An Implementation of a Data-Driven Approach for Forecasting Narrow-Body Aircraft Scheduled Maintenance Workload at GMF Aero-Asia

Gilang Maulana Hidayatullah[1], Tintrim Dwi Ary Widhianingsih[2], Heri Kuswanto[3], Prismahardi Aji Riyantoko[4]

[1] *Interdisciplinary School of Management Technology, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia (6032241019@student.its.ac.id)*
[2]*Department of Statistics, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia (dwi.ary@its.ac.id)*
[3]*Department of Statistics, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia (heri.kuswanto@its.ac.id)*
[4]*Department of Information and Communications Systems, Okayama University, Okayama 700-8530 Japan (pnai2m3s@s.okayama-u.ac.jp)*

ABSTRACT

High volatility in GMF Aero-Asia's narrow-body aircraft scheduled maintenance workload demands better forecasting for more effective capacity planning and operations. Unfortunately, their management used conventional forecasting approach that resulted in a high error rate > 50 %, making it incapable of capturing the complex and dynamic patterns of data fluctuation. In this paper, we propose an implementation and comparison of the performance of two data-driven models, namely *ARIMA (Autoregressive Integrated Moving Average)* and *Artificial Neural Network (ANN)*, to forecast the monthly scheduled maintenance workload. By leveraging the data-driven models, we can develop a more accurate forecasting model to improve resource scheduling efficiency, reduce planning errors, and support the transformation towards a data-driven company. For evaluation, we used the data scheduled maintenance workload at GMF Aero-Asia from the 2020-2024 period that implemented using two-models including *ARIMA* and *ANN* then comparing it with conventional approach. The model performance measured using key metrics indicators. The result showed that *ANN* (lag=9) method proved to be best model with lowest MAPE of 29.02%, outperforming the *ARIMA* (1,1,1) model around 35.38%, and the conventional approach with MAPE 55.25%. This result demonstrates that the *ANN* is capable of capturing non-linear patterns in the data-driven at GMF Aero-Asia, producing smoother predictions in response to fluctuations.

Keywords: *Aircraft Scheduled Maintenance Workload, Forecasting, ANN, ARIMA, GMF Aero-Asia*

1. INTRODUCTION

The aviation Maintenance, Repair, and Overhaul (MRO) sector faces intense pressure to optimize operations and reduce costs, where accurate forecasting of maintenance workloads is crucial for strategic resource allocation [1]. The high volatility in GMF Aero-Asia's narrow-body aircraft scheduled maintenance workload underscores this need, demanding better forecasting methods for effective capacity planning and operational stability.

Unfortunately, the conventional forecasting approach previously used by management is inadequate for this task, resulting in a high error rate with exceeding 50%. This significant inaccuracy renders the method incapable of capturing the complex and dynamic patterns of data fluctuation observed in the company's operations.

Recent studies show that forecasting precision greatly influences efficiency and sustainability in operations, found traditional time series models and neural networks improved accuracy in forecasting [2]. Similarly, in other studies showed that deep learning methods can effectively model complex temporal relationships, surpassing classical approaches like ARIMA [3]. These findings emphasize the growing importance of data-driven and hybrid models for reliable forecasting in dynamic MRO operations.

In this study, we propose the implementation and comparison of two advanced data-driven models: the statistical *Autoregressive Integrated Moving Average (ARIMA)* and the machine learning-based *Artificial Neural Network (ANN)*. The primary objective is to determine which model provides accuracy in forecasting the monthly scheduled maintenance workload at GMF Aero-Asia. By leveraging these data-driven models, this study aims to develop more accurate forecasting models. The intended benefit is to significantly improve resource scheduling efficiency, reduce planning errors, and support the company's strategic transformation towards a data-driven implementation.

For evaluation, we used historical data on scheduled maintenance workload at GMF Aero-Asia from the 2020-2024 period. In this data-data driven implementation, the *ANN* model processes data patterns through its neural network layers to generate forecasts, while the *ARIMA* model relies on statistical differencing and autocorrelation. The performance of both models was compared against the conventional method using key metric indicators, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

This paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the research methodology, data collection, and model configuration. Section 4 presents the results, provides a comprehensive discussion, and compares the model performances. Finally, Section 5 concludes the study by summarizing the findings, acknowledging limitations, and suggesting directions for future research.

2. RELATED WORKS IN LITERATURE

In this section, we review related works in time series forecasting focusing specifically on the application of statistical and machine learning implementation in real world.

In the context of time series forecasting in the energy sector, the study by Mardiana et al. [2] presents two critical findings: first, the Holt-Winters additive method demonstrated superior performance compared to *ARIMA* with MAPE of 1.472% versus 2.108% in predicting Indonesia's gasoline demand; second, implementing a hybrid model combining Holt-Winters with Neural Network successfully improved forecasting accuracy for specific components (MAPE 3.45% vs 4.322%). These findings reinforce previous research indicating that hybrid approaches combining statistical models and machine learning, along with appropriate simple methods, can achieve optimal accuracy in complex energy demand forecasting.

In the study that presented by Abbasimehr et al. [3], they found that the optimized *LSTM* model performed better than traditional methods like *ARIMA* and *ANN*, achieving the lowest error rate (RMSE of 2595.96). This deep learning approach proved effective in capturing fluctuating and unstable data patterns. These findings indicate that properly configured neural networks can be an optimal solution for complex business demand forecasting.

In the comparative study on industrial short-term load forecasting by Ahmed et al. [4] demonstrate that *Gaussian Process (GP)* significantly outperforms other machine learning techniques including *SVM, Decision Tree*, and *ANN* by achieving the lowest prediction errors (MAPE: 2%, MAE: 0.101, RMSE: 0.149). However, this high accuracy comes at the cost of computational efficiency, as *GP* exhibited slower prediction speeds compared to *ANN* and *Decision Tree* models. These findings highlight the critical accuracy-speed trade-off in selecting forecasting models and suggest the potential value of hybrid approaches that leverage the strengths of multiple algorithms.

Based on the research by Li et al. [5] on water demand prediction in Beijing, this study introduces a novel approach using uncertain time series and an *Uncertain Autoregressive (UAR)* model to handle data uncertainty. The results show that the *UAR* model with a confidence level of 0.75 achieved the highest accuracy, reducing the average relative error by 78.36% and the total absolute error by 78.15% compared to the traditional *ARIMA* model. These findings confirm that the uncertainty theory-based approach is not only more reliable in capturing data fluctuations but also capable of representing realistic demand trends, making it highly relevant for water resource planning under uncertain conditions.

Based on the research by Ferbar Tratar et al. [6], this study introduces an *Extended Holt-Winters (EHW)* method that adds a fourth smoothing parameter to the classical model's level equation. The results demonstrate that the *EHW* method significantly outperforms traditional Holt-Winters variants and damped trend methods, achieving average symmetric relative efficiency improvements of 17.53% for quarterly and 16.83% for monthly data from the M3-Competition. These findings confirm that the additional parameter provides crucial flexibility for handling both additive and multiplicative seasonality in noisy demand data, making

EHW particularly effective for short-term forecasting in supply chain management.

For this study addresses a literature gap by implementing *ARIMA* and *ANN* to forecast aircraft maintenance workload a critical operational context that remains underexplored. These methods were selected due to their proven effectiveness in capturing complex, non-linear patterns in volatile time series data across various sectors.

3. RESEARCH METHODOLGY

3.1. Data Scheduled Maintenance Workload

The data used consists of historical narrow-body aircraft scheduled maintenance workload from January 2020 to December 2024, totalling 60 monthly observations. This data provides a sufficiently comprehensive timeframe that captures various operational patterns, seasonal fluctuations, and potential anomaly events, making it suitable for developing reliable forecasting models. The visualization depicting the actual data patterns that form the basis of analysis in this study is presented in Figure 1.

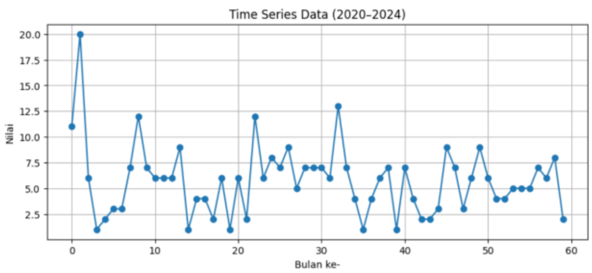

Figure 1 Time series data of monthly narrow-body aircraft maintenance workload (2020-2024)

3.2. Data Collection and Preprocessing

The dataset consisted of a time series of maintenance workload counts. The data was partitioned into a training set and a testing set using an 80:20 split ratio to facilitate model training and validation. Data partitioning that used chronological split as follow

- Training set: 48 observations (January 2020 - December 2023)
- Testing set: 12 observations (January 2024 - December 2024)

3.2. Model Development

3.3.1. ARIMA

ARIMA is a fundamental statistical model for time series forecasting that assumes future values depend on both past values and previous forecast errors [7]. The model requires the data to be stationary, which is achieved through a differencing process. The non-seasonal *ARIMA* model is denoted as *ARIMA* (p, d, q) where p is the order of the autoregressive component, d is the degree of differencing, and q is the order of the moving average component. The combination of these three components enables *ARIMA* to capture various temporal patterns in data.

3.3.1.1. Stationarity Testing

Stationarity testing is a critical step to ensure that time series data maintains constant statistical properties over time, such as stable mean and variance. Testing is conducted visually through data plots and statistically using the *Augmented Dickey-Fuller (ADF)* test with the null hypothesis that the data is non-stationary [9]. If the data is non-stationary, differencing transformation is performed using the equation:

$$y'_t = y_t - y_{t-1} \tag{1}$$

This process is repeated until the data becomes stationary, with the number of required differencing operations becoming parameter d in the *ARIMA* model.

3.3.1.2. Parameter Identification

Parameter identification aims to determine the optimal values of p (*AR* order) and q (*MA* order) through analysis of *Autocorrelation Function (ACF)* and *Partial Autocorrelation Function (PACF)* plots [8]. A cut-off pattern in the *PACF* after lag p indicates an $AR(p)$ component, while a cut-off pattern in the *ACF* after lag q suggests an $MA(q)$ component. For mixed models, the general equation is:

$$y'_t = c + \varphi_1 y'_{t-1} + \cdots + \varphi_p y'_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_p \varepsilon_{t-p} \tag{2}$$

where y'_t is the differenced data, and ε_t is the error term.

3.3.1.3. Model Estimation

Model estimation is performed to calculate the most suitable coefficient values (φ and θ) for the historical data [7]. The *Maximum Likelihood Estimation (MLE)* method is used to maximize the likelihood function representing the probability of obtaining observed data based on model parameters [10]. The estimation output produces coefficient values, standard errors, and ρ-values to test the statistical significance of each parameter. The estimated model is then ready for evaluation and comparison.

3.3.1.4. Model Selection

Optimal model selection is conducted by comparing candidate models using information criteria and diagnostic tests. The *Akaike Information Criterion (AIC)* and *Bayesian Information Criterion (BIC)* are used to assess model quality with the equation [10]:

$$AIC = -2\log(L) + 2k \quad (3)$$
$$BIC = -2\log(L) + k\log(n) \quad (4)$$

where L is the likelihood value, k is the number of parameters, and n is the number of observations. The best model is the one with the lowest *AIC* or *BIC* values and residuals that meet the white noise assumption based on the *Ljung-Box test* [11].

3.3.2. ANN

ANN is a computational model inspired by biological neural networks, designed to recognize complex patterns and relationships in data. The model consists of interconnected layers of artificial neurons that process information through weighted connections and activation functions. Unlike traditional statistical models, *ANN* can learn non-linear relationships directly from data without requiring strong assumptions about data distribution [12]. This makes *ANN* particularly used for forecasting complex time series patterns that may not be captured by linear models.

3.3.2.1. Data Transformation

Data transformation is a crucial preprocessing step to prepare time series data for effective *ANN* training [12]. This typically involves normalization to scale the data into a consistent range, often $[0,1]$ or $[-1,1]$, using min-max scaling or standardization to prevent certain features from dominating the learning process. For time series forecasting, the data must be restructured into supervised learning format through sliding window transformation, creating input-output pairs where previous time steps predict future values [12] [13]. Additionally, the dataset is divided into training, validation, and testing sets to ensure proper model evaluation and prevent overfitting.

3.3.2.2. Network Architecture

The artificial neural network architecture follows a *Multi-Layer Perceptron (MLP)* design with specific layer configurations [14]. The input layer consists of 9 neurons, corresponding to the number of time series lags used as input features. Two hidden layers are implemented with the first layer containing 64 neurons and the second layer containing 32 neurons, both utilizing *ReLU* activation functions to capture non-linear relationships in the data. The output layer employs 1 neuron with linear activation, functioning to generate load workload prediction values in regression format. This architecture forms a $9 - 64 - 32 - 1$ pattern that enables the model to learn complex temporal patterns from historical data.

3.3.2.3. Training Configuration

Training configuration involves setting the optimization parameters that control how the neural network learns from the data. This includes selecting an optimizer like *Adam* or *Stochastic Gradient Descent* (*SGD)*, determining the learning rate that controls parameter updates, and setting the number of epochs and batch size for iterative training [15]. The training process minimizes a loss function, typically Mean Squared Error (MSE) for regression tasks, through backpropagation which adjusts connection weights based on prediction errors. Early stopping techniques and regularization methods are often implemented to prevent overfitting and ensure the model generalizes well to unseen data.

3.3.3. Benchmark Model

To objectively evaluate the predictive performance of the *ARIMA* and *ANN* models, their results were compared against a conventional benchmark approach. The purpose of this comparison is to determine whether the sophisticated modelling techniques provide a significant improvement over a basic, easy to implement forecast, thereby validating their added complexity and ensuring they deliver meaningful predictive power.

3.4. Model Evaluation

The performance of the developed forecasting models was rigorously assessed and compared using a comprehensive set of error metrics. These included Mean Absolute Error (MAE) to measure average absolute deviation, Mean Squared Error (MSE) to emphasize larger errors, Root Mean Squared Error (RMSE) for error interpretation in original units and Mean Absolute Percentage Error (MAPE) to provide a scale independent relative accuracy measure [2]. The combination of these metrics allowed for a multi-faceted evaluation of model accuracy from different perspectives, ensuring a robust comparison between the ARIMA and ANN approaches while maintaining consistency with established forecasting validation practices.

4. EVALUATION

4.1. ARIMA Model

4.1.1. Stationarity Test

Based on the obtained Augmented Dickey-Fuller (ADF) Test results, it can be concluded that the time series data has met the stationarity criteria. The ADF statistic value of -6.1517 is significantly more negative than the critical values at all significance levels, supported by a p-value of 7.53×10^{-8} which is far below the $\alpha = 0.05$ significance level. This result provides strong evidence to reject the null hypothesis stating the presence of a unit root in the data, confirming that the data is stationary at the level. Therefore, the data is ready for time series modeling without requiring further differencing transformation.

4.1.2. Parameter Identification and Model Selection

Following the confirmation of stationarity, the subsequent stage involves identifying the optimal p and q parameters using *ACF* and *PACF* plots. The patterns observed in the *ACF* and PACF graphs suggest potential values for p and q within the range of 0 to 3 that presented in the Figure 2. These candidate values will be systematically tested through grid search to determine the most suitable model configuration.

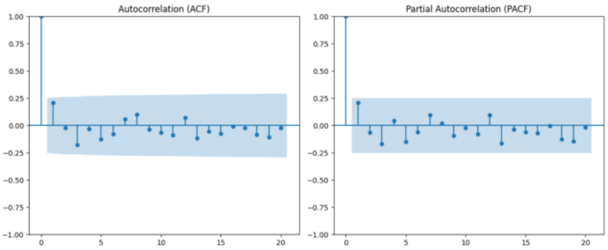

Figure 2 ACF and PCF plotting

The model selection process employs grid search methodology to evaluate all possible $ARIMA(p, d, q)$ combinations within predefined ranges ($p = 0 - 3, d = 0 - 1, q = 0 - 3$) using *AIC* as the selection metric. The optimal model was identified $p = 1, d = 1, q = 1$ as *ARIMA* (1,1,1), which achieved the lowest *AIC* value despite the initial stationarity test indicating stationarity at level. This outcome suggests that first-order differencing effectively enhances model performance by stabilizing minor fluctuations, ultimately yielding more accurate forecasting results.

4.1.3. Model Evaluation

The Figure 3 present a compares the predictions of the *ARIMA* (1,1,1) model with the actual data, showing the model's forecasting performance on the testing data along with the training data line used. The MAE value of 1.48 and RMSE of 1.99 indicate the average deviation between predicted and actual values, while the MAPE of 35.38% suggests that the model's percentage accuracy still requires improvement as the average error exceeds one-third of the actual values. Overall, the *ARIMA* model evaluation is presented in the Table 1.

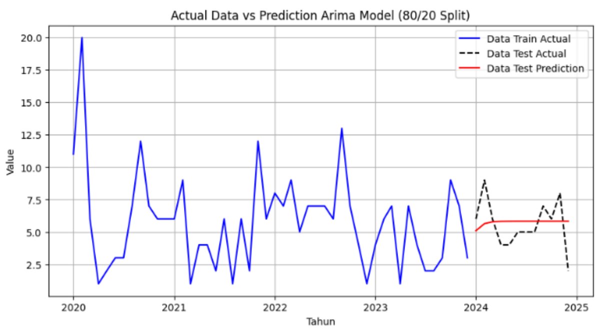

Figure 3 Evaluation results for ARIMA (1,1,1) model

Table 1. The evaluation metric for ARIMA model

Metric	Score
MAE	1.48
MSE	3.98
RMSE	1.99
MAPE	**35.38%**

4.2. Evaluation of ANN Model

4.2.1. Data Transformation

Time series data was converted into a supervised learning format using a sliding window approach, where the current period's workload value is predicted based on several previous periods (*lag*).

4.2.2. Network Architecture and Training Configuration

The Artificial Neural Network model was developed using the *TensorFlow-Keras* framework with the following configuration: (1) an input layer with neurons corresponding to the number of lag (e.g., 9), (2) a first hidden layer with 64 neurons and Re-LU activation, (3) a second hidden layer with 32 neurons and Re-LU activation, and (4) an output layer with a single neuron to generate the predicted workload value. The model was trained using the Adam optimizer, MSE loss function, and Early-Stopping (patience=10) to prevent overfitting.

4.2.3. Model Evaluation

To determine the optimal lag, testing was conducted on several lag values: [3, 5, 6, 9, 12]. The results indicate that a lag of 9 yields the best performance with the lowest MAPE value of 29.02%. Overall, the evaluation of *ANN* model in lag of stage is presented in Table 2.

Table 2. Evaluation of ANN model in lag stage

Lag	MAE	MSE	RMSE	MAPE
3	1.44	3.98	1.99	35.38%
5	1.79	5.37	2.32	47.75%
6	1.84	5.39	2.32	48.47%
9	**1.39**	**4.06**	**2.01**	**29.02%**
12	1.26	3.12	1.77	37.38%

The Figure 4 shows the performance of the forecasting model, showing the alignment between historical actual data and model predictions. While the predicted values generally follow the actual data trend, some deviations are observable at specific time points, indicating areas for potential model improvement.

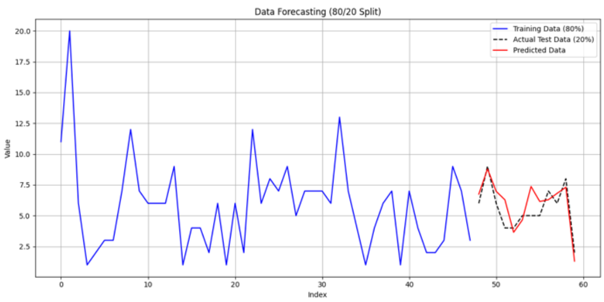

Figure 4 Evaluation result of ANN (lag-9) model

4.2. Comparison Evaluation Model

The *ANN* model (lag=9) achieved the best performance with the lowest MAPE of 29.02% and MAE of 1.39, outperforming the *ARIMA*(1,1,1) model which had a MAPE of 35.38%. Although *ARIMA* showed a slightly lower RMSE (1.99 vs 2.01), *ANN's* superiority in MAPE indicates better capability in predicting non-linear patterns in the data. Significantly, both modern models substantially surpassed the conventional method which recorded a MAPE of 55.25%, demonstrating the effectiveness of advanced modelling approaches in workload forecasting. Overall, the comparison model evaluation metrics is presented in Table 3.

Table 3. Comparing three evaluation model

Model	MAE	MSE	RMSE	MAPE
ANN (lag=9)	**1.39**	**4.06**	**2.01**	**29.02%**
ARIMA (1,1,1)	1.48	3.98	1.99	35.38%
Conventional	2.75	12.08	3.48	55.25%

5. CONCLUSION AND FUTURE WORK

This study implemented and evaluated data-driven forecasting models for narrow-body aircraft maintenance workload at GMF Aero-Asia. The implementation was employed both *ARIMA* and *ANN* model, with the *ANN* model demonstrating good performance with a 29.02% MAPE compared to *ARIMA's* 35.38% and the conventional method's 55.25%. The findings reveal that *ANN's* ability to capture complex non-linear patterns makes it particularly suitable for handling the volatile nature of maintenance workload data. This study provides valuable insights for the aviation MRO industry by demonstrating how data-driven approaches can significantly improve forecasting accuracy over conventional methods. The implementation of these advanced forecasting models can substantially improve resource planning efficiency and support GMF Aero-Asia's transition toward data-driven operations management. The limitation of this study is its reliance solely on historical scheduled maintenance workload data without incorporating external factors such as flight schedules, seasonal patterns, or fleet expansion plans, which could significantly improve forecasting accuracy. For the future research should consider operational and strategic variables to enhance model robustness and adaptability. As more comprehensive and high-quality data become available, forecasting accuracy is expected to further improve.

AUTHORS' CONTRIBUTIONS

This research was collaboratively conducted by all authors, each providing essential input throughout the study process. Gilang Maulana Hidayatullah took the lead in formulating the research objectives, organizing and cleaning the dataset, designing the *ARIMA* and *ANN* forecasting models, and interpreting the experimental outcomes. Heri Kuswanto supervised the methodological direction, ensured the robustness of statistical analysis, and supervised the validation of model performance. Tintrim Dwi Ary Widhianingsih supported the literature exploration and contributed to aligning the research framework with prior studies. Prismahardi Aji Riyantoko provided valuable insights into the research methodology and reviewed the analytical workflow. All authors contributed to the manuscript preparation and approved the final version for submission.

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