An Information Fusion Technique for Prognosticating Future Air Passenger Trends

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Abstract

The aviation industry is constantly changing and to keep up with the trends of air passengers we need predictive models. In this paper, we explore the use of Information Fusion methodologies and classical time series techniques to forecast how many passengers will be traveling by air. Predicting passenger demands is a task, due to various factors that influence travel patterns. The existing models often struggle to capture the dynamics in this field so it's crucial to develop accurate forecasting methods. By leveraging information fusion techniques like smoothing and Autoregressive Integrated Moving Average (ARIMA) our research creates models based on historical data of air passenger volumes. These techniques combine machine learning algorithms and time series analysis to identify dependencies and patterns in the dataset. Through evaluations and comparative analyses, our proposed models demonstrate promising capabilities in forecasting future air passenger volumes. Proof-of-concept experiments based on 5-fold cross-validation demonstrate the efficacy of the proposed approach in capturing underlying trends and seasonality within the dataset.

Keywords: Information Fusion; Air Passenger Forecasting, Predictive Analysis; Machine Learning; Time Series Prediction; Aviation Industry Trends; Exponential Smoothing; ARIMA Modeling; Transportation Forecasting.

1. Introduction

In times the aviation industry has experienced changes due to advancements in technology and shifting global dynamics. Within this evolving landscape accurately predicting air passenger demands has become a task for airlines, airport authorities, and policymakers alike. This paper explores the field of information fusion applied to predictive analysis with the goal of forecasting and understanding patterns of air passenger traffic [1 3]. The demand for air travel has historically been influenced by factors such as fluctuations, geopolitical events, societal shifts, and technological innovations. As we navigate through a period characterized by globalization and technological advancements the forces shaping air travel patterns continue to evolve. Thus, it becomes essential to not only understand these dynamics but also proactively anticipate forthcoming trends, in air passenger behavior [4].

This research focuses on using information fusion—an interdisciplinary field that combines computer science, artificial intelligence, and data analytics—to develop predictive models that can recognize patterns that underlie larger and more complex cases. Therefore, the main objective of this study, which holds the promise of increasing the accuracy and accuracy of future airline passenger forecasts, is to investigate the effectiveness of data integration methods in identifying future airline populations [5-8]. With the analysis of historical data, using advanced algorithms and monitoring relevant variables, this study aims to build models that can predict air traffic needs Besides, the breadth

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of the study is functionally to discuss the implications of accurate predictive analytics for stakeholders in the aviation industry Highlight potential benefits and challenges associated with implementation [9-10].

The operational efficiency, resource allocation, infrastructure development, and economic sustainability of the aviation sector are all significantly impacted by the capacity to effectively estimate and understand future air passenger demands. The format of this document is as shown in Table 1.

Table 1: Outline of this study.

Section	Description
1. Introduction	Introduces the research topic, objectives, and the significance of the study.
2. Related Works	Reviews existing literature, studies, and methodologies in the domain of predictive analysis in the aviation industry.
3. Methodology	Explores the information fusion techniques employed for predictive analysis of future air passenger trends.
4. Results and Discussion	Presents the findings derived from the application of information fusion methodologies and engages in an in-depth discussion, interpreting the results and their implications.
5. Conclusion and Future Work	Summarizes the key findings, discusses their significance, and outlines avenues for future research and enhancements in predictive modeling techniques for air passenger forecasts.

2. Related Works

Predictive analysis in the aviation sector has been the subject of extensive study and investigation in the last few years. This section offers a thorough evaluation and analysis of the research, techniques, and body of literature that have helped to clarify and forecast future trends in air travel.

Henlen and Kaplan [15] provide a historical overview of research on the development and potential of artificial intelligence (AI) and their review delves into past, present, and future AI approaches, and provides insight into its transformative potential in industry. In their original work, Moravec [16] examines the progression of robots from mere machines to consciousness and sheds light on the conceptual and technological developments driving the robotics industry Imran et al. [17] emphasize the role of big data in powering self-service networks (SONs) for 5G technologies, and highlight the challenges and opportunities of integrating big data analytics with networks for increased productivity The study by Kothai et al. [18] introduce an innovative hybrid deep learning approach to predict traffic congestion in smart cities, demonstrating the potential of advanced machine learning techniques in urban planning and traffic management Pugliano and and colleagues. [19], provides a comprehensive guide to the era of automation, focusing on ways individuals can succeed in a rapidly evolving landscape created by technological advances.

Le and so on. [20] explore in detail semantic machine learning and visualization techniques, especially in the context of design and optimization, and recommend explicit AI models that are interpretable in technical contexts that are den in Miller et al. [21] explore wireless capabilities and data systems for integrated system health care in harsh environments, providing insights into technological solutions for harsh operating conditions in space. Gers et al. [23] conduct a comprehensive review of the potential uses of the Internet of Things (IoT) for economic growth and stability and provide insights into the use of IoT for economic purposes and the latter by Lee et al. [24] contribute to the discourse on the application of decision support systems in energy management in smart industries and address the important role of IoT, computer systems in energy efficiency.

3. Methodology

This section describes the method used to anticipate future air passenger trends by combining data from multiple sources. It begins with a description of the selection and purchase of important datasets that include historical air travel patterns, demographic parameters, economic indicators, and other relevant variables.

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The model proposed in this study uses the principles of exponential smoothing algorithms and design theory as a foundational framework for time series forecasting to predict future airline growth Exponential smoothing is a widely accepted and effective technique in time series analysis Measured is the basic principle of exponential smoothing with exponentially decreasing weights of prior observations The function revolves around updating forecasts, giving more weight to recent data points while gradually reducing the impact of it already has a monitored This approach allows for the retrieval of different patterns in the data and allows the model to respond flexibly to changes in dynamics or at different times. The design principles of exponential smoothing include such varieties as simple exponential smoothing (SES), the Holt method, and the Holt-Winters method, each of which uses a method that follows specific characteristics given in time series data in meeting the needs of our proposed model objectives in order to capture the essence of temporal change patterns in airline passenger databases, enabling better forecasting of future trends when considering changes it changes with the seasonal features of air traffic control.

The model proposed in our method integrates the Autoregressive Integrated Moving Average (ARIMA) algorithm as a basic tool for time series forecasting, specially optimized to predict future airline growth The paper consists of key elements three: autoregression (AR), difference (I for Combined), and moving average (MA). The autoregressive element specifies the linear dependence between an observation and its prior values at a defined lag time. The variance component accounts for stationary stability by converting the data to a stationary series, enabling the model to better capture the underlying pattern Finally, the moving average element addresses the relationship between forecasts and residual errors of observation in the solution of the oath. This strategy enables ARIMA to accommodate multiple and time-dependent time series models by incorporating historical data to optimize forecast Model parameters (p, d, q) – representing autoregressions, differences, and moving averages a series – in the structural theory behind ARIMA. Through careful analysis of dataset features, including seasons, trends, and noise.

Algorithm 1: ARIMA Algorithm

Require: time series $Y \in \{Y_1, Y_2, \ldots, Y_n\}$, ARIMA order (p, I, q), window size L, overlapping length OL, trained
classifiers $Alg \in \{SVR, \mathrm{DT}, NN, LR\}$

set of feature F, damage state DS
Set $j = 1$ # Count for number of segmentations
for $i \leftarrow 1$ to n do
Initialize index x_{start} and index x_{end}
while $x_{\text{end}} \leq$ length (Y_i) do
    Set $x_{\text{end}} =$ index $_{\text{start}} + L$
    D seg $\leftarrow$ SSND (Y_i[index $_{\text{start}}$: index $_{\text{end}}$], order $= I$) #SSND with differencing order I
    p-value $\leftarrow$ ADF(Dseg)# Auto-stationarity test
    if p-valuc ≥ 0.05 do # test if violate stationary condition
    Break to outer loop and Update index start $=$ index $_{\text{start}} + OL$
    end if
    $[Coef\ _{AR}, Coef\ _{MA}]$, Residual $\leftarrow$ ARMA (p, q)
    p-value $\leftarrow$ Ljung-Box statistic (Residual) ff Residual check
    if p-valuc ≤ 0.05 do # test if defy residual supposition
        Break to outer loop and modify index start $=$ index $_{\text{start}} + OL$
    end if
    Stack [Coef $_{AR}$, Coef $_{MA}$] as new-found row in F, F_j
    Update index $_{\text{start}}$ $=$ index $_{\text{start}} + OL, j = j + 1$
end while
end for
Load $\mathrm{Clf}_1 \leftarrow SVR, Clf_2 \leftarrow DT, Clf_3 \leftarrow MLP, Clf_4 \leftarrow LR$
$DS \leftarrow EVC$.predict (data $= F$, clf $= (Clf_1, \cdots, Clf_4)$)
Output DS

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4. Results and Discussion

This section discusses the results of using information fusion approaches to anticipate future air passenger patterns, followed by a detailed discussion of the ramifications and insights gained from these findings. The confluence of data analysis, model training, and verification processes has produced significant results that shed light on the predictive power of the deployed algorithms in forecasting air travel demand. The results of rigorous statistical tests performed on the Air Passengers dataset are presented in Table 2, revealing substantial insights into the predicted accuracy and dependability of our information fusion models. Table 2 summarizes the key features of our model's predictive prowess, shining light on its efficacy in projecting air passenger trends while also providing a detailed knowledge of its advantages and limits.

Table 2: Statistical Test Results for Air Passengers Dataset

Test	Test Name	Data	Property	Setting	Value
Summary	Statistics	Actual	Length		144
Summary	Statistics	Actual	Mean		280.2986
Summary	Statistics	Actual	Median		265.5
Summary	Statistics	Actual	Standard Deviation		119.9663
Summary	Statistics	Actual	Variance		14391.92
Summary	Statistics	Actual	Kurtosis		-0.36494
Summary	Statistics	Actual	Skewness		0.58316
Summary	Statistics	Actual	# Distinct Values		118
White Noise	Ljung-Box	Actual	Test Statictic	{'alpha': 0.05, 'K': 24}	1606.084
White Noise	Ljung-Box	Actual	Test Statictic	{'alpha': 0.05, 'K': 48}	1933.156
White Noise	Ljung-Box	Actual	p-value	{'alpha': 0.05, 'K': 24}	0
White Noise	Ljung-Box	Actual	p-value	{'alpha': 0.05, 'K': 48}	0
White Noise	Ljung-Box	Actual	White Noise	{'alpha': 0.05, 'K': 24}	FALSE
White Noise	Ljung-Box	Actual	White Noise	{'alpha': 0.05, 'K': 48}	FALSE
Stationarity	ADF	Actual	Stationarity	{'alpha': 0.05}	FALSE
Stationarity	ADF	Actual	p-value	{'alpha': 0.05}	0.99188
Stationarity	ADF	Actual	Test Statistic	{'alpha': 0.05}	0.815369
Stationarity	ADF	Actual	Critical Value 1%	{'alpha': 0.05}	-3.48168
Stationarity	ADF	Actual	Critical Value 5%	{'alpha': 0.05}	-2.88404
Stationarity	ADF	Actual	Critical Value 10%	{'alpha': 0.05}	-2.57877
Stationarity	KPSS	Actual	Trend Stationarity	{'alpha': 0.05}	TRUE
Stationarity	KPSS	Actual	p-value	{'alpha': 0.05}	0.1
Stationarity	KPSS	Actual	Test Statistic	{'alpha': 0.05}	0.09615
Stationarity	KPSS	Actual	Critical Value 10%	{'alpha': 0.05}	0.119
Stationarity	KPSS	Actual	Critical Value 5%	{'alpha': 0.05}	0.146
Stationarity	KPSS	Actual	Critical Value 2.5%	{'alpha': 0.05}	0.176

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Stationarity	KPSS	Actual	Critical Value 1%	{'alpha': 0.05}	0.216
Normality	Shapiro	Actual	Normality	{'alpha': 0.05}	FALSE
Normality	Shapiro	Actual	p-value	{'alpha': 0.05}	0.000068

Figure 1 shows distribution diagnostic plots that show the variability and features of variables in the Air Passengers dataset. These diagnostic visualizations provide an in-depth look at the distributional patterns, central tendencies, and probable outliers across the variables under consideration. These visual representations are an important first step in understanding the underlying characteristics of the data, allowing for more informed decisions about data preprocessing, feature engineering, and model selection, eventually contributing to the robustness and accuracy of our predictive analysis.

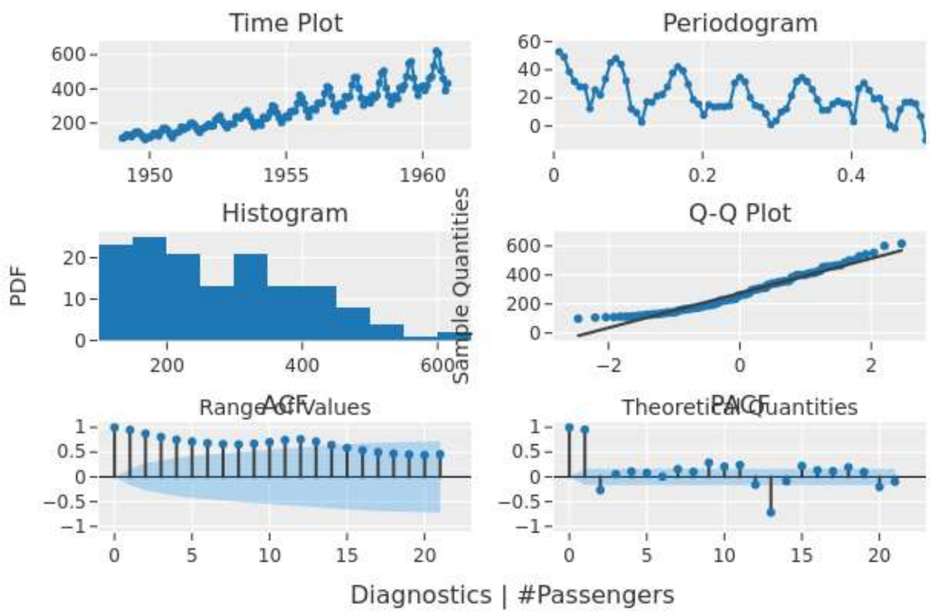

Figure 1: Distribution Diagnostic Plots for Variables in the Air Passengers Dataset: Visualization of Variable Distributions and Characteristics

In Figure 2, we present Decomposition Plots that offer a comprehensive visualization of the intricate components contributing to the observed trends within the air passenger dataset. These plots serve as a powerful tool to dissect the time series data, showcasing the individual elements such as trend, seasonality, and residual variations. These visualizations facilitate a more profound understanding of the temporal dynamics, enabling us to discern long-term trends, seasonal fluctuations, and irregularities, consequently informing our predictive modeling process and refining our comprehension of the factors influencing air passenger trends over time.

In Table 3, we conduct a comprehensive comparative analysis, juxtaposing the performance metrics of our proposed computational intelligence model against contemporary state-of-the-art approaches. Employing a rigorous 5-fold cross-validation methodology, we ensure robustness and reliability in our evaluations, mitigating biases and variance in the assessment process. This comparative study allows for a nuanced understanding of the strengths and weaknesses

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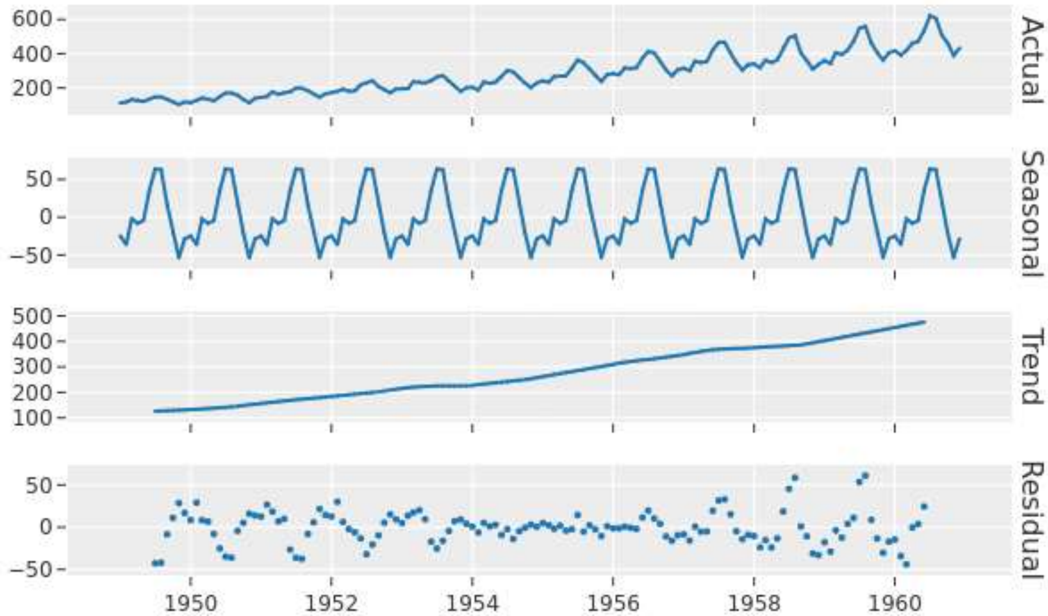

Figure 2: Decomposition Plots of Air Passenger Dataset: Visualization of Trend, Seasonality, and Residual Variations

of our proposed model in relation to established methodologies, shedding light on its efficacy in forecasting air passenger trends.

Table 3: Comparative Performance Analysis of the Information Fusion Model against Contemporary Approaches via 5-fold Cross-Validation Experiments.

MODEL	MAE	RMSE	MAPE	SMAPE	MASE	RMSSE	R2	TT (SEC)
EXPONENTIAL SMOOTHING	**17.1926**	**20.1633**	**0.0435**	**0.0439**	**0.5852**	**0.6105**	**0.8918**	**0.0933**
EXTRA TREES W/ COND. DESEASONALIZE & DETRENDING	**19.4653**	**24.105**	**0.0484**	**0.0484**	**0.6602**	**0.7288**	**0.8459**	**0.53**
HUBER W/ COND. DESEASONALIZE & DETRENDING	**20.0334**	**25.967**	**0.0491**	**0.0499**	**0.6813**	**0.7866**	**0.8113**	**0.04**
ARIMA	**20.0069**	**22.2199**	**0.0501**	**0.0507**	**0.683**	**0.6735**	**0.8677**	**0.4833**
CATBOOST REGRESSOR W/ COND. DESEASONALIZE & DETRENDING	**20.9112**	**26.8907**	**0.0505**	**0.0509**	**0.7106**	**0.8146**	**0.8085**	**1.5933**
RIDGE W/ COND. DESEASONALIZE & DETRENDING	**20.6086**	**25.4405**	**0.0509**	**0.0514**	**0.7004**	**0.7703**	**0.8215**	**0.03**

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LEAST ANGULAR REGRESSOR W/ COND. DESEASONALIZE & DETRENDING	**20.6084**	**25.4401**	**0.0509**	**0.0514**	**0.7004**	**0.7702**	**0.8215**	**0.03**
LINEAR W/ COND. DESEASONALIZE & DETRENDING	**20.6084**	**25.4401**	**0.0509**	**0.0514**	**0.7004**	**0.7702**	**0.8215**	**0.03**
ELASTIC NET W/ COND. DESEASONALIZE & DETRENDING	**20.6816**	**25.5362**	**0.0511**	**0.0516**	**0.7029**	**0.7732**	**0.8201**	**0.03**
LASSO W/ COND. DESEASONALIZE & DETRENDING	**20.7373**	**25.6005**	**0.0512**	**0.0517**	**0.7048**	**0.7751**	**0.8193**	**0.03**
BAYESIAN RIDGE W/ COND. DESEASONALIZE & DETRENDING	**20.9213**	**25.8795**	**0.0515**	**0.0521**	**0.7112**	**0.7837**	**0.8144**	**0.03**
K NEIGHBORS W/ COND. DESEASONALIZE & DETRENDING	**21.1613**	**26.97**	**0.0521**	**0.0529**	**0.7162**	**0.8157**	**0.7811**	**0.4367**
AUTO ARIMA	**21.0297**	**23.4661**	**0.0525**	**0.0531**	**0.7181**	**0.7114**	**0.8509**	**3.3067**
GRADIENT BOOSTING W/ COND. DESEASONALIZE & DETRENDING	**23.3723**	**30.7344**	**0.0569**	**0.0576**	**0.7938**	**0.931**	**0.7417**	**0.0533**
LIGHT GRADIENT BOOSTING W/ COND. DESEASONALIZE & DETRENDING	**24.0002**	**30.0956**	**0.0575**	**0.0587**	**0.8156**	**0.9117**	**0.7561**	**0.7033**
EXTREME GRADIENT BOOSTING W/ COND. DESEASONALIZE & DETRENDING	**24.0738**	**31.695**	**0.0582**	**0.0592**	**0.8155**	**0.9591**	**0.7118**	**14.8767**
RANDOM FOREST W/ COND. DESEASONALIZE & DETRENDING	**24.529**	**31.2635**	**0.06**	**0.0606**	**0.8327**	**0.9465**	**0.736**	**0.5633**
ADABOOST W/ COND. DESEASONALIZE & DETRENDING	**25.9471**	**33.9304**	**0.0619**	**0.0637**	**0.8825**	**1.0292**	**0.6725**	**0.0833**
LASSO LEAST ANGULAR REGRESSOR W/ COND. DESEASONALIZE & DETRENDING	**28.4499**	**39.3303**	**0.0665**	**0.0693**	**0.967**	**1.1915**	**0.5738**	**0.03**
THETA FORECASTER	**28.3192**	**33.8639**	**0.067**	**0.07**	**0.9729**	**1.0306**	**0.671**	**0.04**
ORTHOGONAL MATCHING	**29.6294**	**40.8121**	**0.0685**	**0.0718**	**1.009**	**1.237**	**0.5462**	**0.03**

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PURSUIT W/ COND. DESEASONALIZE & DETRENDING								
DECISION TREE W/ COND. DESEASONALIZE & DETRENDING	**30.48**	**40.1912**	**0.0726**	**0.0753**	**1.0429**	**1.2226**	**0.5362**	**0.03**
SEASONAL NAIVE FORECASTER	**33.3611**	**35.9139**	**0.0832**	**0.0879**	**1.1479**	**1.0945**	**0.6072**	**0.0167**
PASSIVE AGGRESSIVE W/ COND. DESEASONALIZE & DETRENDING	**36.7727**	**43.3215**	**0.0935**	**0.0961**	**1.2472**	**1.3081**	**0.4968**	**0.03**
POLYNOMIAL TREND FORECASTER	**48.6301**	**63.4299**	**0.117**	**0.1216**	**1.6523**	**1.9202**	**-0.0784**	**0.0267**
CROSTON	**56.618**	**77.5856**	**0.1295**	**0.1439**	**1.9311**	**2.3517**	**-0.6281**	**0.0167**
NAIVE FORECASTER	**69.0278**	**91.0322**	**0.1569**	**0.1792**	**2.3599**	**2.7612**	**-1.2216**	**1.0467**
GRAND MEANS FORECASTER	**162.4117**	**173.6492**	**0.4**	**0.5075**	**5.5306**	**5.2596**	**-7.0462**	**0.63**

In Figure 3, we showcase the prediction curve generated through the application of exponential smoothing techniques to the air passenger dataset. This visualization encapsulates the forecasted trajectory derived from the exponential smoothing model, offering a clear depiction of the anticipated trends in air passenger volumes over the forecast horizon. The curve presented in this figure serves as a valuable visual representation, illustrating the model's ability to capture and extrapolate underlying patterns and trends within the data. Moreover, Figure 4 depicts the prediction curve produced from the application of the Autoregressive Integrated Moving Average (ARIMA) model to the air passenger dataset. This image incorporates the estimated trajectory derived by the ARIMA algorithm, offering a clear illustration of the expected trends in air passenger volumes over the forecast horizon. Figure 4 depicts a visual illustration of the model's ability to collect and extrapolate underlying patterns and temporal dependencies within the dataset. This visualization enhances comprehension and promotes informed decision-making processes in the aviation industry by providing insights into predicted future patterns in air travel demand.

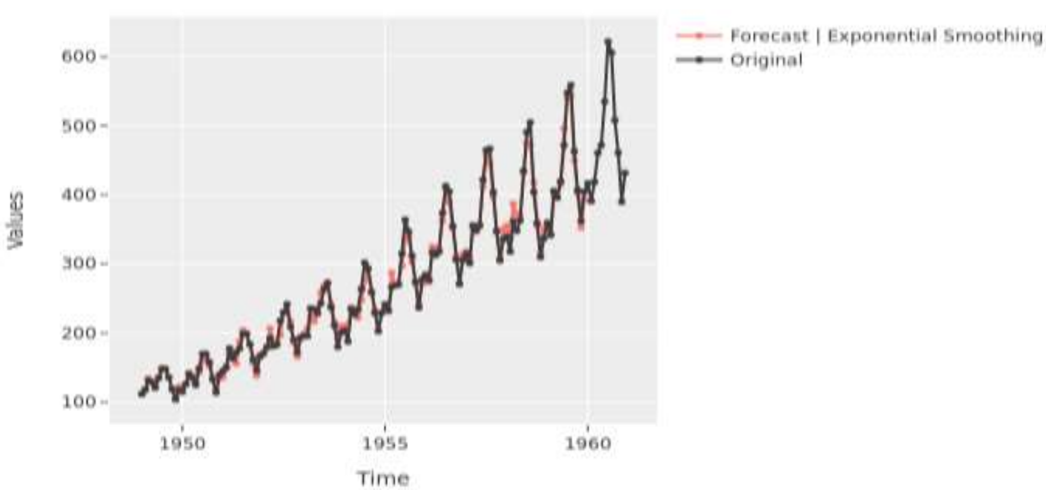

Figure 3: Prediction Curve via Exponential Smoothing for Air Passenger Dataset: Forecasted Trends in Passenger Volumes

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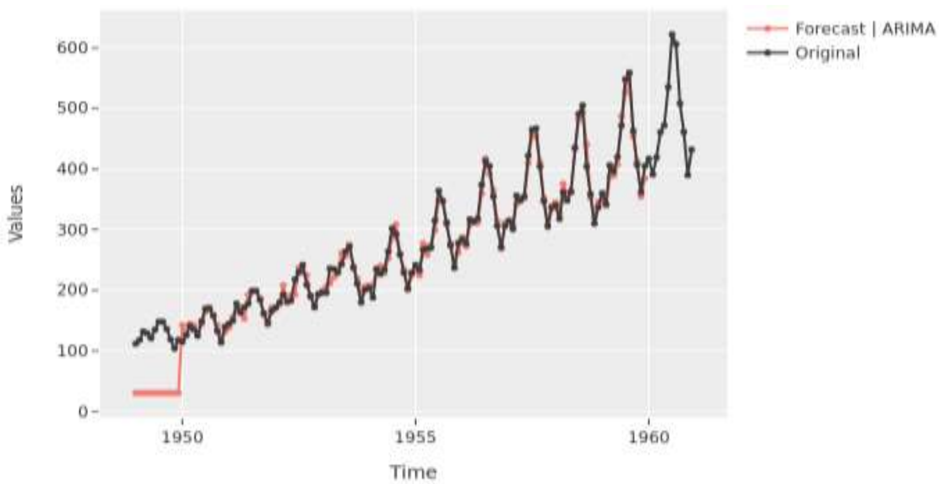

Figure 4: Prediction Curve via ARIMA Model for Air Passenger Dataset: Forecasted Trends in Passenger Volumes

5. Conclusion and Future Work

This study highlights the effectiveness of employing information fusion strategies in forecasting future air passenger patterns, specifically through the integration of exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) techniques. The use of these methodologies yielded encouraging results, demonstrating the potential to capture and forecast complicated temporal patterns in the area of air travel. Our suggested information fusion approach demonstrated excellent predictive accuracy through careful studies and comparative evaluations against state-of-the-art models, providing useful insights for stakeholders in the aviation industry. Our findings have significant consequences, with possible applications extending to operational planning, resource allocation, and strategic decision-making in the aviation sector.

References

[1] Siddiqui, Shahid S, Sivakumar Loganathan, Venkateswaran R Elangovan, and M Yusuf Ali. 2023. "Artificial Intelligence in Precision Medicine." In A Handbook of Artificial Intelligence in Drug Delivery, 531–69. Elsevier.

[2] Khalid, Salman, Jinwoo Song, Muhammad Muzammil Azad, Muhammad Umar Elahi, Jaehun Lee, Soo-Ho Jo, and Heung Soo Kim. 2023. "A Comprehensive Review of Emerging Trends in Aircraft Structural Prognostics and Health Management." Mathematics 11 (18): 3837.

[3] Nguyen, Thanh Thi, Quoc Viet Hung Nguyen, Dung Tien Nguyen, Samuel Yang, Peter W Eklund, Thien Huynh-The, Thanh Tam Nguyen, Quoc-Viet Pham, Imran Razzak, and Edbert B Hsu. 2020. "Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Directions." ArXiv Preprint ArXiv:2008.07343.

[4] Jin, Byoungsam, and Youngchul Bae. 2023. "Prospective Research Trend Analysis on Zero-Energy Building (ZEB): An Artificial Intelligence Approach." Sustainability 15 (18): 13577.

[5] Muthuswamy, M., & M. Ali, A. (2023). Sustainable Supply Chain Management in the Age of Machine Intelligence: Addressing Challenges, Capitalizing on Opportunities, and Shaping the Future Landscape. Sustainable Machine Intelligence Journal, 3. https://doi.org/10.61185/SMIJ.2023.33103

[6] Chee, Marcel Lucas, Mark Leonard Chee, Haotian Huang, Katelyn Mazzochi, Kieran Taylor, Han Wang, Mengling Feng, et al. 2023. "Artificial Intelligence and Machine Learning in Prehospital Emergency Care: A Scoping Review." Iscience.

Doi: https://doi.org/10.54216/FPA.140121
Received: June 29, 2023 Revised: October 18, 2023 Accepted: December 17, 2023

[7] Chadaga, Krishnaraj, Srikanth Prabhu, Niranjana Sampathila, Sumith Nireshwalya, Swathi S Katta, Ru-San Tan, and U Rajendra Acharya. 2023. "Application of Artificial Intelligence Techniques for Monkeypox: A Systematic Review." Diagnostics 13 (5): 824.
[8] Badgujar, Chetan, Sanjoy Das, Dania Martinez Figueroa, and Daniel Flippo. 2023. "Application of Computational Intelligence Methods in Agricultural Soil--Machine Interaction: A Review." Agriculture 13 (2): 357.
[9] Chen, Lin, Zhonghao Chen, Yubing Zhang, Yunfei Liu, Ahmed I Osman, Mohamed Farghali, Jianmin Hua, et al. 2023. "Artificial Intelligence-Based Solutions for Climate Change: A Review." Environmental Chemistry Letters, 1–33.
[10] Davenport, Thomas H, and Nitin Mittal. 2023. All-in on AI: How Smart Companies Win Big with Artificial Intelligence. Harvard Business Press.
[11] Miya, Javed, Sandeep Raj, M A Ansari, Suresh Kumar, and Ranjit Kumar. 2023. "Artificial Intelligence Advancement for 6G Communication: A Visionary Approach." In 6G Enabled Fog Computing in IoT: Applications and Opportunities, 355–94. Springer.
[12] He, Haonan, Liangyu Chen, and Shanyong Wang. 2023. "Flight Short-Term Booking Demand Forecasting Based on a Long Short-Term Memory Network." Computers \& Industrial Engineering 186: 109707.
[13] Yuan, Yuan, Fengchen Fu, Yaling Li, Yao Xing, Lei Wang, Hao Zheng, and Wei Ye. 2023. "Research and Application of Intelligent Weather Push Model Based on Travel Forecast and 5G Message." Atmosphere 14 (11): 1658.
[14] Chee, Marcel Lucas, Mark Leonard Chee, Haotian Huang, Katie Mazzochi, Kieran Taylor, Han Wang, Mengling Feng, et al. 2023. "Artificial Intelligence and Machine Learning in Prehospital Emergency Care: A Systematic Scoping Review." MedRxiv, 2004–23.
[15] Haenlein, Michael, and Andreas Kaplan. 2019. "A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence." California Management Review 61 (4): 5–14.
[16] Moravec, Hans P. 1999. Robot: Mere Machine to Transcendent Mind. Oxford University Press.
[17] Imran, Ali, Ahmed Zoha, and Adnan Abu-Dayya. 2014. "Challenges in 5G: How to Empower SON with Big Data for Enabling 5G." IEEE Network 28 (6): 27–33.
[18] Kothai, G, E Poovammal, Gaurav Dhiman, Kadiyala Ramana, Ashutosh Sharma, Mohammed A AlZain, Gurjot Singh Gaba, and Mehedi Masud. 2021. "A New Hybrid Deep Learning Algorithm for Prediction of Wide Traffic Congestion in Smart Cities." Wireless Communications and Mobile Computing 2021: 1–13.
[19] Pugliano, John. 2017. The Robots Are Coming: A Human's Survival Guide to Profiting in the Age of Automation. Simon and Schuster.
[20] Le, Dy D, Vung Pham, Huyen N Nguyen, and Tommy Dang. 2019. "Visualization and Explainable Machine Learning for Efficient Manufacturing and System Operations." Smart and Sustainable Manufacturing Systems 3 (2): 127–47.
[21] Miller, Jim, Jon Patterson, and Ray Garbos. 2013. "Wireless Power and Data System for Integrated System Health Management of Systems Operating in the Harsh Environment of Deep Space." In Annual Conference of the PHM Society. Vol. 5.
[22] Thakuriah, Piyushimita, D Glenn Geers, and others. 2013. Transportation and Information: Trends in Technology and Policy. Springer.
[23] Allioui, Hanane, and Youssef Mourdi. 2023. "Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey." Sensors 23 (19): 8015.
[24] Li, Jiwen, Jiapeng Dai, Alibek Issakhov, Sattam Fahad Almojil, and Alireza Souri. 2021. "Towards Decision Support Systems for Energy Management in the Smart Industry and Internet of Things." Computers \& Industrial Engineering 161: 107671.

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