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Climb Performance Prediction in High Drag Configuration Middle-Class Transportation Aircraft: An Ensemble Learning Approach

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Abstract

This study addresses the application of machine learning and artificial neural network models for predicting the climb speed of the C-130H military transport aircraft. Random Forest, Neural Network, and Ensemble models were developed to overcome limitations of traditional chart reading and interpolation methods. Models were trained on flight manual data, considering factors such as gross weight, pressure altitude, drag index, temperature deviation, and engine efficiency. Comparative analysis revealed the Ensemble approach, combining Random Forest and Neural Network techniques, provided the highest accuracy ($R^2 \approx 0.4532$), followed by Random Forest ($R^2 \approx 0.4303$) and Neural Network ($R^2 \approx 0.3765$) models. All significantly outperformed the traditional Young Method ($R^2 = -1.2673$). Feature importance analysis identified pressure altitude, gross weight, and engine efficiency as critical factors influencing climb speed. The ensemble approach demonstrated more reliable and accurate results in predicting C-130H climb rates, reducing risks associated with single-model reliance. This research highlights the potential of machine learning in aircraft performance prediction, offering possibilities for improving pre-flight preparation, reducing workload, and enhancing flight safety. Implications for the aviation industry and future research directions are discussed, emphasizing the role of advanced predictive models in shaping future flight operations and aircraft performance management.

1. Introduction

Due to the fact that aircrafts fly in a wide range of mission areas for cargo, passenger, tactical and military purposes, manufacturers conduct a number of test flights to determine the aerodynamic characteristics, design requirements and flight performance limits of the aircraft (Baklacıoğlu, 2010). During the test flights, all the forced physical and environmental conditions of the aircraft are tested and finally performance charts are obtained. The manufacturer has developed many different versions of the aircrafts, which have different mission versatility and airspaces. Each version is designed to fly in different environmental conditions (Oktay et al., 2022).

Because of changing environmental conditions of the flight missions, it is extremely important to analyze the performance characteristics of the aircraft in order to ensure both fuel economy and flight safety. For this purpose, manufacturers determine the flight envelope by testing different flight scenarios in all flight phases. In other words, flight performance parameters are investigations that reveal the aerodynamic characteristics of the aircraft and determine the limits of use. (Filippone, 2008).

In order to determine aircraft limits, aircraft performance calculations involve the calculation of numerous parameters; including take-off, cruise, climb and landing speeds, torque, cruising altitudes, and maximum aircraft weight. These parameters are obtained by manual use of a variety of charts (Erdmański et al., 2010). The use of these charts presents several challenges, including time-consuming calculations, low accuracy of the results obtained from the calculations, and the necessity of performing these calculations separately for each phase of the flight. This is due to the fact that many charts must be used simultaneously to reach the correct result. Additionally, the lack of chart-specific equations and the fact that the curves do not exhibit the same characteristics at every point depending on the changing parameters also contribute to an excessive workload and time loss (Güleç, 2002).

When the studies on aircraft performance parameters in the literature are examined, it is observed that artificial neural networks are intensively preferred due to obtaining the closest results to the real values and being more easily adaptable in practice. Among these studies, (Altuntaş, 2007) created a fuel consumption model for Boeing 737-800 aircraft. (Türkmen et al. 2017) developed an alternative airspeed calculation method for Boeing 737-400 aircraft. (Yildirim et al. 2017) created a prediction model for low-pressure turbine vibration in Boeing 737-500 aircraft. (Türkmen et al. 2022) used neural networks to predict angle of attack and Mach number for Boeing 757 aircraft. (Fenar et al. 2014) developed a model to predict aircraft icing risk. (Yildirim Dalkiran et al. 2021) created a prediction model for engine thrust calculation in Airbus A319 aircraft. (Baklacıoğlu, 2010) created an aircraft performance model using genetic algorithms for trajectory prediction. (İlbaş et al. 2012) developed an exhaust gas temperature prediction model for CFM56-7B turbofan engines.

Flight performance parameters can be examined in many flight phases such as taxi, take-off, climb, level flight, descent and landing. When we consider the climb phase in order to examine the performance parameters, the climb speed during the flight period required for an aircraft to climb to the desired altitude after take-off is of great importance (Konar et al. 2020; Altuntaş, 2007). The climb speed, which directly affects fuel consumption, varies depending on variables such as gross weight of the aircraft, altitude change, temperature deviations, engine efficiency, drag coefficient. By analyzing the climb speed, fuel optimization can be achieved and flight performance can be improved (Türkmen et al., 2022; PHAC, 2023).

In this study, the climb performance of middle-class transportation C-130H aircraft with high drag coefficient, turboprop Allison T56-A-15 four-engine is investigated. When examining the performance limits of the C-130H aircraft, since the service ceiling is 30,000 feet and the maximum gross weight is 175,000 pounds, the data sets were limited to these values when developing the climb speed prediction model. As a result of this study, it is aimed to create a prediction model by using artificial neural networks and machine learning methods instead of the classical method. In the classical method, climb speeds are obtained manually from the climb performance charts in the flight manual for the prediction of the climb speed on the Take-Off and Landing card called TOLD card, which must be prepared by the ground crew before take-off. The study yielded faster and more reliable forecasting results through the application of machine learning and artificial neural networks. As a practical benefit, it is aimed to reduce workload and time loss and to ensure flight safety at a high level.

2. Methods

In this study, data sets were obtained by utilizing the charts in the high drag C-130H aircraft flight manual climb performance section (USAF, 2002). Gross weight, pressure altitude, drag index, temperature deviation, engine efficiency, uncorrected indicated air speed was used as inputs from the obtained data sets and an alternative prediction model to the classical calculation method was created by estimating the climb speed as output. Figure 1 shows the block diagram of the proposed models.

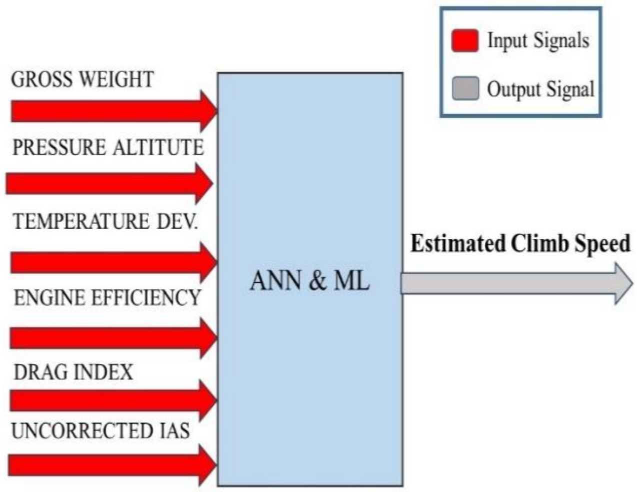

Figure 1. Block Representation of Trained ANN&ML Model

Each variable used in the input set has different effects on the climbing speed and hence climbing performance obtained in the model output. In order to determine the verified climbing speed, it is necessary to use each effect as a correction factor.

Gross Weight: It is expressed as the sum of the aircraft's payloads such as oil, fuel, cargo and the weight of the basic configuration elements, which we call basic aircraft weight. With the increase in the weight of the aircraft, the aircraft will need to fly with a higher angle of attack in order to maintain the altitude and speed at which it flies. This will lead to increase the parasitic drag on the aircraft and the induced drag on the wings. In order to overcome the drag effect, thrust must be increased (Erdmański et al., 2010). Therefore, aircraft manufacturers prefer to low weight aircraft designs in order to increase aircraft performance due to drag effects (Boztepe et al., 2001).

Pressure Altitude: 29.92 inches or 1013.2 millibars is the altitude indicated by an altimeter set to standard sea level atmospheric pressure. Increasing the altitude at which aircraft fly means that an aircraft flying at level flight climbs to a higher altitude. This will lead to increase the required power while decreasing the available power in the engines. Thus, the climb performance of the aircraft will decrease as the engine performance is affected by the increase in altitude (Pooley Dorothy et al., 2010).

Temperature Deviation: In international standard atmospheric conditions, air temperature is accepted as 15 ºC. When the aircraft is in the climb phase, the outside temperature decreases by 2 ºC for every 1000 feet (Batchelor, 1967). In this case, the climb performance is affected by the decrease in the temperature of the air entering the engines (AFH, 2011).

Engine Efficiency: Even though engine efficiency is theoretically accepted as 100%, in practice, engines are usually operated at 95% efficiency for longer engine life. Again, this has a direct impact on climb performance (USAF, 2002).

Drag Index: As a result of the increase in drag coefficients in aircraft, it is necessary to increase the required power by setting the engines to a thrust value higher than the set thrust value in order to realize the climb process. Again, as a result of this situation, the increase in the drag coefficient of the aircraft has a negative effect on the climb performance (Boztepe et al., 2001; Eken, 2009).

Data were collected from the high drag C-130H aircraft flight manual (USAF 2002). Preprocessing steps included normalizing continuous variables and encoding categorical variables to ensure the data were suitable for machine learning algorithms. Any missing or inconsistent data were handled appropriately. Specifically, outliers were removed using the Z-score method, and the data were split into training (70%), validation (15%), and test (15%) sets. Feature engineering and robust normalization were applied to enhance model performance. Two data sets were used:

- Primary Data Set: This data set was used for training, validation, and testing the models. It includes features such as gross weight, pressure altitude, drag index, temperature deviation, engine efficiency, and uncorrected indicated airspeed. The data were preprocessed to remove outliers, normalize features, and split into training (70%), validation (15%), and test (15%) sets.
- Comparison Data Set: This data set was used to compare the model predictions with the actual climb speed and the Young Method. It includes similar features as the primary data set but is used solely for evaluating the final model performance.

Two rows of examples from each data set are given in Tables 1 and 2.

Table 1. Two-row transposed sample of the primary data set (1312 rows in all)

	Row 1	Row 2	Row …
1. Input	-1000	-1000	…
2. Input	130000	131000	…
3. Input	173.7519	174.0019	…
4. Input	179.2465	179.4942	…
5. Input	177.3369	177.5845	…
6. Input	176.78	177.03	…
Real Climb Speed	157.8431	157.1172	…

Table 2. Two-row transposed example of the comparison dataset (634 rows in all)

	Row 1	Row 2	Row …
1. Input	-1000	-1000	…
2. Input	80000	85000	…
3. Input	160	160.9996	…
4. Input	164.9996	165.9492	…
5. Input	160.4671	161.4941	…
6. Input	154.4904	155.5688	…
Young Method Prediction	145.5159	146.7486	…
Real Climb Speed	154.4904	155.5688	…

In this study, four different models were used: Random Forest, Neural Network, Ensemble, and Young Method. The performance of these models was evaluated using mean squared error (MSE), root mean square error (RMSE), and the R^2 coefficient of determination.

2.1. Random Forest Model

The Random Forest model employs multiple decision trees to make predictions, which are then averaged to improve accuracy and robustness against overfitting. Each decision tree is trained on a random subset of the dataset and branches by selecting a certain number of attributes. This approach increases the generalizability of the model and reduces overfitting (Cutler et al. 2012). Figure 2 shows the block diagram of the Random Forest Model.

Parameters used:

- Number of trees: 200
- Minimum leaf size: 5
- Number of predictors to sample: All

The Random Forest model can be described as follows:

$$\hat{f}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \quad (1)$$

where B is the number of trees, and $T_b(x)$ is the prediction from the b-th tree.

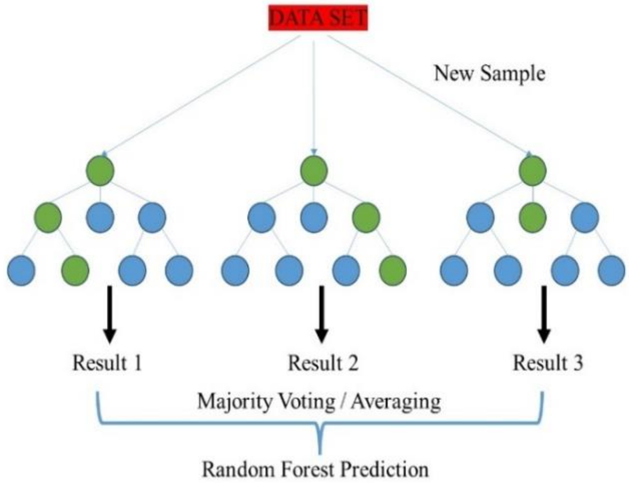

Figure 2. Random Forest Machine Learning Model

2.2. Neural Network Model

The Neural Network model used in this study was trained using the Levenberg-Marquardt algorithm, an optimization technique that combines the speed of the Gauss-Newton method with the robustness of the gradient descent method. The Levenberg-Marquardt method is a least squares computation method based on the idea of maximum neighborhood. This algorithm combines the best features of the Gauss-Newton and Steepest-Descent algorithms. The LM algorithm avoids the limitations of the two aforementioned methods and is not affected by slow convergence problems (Sağıroğlu et al., 2003). Figure 3 shows the block diagram of the Levenberg-Marquardt ANN Learning Model.

The architecture of the neural network included:

- Input layer with normalized features
- Multiple hidden layers with poslin activation functions (a variant of ReLU that allows small positive values to pass through unchanged)
- Output layer with a linear activation function

Poslin (Positive Linear) is closely related to ReLU (Rectified Linear Unit). While ReLU sets all negative values to zero, poslin allows small positive values to pass through unchanged, providing a slight smoothing effect. This choice maintains the benefits of ReLU in addressing the vanishing gradient problem while potentially offering improved model stability.

Optimization was performed using Bayesian optimization to determine the best hyperparameters:

- Hidden layer size: 5 to 30
- Learning rate: 10^{-4} to 10^{-2}
- Regularization parameter: 10^{-4} to 10^{-1}

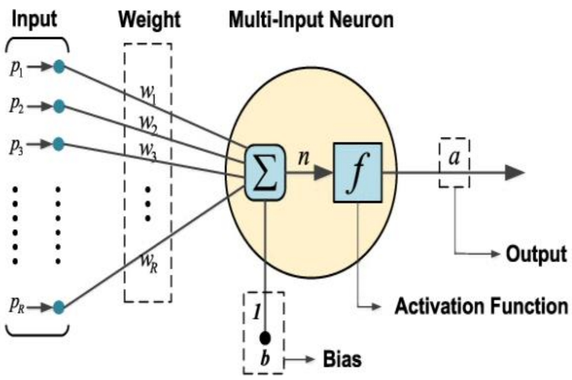

Figure 3. Levenberg-Marquardt ANN Learning Model

In equation $E(w)$ is an objective error function. $e_i^2(w)$ for m error terms is given in equation 2. The explicit form of $e_i^2(w)$ in this equation is shown in equation 3.

$$E(w) = \sum_{i=1}^{m} e_i^2(w) = \|f(w)\|^2 \quad (2)$$

$$e_i^2(w) = (y_{di} - y_i)^2 \quad (3)$$

In this context, the objective function $f(.)$ and its Jacobian J are assumed to be known at some point in time. The LM method is employed to identify the parameter vector w when $E(w)$ is at a minimum. Using the LM, one tries to calculate w_{k+1} from w_k shown in equation 4.

$$w_{k+1} = w_k + \delta w_k \quad (4)$$

Here δx_k is given by the following.

$$(J_k^T J_k + \lambda I)\delta w_k = -J_k^T f(w_k) \quad (5)$$

where J_k is Jacobian substituted for w_k in f, λ is Marquardt parameter, I is Unit matrix.

2.3. Ensemble Model

The ensemble learning model aims to achieve more reliable and accurate predictions by combining the strengths of different machine learning models. This model is effective in reducing high variance and improving performance. In traditional classification methods, different classification algorithms are used to build a model on a pre-labeled dataset. Since each algorithm has certain weaknesses, the ensemble learning model aims to provide better classification by combining the strengths of different algorithms (Dong et al., 2020; Matloob et al., 2021; Güzel et al., 2019). The ensemble model in this study is an approach that combines predictions from two different machine learning techniques - Artificial Neural Networks (ANN) and Random Forest. Ensemble learning aims to obtain more reliable and accurate predictions by combining the strengths of different models. In this model, ANN contributes with its ability to learn complex non-linear relationships. Random Forest contributes with its strength in reducing overfitting and determining feature importance. The predictions of these two models are combined using optimal weights. The weights are determined to minimize the ensemble error. The ensemble model is:

$$\hat{f}_{ensemble}(x) = w_1\hat{f}_1(x) + w_2\hat{f}_2(x) \quad (6)$$

where $\hat{f}_1(x)$ and $\hat{f}_2(x)$ are the predictions from the Neural Network and Random Forest models, respectively, and $w_1$and w_2 are the weights optimized to minimize the ensemble error using a constrained optimization approach.

2.4. Young Method

The Young Method is a traditional interpolation method applied to performance charts to estimate climb speeds (Young, 2019). This method serves as a benchmark for demonstrating the enhancement provided by machine learning techniques. Especially when it is difficult to obtain some performance parameters from charts, this method is used to obtain unknown values by curve fitting based on known values. However, in this method, deviations from the actual values should be carefully monitored and it should be ensured that the performance data obtained are within the safe range (within the tolerance given in the technical order).

This method uses interpolation to determine unknown values based on known data points from performance charts. It is used to calculate climb speed by taking into account factors such as gross weight, pressure altitude, and temperature deviation. Using the pressure altitude and gross weight, determine the base climb speed from the charts:

$$\begin{aligned} V_{ucs} = \Big[\big((52 * 10^{-10}) * \textstyle\sum(w)\big) \\ - \big((1329558 * 10^{-9}) * \Delta P\big)\big) \\ + \big((25 * 10^{-5}) * \textstyle\sum(w)\big) + 140\Big] \end{aligned} \quad (7)$$

In the formula here, Gross Weight is symbolized by $\sum(w)$ and Pressure Altitude is symbolized by *ΔP.* Also *ΔT* denotes temperature deviation.

By interpolating the charts for all factors such as gross weight, altitude change, temperature deviation, drag index and engine efficiency affecting the climb speed, a validated climb speed formula was obtained (Young, 2019).

$$\begin{aligned} V_{ccs} = [1.0071 * ((9995 * 10^{-4}) \\ * ((9 * 10^{-10}) * \Delta T^4 + (85 \\ * 10^{-9}) * \Delta T^3 - (151444 \\ * 10^{-10}) * \Delta T^2 + (4865344 \\ * 10^{-10}) * \Delta T + 1.0023015873) \\ * \big((52 * 10^{-10}) * \textstyle\sum(w) \\ - (1329558 * 10^{-9}) * \Delta P + 25 \\ * 10^{-5} * \textstyle\sum(w) + 140.42169 \\ - 0.5\big) + (-(58858 * 10^{-10}) \\ * \Delta T^3 + (10638236 * 10^{-10}) \\ * \Delta T^2 - (2924101117 * 10^{-10}) \\ * \Delta T - (1798236332 * 10^{-10}) \\ - 1.82) - 19.429] \end{aligned} \quad (8)$$

2.5. Performance Evaluation

In this study, mean square error (MSE), root mean square error (RMSE) and the R² value, which is called the determination coefficient were chosen as the performance functions. MSE represents a general error value for all neurons in the output layer and is defined as:

$$MSE = E(w) = \frac{1}{n}\sum_{i=1}^{n} {e_i}^2(w) \quad (9)$$

The root mean square error (RMSE) determines the error ratio between the actual value and the estimated value. The increase in the predictive ability of the ANN model is understood to be the approach of the RMSE value to zero. The number of data sets used, the estimated value obtained from the neural network, the real value of RMSE is calculated by the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_{d_i})^2} \quad (10)$$

The R² value, which is called the determination coefficient, indicates the degree of conformity for the ANN model. The fact that the value of R² is close to 1 indicates that the predicted values are very close to the real values and that the predicted values are very far from the true values. The R² value is expressed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_{d_i})^2}{\sum_{i=1}^{n}(y_{d_i} - y_m)^2} \quad (11)$$

3. Result and Discussion

The application of machine learning and artificial neural network models to predict the climb speed of the C-130H military transport aircraft yielded significant findings.

Our analysis encompassed Random Forest, Neural Network, and Ensemble models, each providing unique insights into the factors affecting climb speed prediction. Figure 4 illustrates the feature importance in the Random Forest model, offering a clear visualization of the most influential factors in our prediction task.

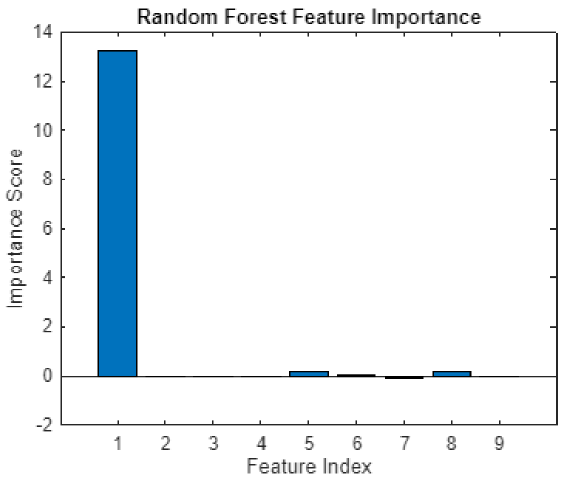

Figure 4. Feature Importance in Random Forest Model

The feature importance analysis of the Random Forest model revealed that pressure altitude (Feature 1) is the most critical factor in predicting climb speed, which can be attributed to its direct impact on air density and aircraft performance. Gross weight (Feature 2) and engine efficiency (Feature 5) also emerged as significant factors, albeit with considerably less influence compared to pressure altitude. Three derived features (Features 7, 8, and 9) were created to capture complex relationships between the original inputs. While these derived features show low importance individually, they may contribute to the model's overall performance. The relatively low importance of other original inputs (drag index, temperature deviation, and uncorrected indicated air speed) suggests they may have less direct impact on the C-130H aircraft's climb speed. However, removing these factors from the model is not recommended as they may still be significant under specific flight conditions.

The Neural Network model's performance was evaluated using various activation functions and hyperparameter configurations. Table 3 presents the performance comparison of different activation functions.

Table 3. Performance Comparison of Activation Functions

Activation Function	MSE	RMSE	R^2
poslin	0.00001	0.0060	0.9946
tansig	0.00003	0.0024	0.9991
logsig	0.0001	0.0116	0.9798
purelin	0.00003	0.0019	0.9995

As seen in Table 3, the logsig function clearly demonstrated the lowest performance among all tested activation functions, with notably higher MSE and RMSE values and a lower R^2 score. The other three functions (poslin, tansig, and purelin) showed very close performance, with purelin slightly outperforming the others in terms of RMSE and R^2. However, considering the overall stability, generalization ability of the model, and the need to capture potential non-linear relationships in the data, the 'poslin' (positive linear) activation function was chosen for our final model. This choice aims to strike a balance between the model's ability to represent complex patterns and its resistance to overfitting, especially given the close performance of poslin to the best-performing purelin function.

The architecture of the neural network included multiple hidden layers, with the number of neurons in these layers being a crucial hyperparameter. The optimization process explored various configurations, ranging from 5 to 30 neurons in the hidden layers. This exploration aimed to find the right balance between model complexity and generalization ability.

The hyperparameter optimization process and its results are illustrated in Figure 5. This figure shows the minimum objective value versus the number of function evaluations during the optimization process.

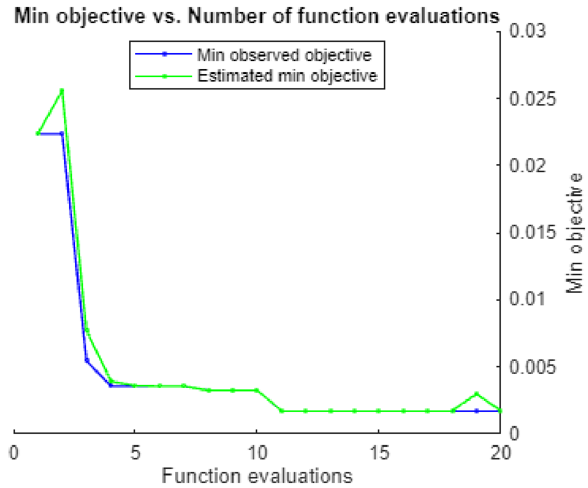

Figure 5. Minimum Objective vs. Number of Function Evaluations

As seen in Figure 5, there is a rapid convergence of both observed and estimated minimum objective values after approximately 10 evaluations. This indicates the efficiency of the Bayesian optimization approach in exploring the hyperparameter space. The best configuration achieved an objective function value of 0.0017079, with 30 neurons in the hidden layer, a learning rate of 0.00090854, and a regularization parameter of 0.00040608.

This optimal configuration suggests that the model benefits from a relatively complex architecture with 30 neurons in the hidden layer to capture the intricacies of the C-130H climb speed prediction task. The low learning rate (0.00090854) indicates a careful, gradual approach to updating the model's weights during training, which can help in finding a more precise minimum and avoiding overshooting. The small regularization parameter (0.00040608) suggests that the model did not require strong regularization to prevent overfitting, indicating a good balance between fitting the training data and maintaining generalization ability.

The Ensemble Model's performance, which combines the strengths of both Random Forest and Neural Network approaches, is illustrated in Figures 6 and 7.

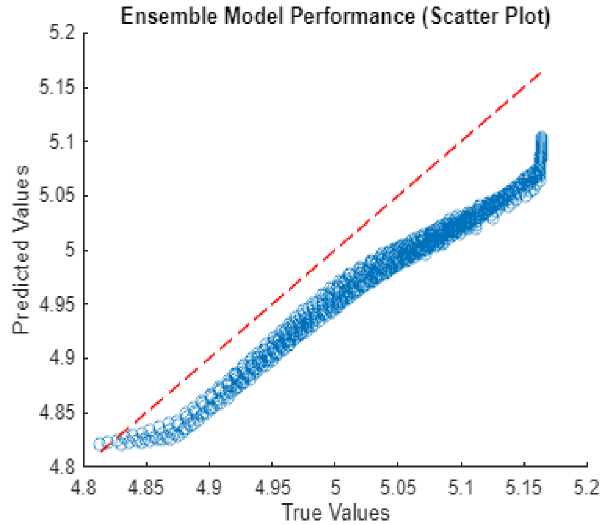

Figure 6. Ensemble Model Performance (Scatter Plot)

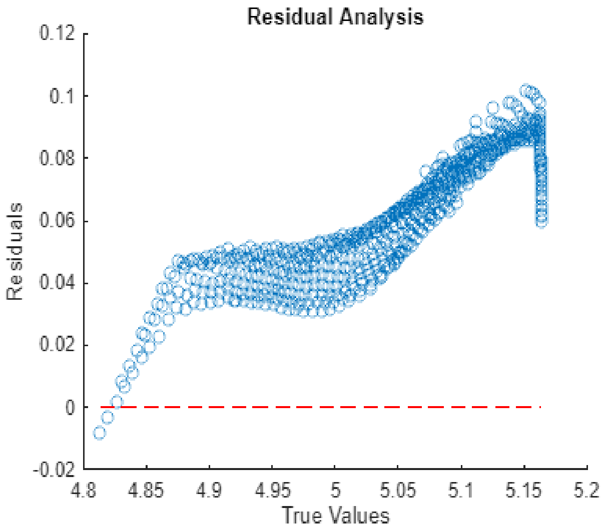

Figure 7. Residual Analysis Graph

Figure 6 demonstrates the Ensemble Model's predictive accuracy through a scatter plot of predicted versus true values. The clustering of points around the ideal line (red dashed line) indicates high overall predictive accuracy. The model shows particularly strong performance in the mid-range of climb speeds, with a slight tendency to underestimate at higher speeds.

The residual analysis in Figure 7 provides further insights into the model's performance. The distribution of residuals shows a generally consistent pattern, with a slight widening at higher true values. This suggests that the model maintains good predictive power across most of the range, with a minor decrease in precision for very high climb speeds.

Overall, these figures demonstrate the Ensemble Model's robust performance in predicting the C-130H aircraft's climb speed. The model effectively captures the complex relationships between input variables and climb speed, showcasing the advantages of combining multiple machine learning techniques. While there's always room for refinement, especially in extreme value predictions, the Ensemble Model proves to be a reliable tool for climb speed estimation in various flight conditions.

The overall performance of our models is illustrated in Figures 8 and 9, providing a comprehensive comparison of the different approaches used in this study.

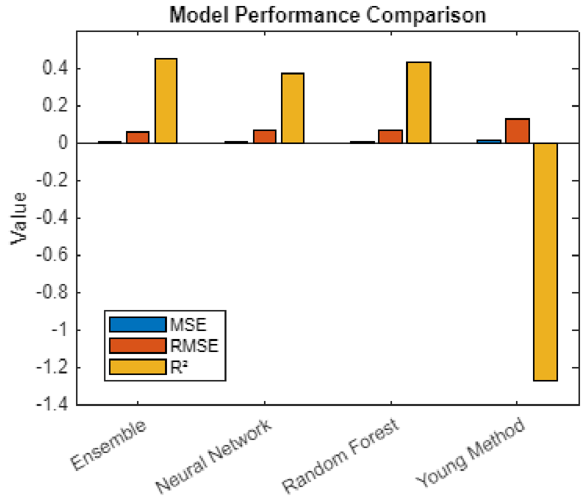

Figure 8. Model Performance Comparision (Bar Plot)

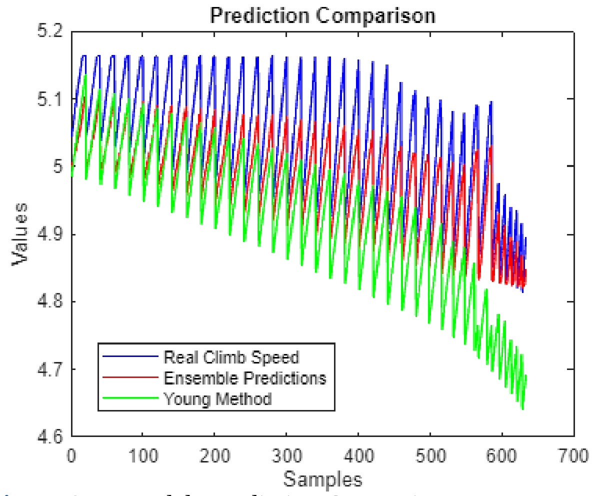

Figure 9. Models Prediction Comparison

Figure 8 presents a bar plot comparing the performance metrics (MSE, RMSE, and R^2) for each model. The Ensemble model demonstrates the best overall performance, with the highest R^2 value (approximately 0.45) and the lowest MSE and RMSE. The Random Forest model follows closely, while the Neural Network shows slightly lower performance. Notably, the Young Method exhibits significantly poorer performance, with a negative R^2 value.

The negative R^2 value for the Young Method indicates that this traditional approach performs worse than a horizontal line (the mean of the observed data) in predicting climb speeds. This underscores the limitations of conventional methods and highlights the advantages of machine learning approaches in capturing complex relationships within the data.

Figure 9 provides a visual comparison of the predictions made by the Ensemble model and the Young Method against the real climb speed values. The graph clearly shows that the Ensemble model's predictions (red line) closely follow the pattern of real climb speeds (blue line), while the Young Method's predictions (green line) deviate significantly, often underestimating the climb speed.

These results demonstrate the superior performance of the Ensemble model in predicting C-130H aircraft climb speeds. By combining the strengths of Random Forest and Neural Network approaches, the Ensemble model achieves more accurate and reliable predictions compared to both individual machine learning models and traditional methods. The significant improvement over the Young Method, as evidenced by the negative R^2 value, underscores the potential of machine learning techniques in enhancing aircraft performance predictions and flight planning processes.

4. Conclusion

In this study, a comprehensive analysis of machine learning and artificial neural network models for predicting the climb speed of the C-130H military transport aircraft has been presented. The research was aimed at overcoming the limitations of traditional graph reading and interpolation methods through the development and comparison of Random Forest, Neural Network, and Ensemble models.

It has been demonstrated that the Ensemble model exhibited superior performance ($R^2 \approx 0.4532$) compared to the individual Random Forest ($R^2 \approx 0.4303$) and Neural Network ($R^2 \approx 0.3765$) models, and significantly outperformed the traditional Young Method ($R^2 = -1.2673$). This superiority can be attributed to the Ensemble model's ability to capture complex, non-linear relationships in the data and its robustness against overfitting. The Ensemble approach, which combines the strengths of both Random Forest and Neural Network models, has proven to be particularly effective, providing more reliable and accurate results while mitigating the risks associated with relying on a single model.

The feature importance analysis revealed that pressure altitude, gross weight, and engine efficiency are the most critical factors in predicting the climb speed of the C-130H aircraft. This insight provides valuable guidance for future model development and optimization efforts.

In the Neural Network model, we tested various activation functions and found that while purelin showed slightly better performance, the poslin function was chosen for its balance between performance and ability to capture non-linear relationships. The hyperparameter optimization process led to a model with 30 neurons in the hidden layer, demonstrating the complexity required to accurately predict climb speeds.

The practical implications of this research for the aviation industry are significant. It is anticipated that the improved pre-flight preparation can be achieved through these models, potentially reducing the time and effort required for calculating climb speeds and allowing for more efficient pre-flight planning. Enhanced flight safety can be expected as more accurate climb speed predictions contribute to safer flight operations, especially in challenging conditions or when operating near performance limits. Furthermore, better climb speed predictions can lead to more efficient flight profiles, potentially reducing fuel consumption and environmental impact. The automation of climb speed calculations can significantly reduce the workload on ground crews and pilots, allowing them to focus on other critical tasks.

While the potential of machine learning in aircraft performance prediction has been demonstrated in this study, some limitations have been identified. The models were trained and tested on data specific to the C-130H aircraft, and their generalizability to other aircraft types needs further investigation. Additionally, the unexpectedly low performance of the Neural Network model suggests that further optimization of its architecture and hyperparameters might be beneficial.

Several directions for future research have been identified. The approach could be extended to other aircraft types and performance parameters. The incorporation of real-time flight data could be explored to improve model accuracy and adaptability. The integration of these models into existing flight management systems could be investigated. Furthermore, the use of deep learning techniques for even more accurate predictions could be explored.

In conclusion, the significant potential of machine learning techniques in aircraft performance prediction has been highlighted by this research. By providing more accurate and reliable climb speed predictions, these models offer possibilities for improving pre-flight preparation processes, reducing workload, enhancing flight safety, and optimizing fuel consumption. As the aviation industry continues to evolve, it is anticipated that the integration of such advanced predictive models could play a crucial role in shaping the future of flight operations and aircraft performance management.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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