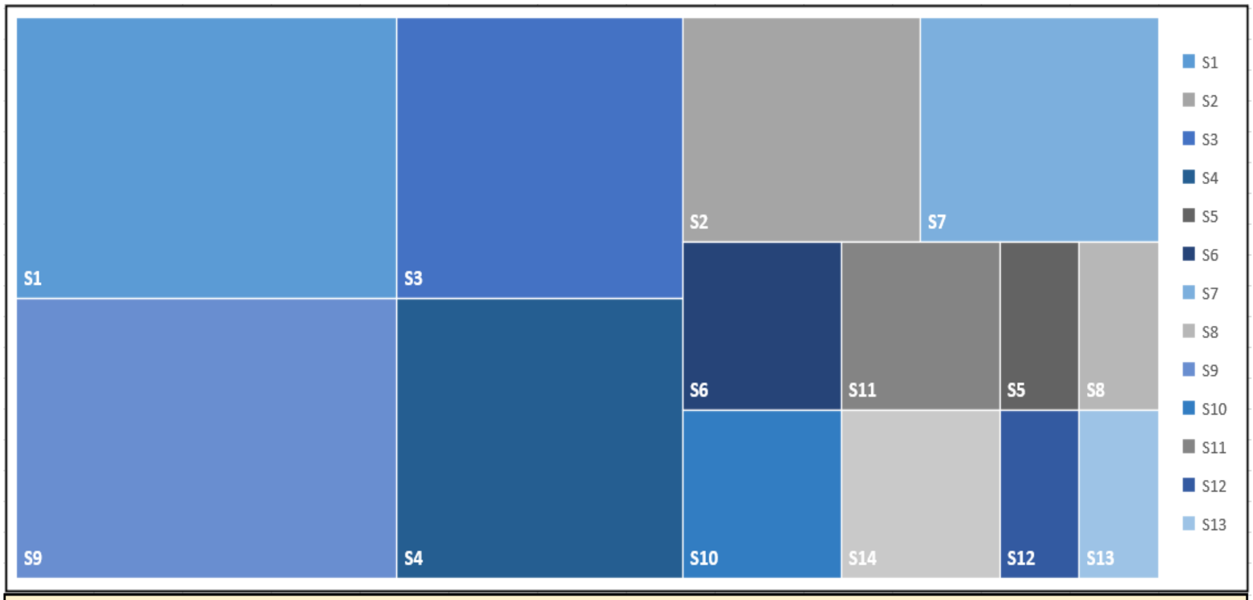
Figure 1: Techniques used in problem solving

When Figure 1 is examined, it is understood that survey studies on the subject have been carried out intensively. Among the methods, it is observed that LSTM, a deep learning method, is frequently used in solving the problem. ARIMA and Hybrid methods are other frequently used methods. It is inferred from the figure that the Time Series method follows these methods.

Table 2: Problem specification index

Spesification	Method Index	Spesification	Method Index
CO2 Emisyonu	1	Uncertain demand forecasting	8
Economic indicators	2	Pandemic	9
Survey	3	Air Traffic/Passenger Trafic	10
Passenger/Cargo numbers demand	4	Delays	11
Decision making	5	Fuel Consumption	12
Spare parts demand	6	Engine Performance	13
Accident risk/Aviation safety	7	Meteorological Indicator	14

Table 2 summarizes the topics covered in the articles and Graph 2 shows the number of times the topics were considered. According to this graph, pandemic and CO2 emissions were the two most studied topics. It was determined from the articles that the pandemic period, the effects of the pandemic on aviation and the recovery of aviation after the pandemic were taken into consideration and the process was tried to be predicted. In addition, the change in CO2 emissions in aviation over the years and emission reduction strategies have been another topic of interest to researchers. Survey studies and forecasting passenger/cargo demands have been among the intensively studied topics in aviation. Economic indicators and accident risks/aviation safety are the topics that researchers focus on.



S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14
8	4	6	6	1	2	4	1	8	2	2	1	1	2

Figure 2: Problems considered in the papers

The results in Figures 1 and 2 show that statistical analysis, machine learning and deep learning are used extensively in aviation forecasting. The lack of utilization of Optimization Techniques and Metaheuristic Algorithms in this field has been identified as a gap. It was also observed that the consideration of uncertainty in demand forecasting, prediction of engine health based on failure data and flight delays is a virgin area.

4. Discussion and Conclusion

In this article, forecasting studies conducted in the aviation sector between 2020 and 2024 are systematically analyzed in terms of the topics addressed and the methods used. As a result of the study, it was determined that researchers focused on the impact of the pandemic on aviation and CO2 emissions. It was determined that LSTM, ARIMA and Hybrid Methods were used extensively in solving the problem. In addition, accident risks, aviation safety and economic indicators have been of interest to researchers. Through this paper, the direction, strengths, weaknesses and potential issues of forecasting in aviation are presented to academicians. It is suggested that researchers should solve the problems mentioned with optimization techniques in future studies, uncertainty and dynamism issues should be taken more into account in studies, and engine health and flight delays should be focused more.

References

[1] Yang, H., and O'Connell, J. F. (2020). Short-term carbon emissions forecast for aviation industry in Shanghai. Journal of cleaner production, 275, 122734.

[2] Liao, H., Fang, Z., Wang, C., and Liu, X. (2020). Economic development forecast of china's general aviation industry. Complexity, 2020(1), 3747031.

[3] Chung, S. H., Ma, H. L., Hansen, M., and Choi, T. M. (2020). Data science and analytics in aviation. Transportation research part E: logistics and transportation review, 134, 101837.

[4] Ryley, T., Baumeister, S., and Coulter, L. (2020). Climate change influences on aviation: A literature review. Transport Policy, 92, 55-64.

[5] Liu, J., Qiao, P., Ding, J., Hankinson, L., Harriman, E. H., Schiller, E. M., ... and Zhang, H. (2020). Will the aviation industry have a bright future after the COVID-19 outbreak? Evidence from Chinese airport shipping sector. Journal of Risk and Financial Management, 13(11), 276.

[6] Jin, F., Li, Y., Sun, S., and Li, H. (2020). Forecasting air passenger demand with a new hybrid ensemble approach. Journal of Air Transport Management, 83, 101744.

[7] Dou, X. (2020). Big data and smart aviation information management system. Cogent Business & Management, 7(1), 1766736.

[8] Kanavos, A., Kounelis, F., Iliadis, L., and Makris, C. (2021). Deep learning models for forecasting aviation demand time series. Neural Computing and Applications, 33(23), 16329-16343.

[9] Dahooie, J. H., Mohammadi, N., Daim, T., Vanaki, A. S., and Zavadskas, E. K. (2021). Matching of technological forecasting technique to a technology using fuzzy multi-attribute decision-making methods: Case study from the aerospace industry. Technology in Society, 67, 101707.

[10] Baisariyev, M., Bakytzhanuly, A., Serik, Y., Mukhanova, B., Babai, M. Z., Tsakalerou, M., and Papadopoulos, C. T. (2021). Demand forecasting methods for spare parts logistics for aviation: a real-world implementation of the Bootstrap method. Procedia manufacturing, 55, 500-506.

[11] Sun, Y., and Geng, N. (2021). Forecasting civil aviation incident rate in china using a combined prediction model. Journal of advanced transportation, 2021(1), 5521526.

[12] Verma, S., and Kumar, P. (2021, February). A Comparative Overview of Accident Forecasting Approaches for Aviation Safety. In Journal of Physics: Conference Series (Vol. 1767, No. 1, p. 012015). IOP Publishing.

[13] Şahin, M., Eldemir, F., and Turkyilmaz, A. (2021). Inventory cost minimization of spare parts in aviation industry. Transportation Research Procedia, 59, 29-37.

[14] Zheqi, Z., Bo, R., Xiaofeng, Z., Hang, Z., Tao, X., and Qingge, C. (2021). Neural network-based probability forecasting method of aviation safety. In IOP Conference Series: Materials Science and Engineering (Vol. 1043, No. 3, p. 032063). IOP Publishing.

[15] Romani, D. D., Nasution, D., Syahputra, A., Usman, U., and Prayitno, H. (2021). Artificial Neural Network Model In Forecasting Post-Covid-19 Aviation Business Development Using Multi Layer Perceptron (MLP). Budapest International Research and Critics Institute-Journal (BIRCI-Journal), 4(4).

[16] Gole, I., Dobrea, R. C., and Gombos, C. C. (2021). Aviation industry-challenges and uncertainties after the Covid-19 pandemic. In SHS Web of Conferences (Vol. 92, p. 01010). EDP Sciences.

[17] Gudmundsson, S. V., Cattaneo, M., and Redondi, R. (2021). Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. Journal of Air Transport Management, 91, 102007.

[18] Ovdiienko, O., Hryhorak, M., Marchuk, V., and Bugayko, D. (2021). An assessment of the aviation industry's impact on air pollution from its emissions: worldwide and the Ukraine. Environmental & Socio-economic Studies, 9(2), 1-10.

[19] Cui, X., Ai, P., He, J., and Wang, S. (2021, March). The research of Monte-Carlo method for aviation materials demand forecast based on the life of the reliability. In Journal of Physics: Conference Series (Vol. 1838, No. 1, p. 012009). IOP Publishing.

[20] Khafidli, M. K., and Choiruddin, A. (2022, July). Forecast of Aviation Traffic in Indonesia Based on Google Trend and Macroeconomic Data using Long Short-Term Memory. In 2022 International Conference on Data Science and Its Applications (ICoDSA) (pp. 220-225). IEEE.

[21] Hanson, D., Delibasi, T. T., Gatti, M., and Cohen, S. (2022). How do changes in economic activity affect air passenger traffic? The use of state-dependent income elasticities to improve aviation forecasts. Journal of Air Transport Management, 98, 102147.

[22] Jiang, X., Zhang, Y., Li, Y., and Zhang, B. (2022). Forecast and analysis of aircraft passenger satisfaction based on RF-RFE-LR model. Scientific reports, 12(1), 11174.

[23] Kitsou, S. P., Koutsoukis, N. S., Chountalas, P., and Rachaniotis, N. P. (2022). International passenger traffic at the Hellenic Airports: Impact of the COVID-19 pandemic and mid-term forecasting. Aerospace, 9(3), 143.

[24] Demir, A. S. (2022). Modeling and forecasting of CO2 emissions resulting from air transport with genetic algorithms: The United Kingdom case. Theoretical and Applied Climatology, 150(1), 777-785.

[25] Ayaydın, A., and Akcayol, M. A. (2022). Deep learning based forecasting of delay on flights. Bilişim Teknolojileri Dergisi, 15(3), 239-249.

[26] Flores, B., Rios Insua, D., Alfaro, C., and Gomez, J. (2022). Forecasting aviation safety occurrences. Applied Stochastic Models in Business and Industry, 38(3), 545-567.

[27] Zachariah, R. A., Sharma, S., and Kumar, V. (2023). Systematic review of passenger demand forecasting in aviation industry. Multimedia tools and applications, 82(30), 46483-46519.

[28] Li, G., Yang, Z., and Yang, H. (2023). A new hybrid short-term carbon emissions prediction model for aviation industry in China. Alexandria Engineering Journal, 68, 93-110.

[29] Yang, L., Hu, Y. J., Wang, H., Li, C., Tang, B. J., Wang, B., and Cui, H. (2023). Uncertainty quantification of CO2 emissions from China's civil aviation industry to 2050. Journal of Environmental Management, 336, 117624.

[30] Bain, H. M., Onsager, T. G., Mertens, C. J., Copeland, K., Benton, E. R., Clem, J., ... and Pulkkinen, A. (2023). Improved space weather observations and modeling for aviation radiation. Frontiers in Astronomy and Space Sciences, 10, 1149014.

[31] Filelis-Papadopoulos, C. K., Kirshner, S. N., and O'Reilly, P. (2024). Sustainability with Limited Data: A Novel Predictive Analytics Approach for Forecasting CO2 Emissions. Information Systems Frontiers, 1-25.

[32] Zhong, W., Zhai, D., Xu, W., Gong, W., Yan, C., Zhang, Y., and Qi, L. (2024). Accurate and efficient daily carbon emission forecasting based on improved ARIMA. Applied Energy, 376, 124232.

[33] Anupam, A., and Lawal, I. A. (2024). Forecasting air passenger travel: A case study of Norwegian aviation industry. Journal of Forecasting, 43(3), 661-672.

[34] Gür, Y. E. (2024). Stock Price Forecasting Using Machine Learning and Deep Learning Algorithms: A Case Study for the Aviation Industry. Fırat Üniversitesi Mühendislik Bilimleri Dergisi, 36(1), 25-34.

[35] Setiyawan, A. P., Wibowo, W., and Atok, R. M. (2024). Forecast sales volume of aviation fuel in Jakarta using ARIMA Method to support inventory control. Indonesian Journal of Multidisciplinary Science, 3(4), 355-361.

[36] Kilic, U., Villareal-Valderrama, F., Ayar, M., Ekici, S., Amezquita-Brooks, L., and Karakoc, T. H. (2024). Deep learning-based forecasting modeling of micro gas turbine performance projection: An experimental approach. Engineering Applications of Artificial Intelligence, 130, 107769.

[37] Raj, S., Deo, R. C., Sharma, E., Prasad, R., Dinh, T., and Salcedo-Sanz, S. (2024). Atmospheric Visibility and Cloud Ceiling Predictions with Hybrid IIS-LSTM Integrated Model: Case Studies for Fiji's Aviation Industry. IEEE Access.

[38] Gu, W., Guo, B., Zhang, Z., and Lu, H. (2024). Civil Aviation Passenger Traffic Forecasting: Application and Comparative Study of the Seasonal Autoregressive Integrated Moving Average Model and Backpropagation Neural Network. Sustainability, 16(10), 4110.

[39] Chen, W., and Ai, Y. (2024). Research on the Carbon Emission Prediction and Reduction Strategies for the Civil Aviation Industry in China: A System Dynamics Approach. Sustainability, 16(20), 8950.

[40] Wang, S., Li, Y., Yang, B., and Duan, R. (2024). Short-Term Forecasting of Convective Weather Affecting Civil Aviation Operations Using Deep Learning. IEEE Access.