

DNN-Based Surrogate Modelling-Based Aircraft Performance: Take Off and Landing Distance

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Abstract. In the early stages of aircraft design, available information is often limited to theoretical models supported by sparse experimental or flight test data for calibration. While these preliminary models provide a useful foundation, they can be unreliable due to simplifying assumptions inherent in theoretical formulations. In such cases, data-driven methods such as neural network-based surrogate models can serve as valuable alternatives, effectively leveraging limited experimental data to enhance the accuracy and reliability of predictions. In this work a real-world dataset comprising take-off and landing distances from Boeing 737 aircraft was utilized to develop a data-driven model. This model relies on a limited set of basic input features to predict take-off and landing distances, without requiring knowledge of the aircraft's aerodynamic properties or solving physics equations.

Keywords. Optimization, Deep Neural Network, Aerospace Engineering, Aircraft Design, Aircraft Performance, Data Driven Methods, Machine Learning.

1 Introduction

Accurate prediction of aircraft performance metrics such as takeoff and landing distances is essential in both preliminary design and operational planning [1], [2]. During the early stages of aircraft design, engineers often rely on simplified theoretical or empirical models to estimate these quantities. However, these models are typically derived under idealized assumptions and may not accurately capture the complex interactions between design variables and flight conditions. Furthermore, the availability of experimental or flight test data at this stage is often limited, making it challenging to validate or refine these theoretical predictions [3], [4].

With recent advances in machine learning, data-driven approaches have emerged as promising tools for aerospace applications. Neural networks, in particular, offer the ability to approximate complex nonlinear relationships using limited input data, making them well suited for early stage modeling tasks where comprehensive aerodynamic data may not yet be available [5], [6], [7], [8]. By learning directly from observed data, such surrogate models can complement or enhance traditional analytical formulations, improving prediction reliability even when experimental information is sparse.

Moreover, they are smooth and interpolatable, making them suitable for use in flight simulators, optimization routines, and trajectory analyses. Also, regression or surrogate models provide continuous

and differentiable representations of aircraft behavior, enabling sensitivity and gradient-based design studies that are essential for performance evaluation and optimization [9], [10], [11], [12].

In this study, a neural network based surrogate model is developed to predict the take-off and landing distances of Boeing 737 aircraft. The model utilizes a real-world dataset and a limited number of basic input parameters, eliminating the need for detailed aerodynamic modeling or physics-based computations. The goal here is not to replicate the full physical complexity of aircraft performance modeling, but rather to demonstrate the potential of DNN-based surrogate models in accurately approximating performance metrics from limited data. This approach highlights how modern data-driven techniques can complement traditional physics-based methods in aerospace performance analysis.

This approach allows for rapid estimation of aircraft performance while retaining a reasonable level of accuracy. Although it lacks the detailed physical fidelity of a full aerodynamic-propulsion model, it provides a computationally efficient and accessible tool for performance analysis, optimization, or preliminary design studies where only limited data are available.

Multilayered artificial neural networks are becoming a universal tool in a host of application fields. At the heart of this deep learning revolution there are familiar concepts from applied and computational mathematics, notably from calculus, approximation theory, optimization, and linear algebra. [13], [14], [15], [16]. Training a neural network, which essentially involves solving an optimization problem, represents the primary computational challenge in this field [17], [18], [19], [20]. A variety of traditional and modern optimization algorithms have been developed to handle large-scale training datasets, ranging from gradient descent methods to adaptive moment estimation (Adam) and its variants [21], [22], [23]. Each approach has its advantages and limitations, performing differently depending on the characteristics of the dataset. Additionally, the learning rate plays a crucial role, as it can significantly influence both the convergence rate and the stability of the training process. The current study also performs a parametric study to explore neural network optimization techniques, emphasizing the influence of learning rates and network depths on model performance.

2 Boeing 737 Performance Data Set

The takeoff and landing distances of an aircraft are fundamental metrics in assessing its overall performance, safety, and operational capability. These parameters define the runway length required for an aircraft to accelerate to lift-off speed and safely climb out (takeoff), or to decelerate from touchdown to a complete stop (landing). They are critical considerations in aircraft design, airport infrastructure planning, and regulatory certification processes. From an operational standpoint, they determine which airports an aircraft can safely use under given environmental conditions, and they directly influence payload, fuel load, and route flexibility [24], [25].

From physics perspective, the takeoff and landing process involves the interplay between aerodynamic lift, drag, thrust, and rolling friction. The aircraft must accelerate along the runway until the lift force generated by the wings equals or exceeds the aircraft's weight. Similarly, during landing, the distance depends on aerodynamic drag, reverse thrust, braking efficiency, and ground friction as the aircraft decelerates from touchdown speed to rest [26]. These performance metrics are highly sensitive to atmospheric and operational conditions. Air density, affected by altitude, temperature, and pressure, influences both lift and engine thrust. Wind direction and speed modify the required ground roll, while runway slope and surface condition (dry, wet, or icy) alter effective acceleration or deceleration forces. Because of these interdependencies, accurate prediction of takeoff and landing distances typically requires detailed aerodynamic models (to provide lift and drag characteristics), propulsion models (to

account for thrust variations with speed and altitude), and atmospheric models (to capture temperature and pressure effects) [27], [28].

In this study, required take off distances for Boeing 737-900 and landing distances for Boeing 737-500 extracted from the charts and tables of [29] and utilized as the training data. Obtaining detailed performance data for commercial aircraft poses a significant challenge, as such information is typically proprietary and not publicly accessible. Manufacturers and operators rarely release full datasets from flight tests or certification campaigns. Therefore, in this study, the performance charts available for the Boeing 737 are used as a surrogate source of real data. These charts are assumed to represent ground truth, and validated flight test results and certified performance information, making them a reasonable basis for developing and evaluating data-driven models. Figure 1 and Figure 2 demonstrate representative charts from [29].

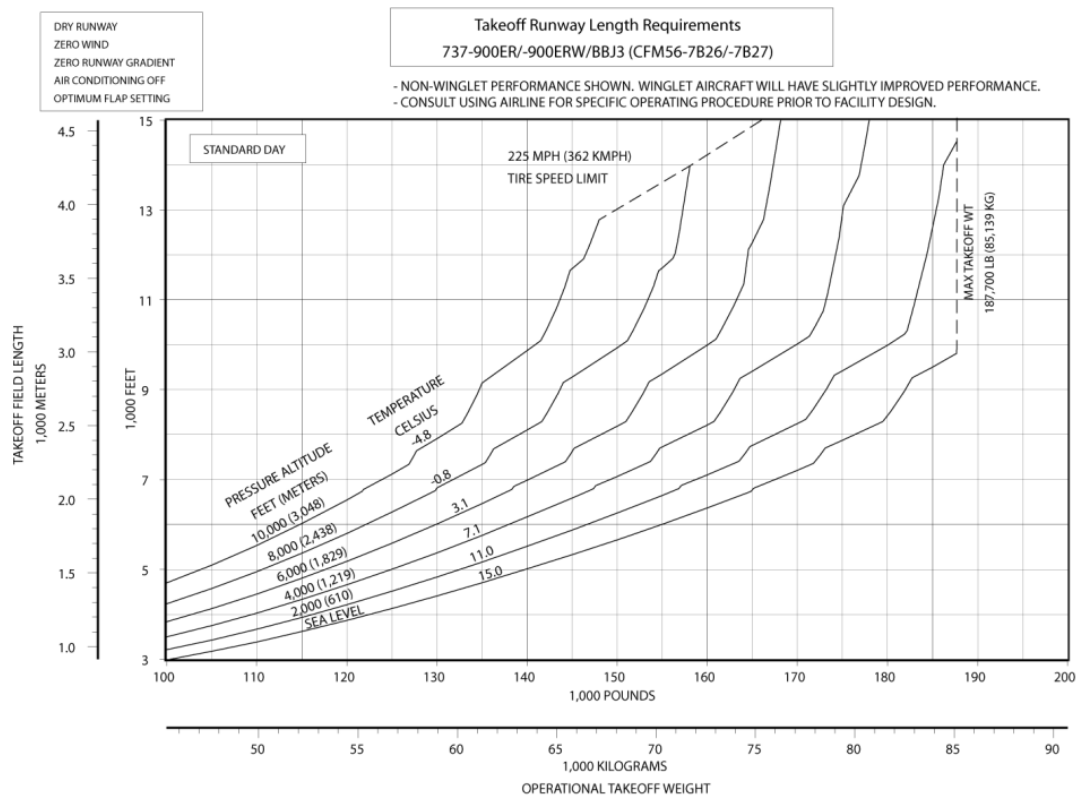


Figure 1: Representative Take-Off Distance Chart for Boeing 737-900 (ISA 0°)

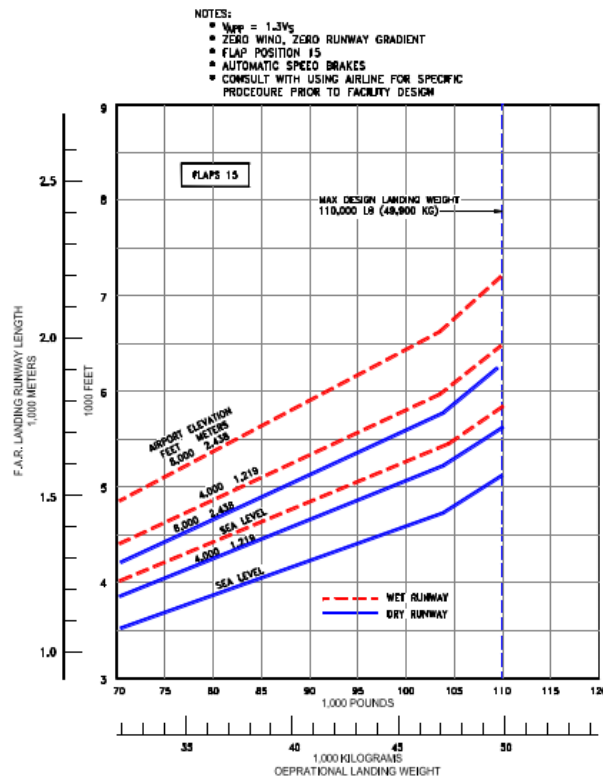


Figure 2: Representative Landing Distance Chart for Boeing 737-500 (Flaps 15° Configuration)

3 Results and Discussion

In this study, seven different optimization methods: Stochastic Gradient Descent (SGS) [17], Adam [18], Adagrad [19], Adadelata [20], AdamW [21], NAdam [22] and RMSprop are used to train a shallow and deep neural network with three different learning rates. The final error loss values and convergence performance are analyzed and compared. Pytorch optimizers with ReLU activation function is employed throughout all normalized training data discussed in this paper, serving as the primary framework for model development and experimentation.

For the takeoff case three parameters are taken as input: aircraft weight, air temperature deviation from standard atmosphere (i.e. ISA deviation) [30] and airport altitude and the output is take off distance.

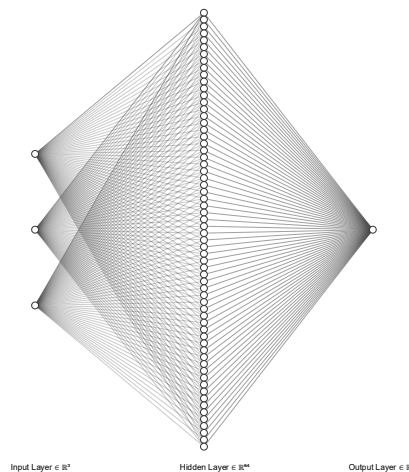


Figure 3: Shallow Network Diagram for 737-900 Take Off Data Set

To achieve our objective, two distinct neural network architectures are examined: one shallow and the other deep, as illustrated in Figure 3 and Figure 4. The shallow neural network is characterized by only one layer with 64 neurons, making it suitable for simpler tasks with less complex data patterns. Conversely, the deep neural network using the rule-of-thumb heuristic comprises 3 layers with each having 64, 64, 32 neurons at each layer respectively, enabling it to model intricate relationships within data, which is advantageous for complex scenarios. The comparison between these architectures highlights their respective strengths and limitations, providing insights into their appropriate applications in various machine learning tasks. Understanding the differences between shallow and deep neural networks is essential for selecting the most suitable model based on the specific requirements of a project, such as accuracy, computational resources, and data complexity. This analysis underscores the importance of architecture choice in designing effective neural network models for diverse applications in artificial intelligence and data science [31], [32], [33].

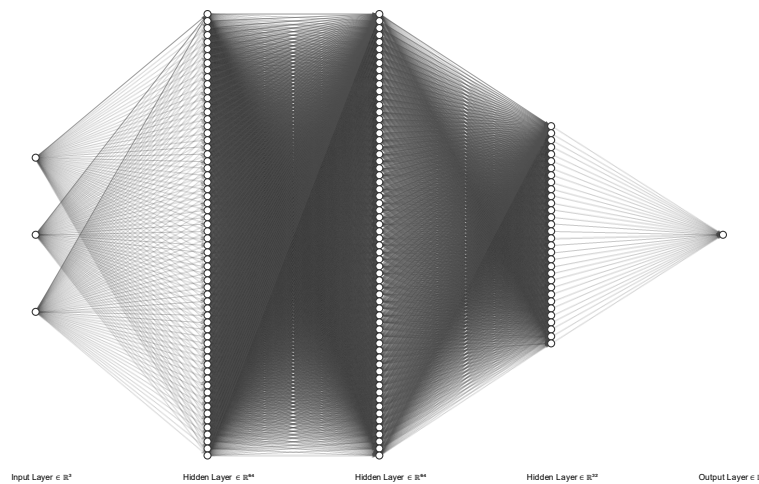


Figure 4: Deep Network Diagram for 737-900 Take Off Data Set

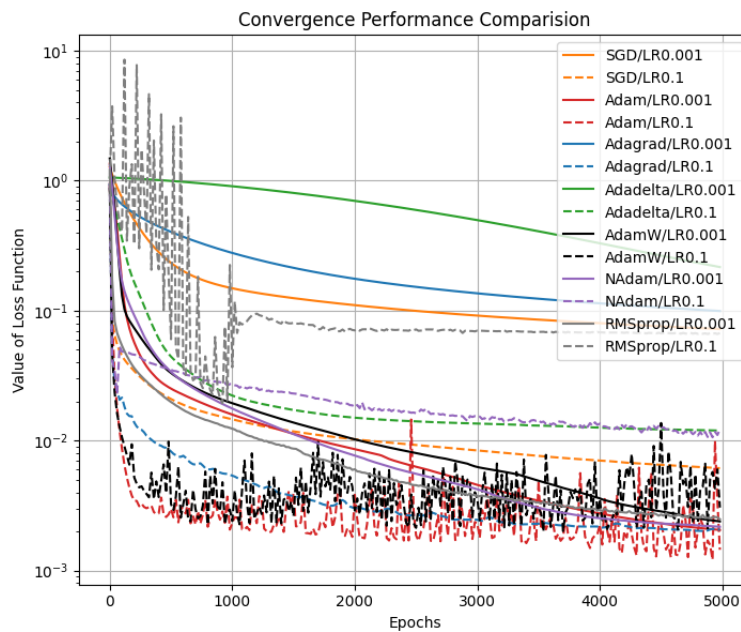


Figure 5: Convergence Performance for 737-900 Takeoff Data Set with Shallow Network

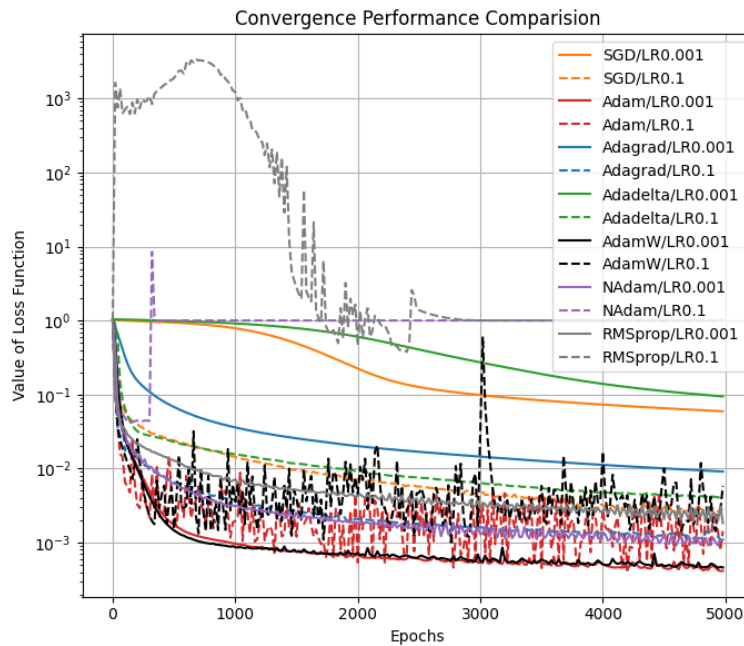


Figure 6: Convergence Performance for 737-900 Takeoff Data Set with Deep Network

Figure 5 and Figure 6 illustrate the convergence behaviour of various optimization algorithms used in training both shallow and deep neural networks. It is observed that some optimizers operating with low learning rates tend to converge slowly, which is an expected outcome given the reduced step sizes. Conversely, optimizers such as Adam and AdamW demonstrate robust performance with relatively higher learning rates, achieving rapid, smooth, and stable convergence.

The dataset is partitioned into an 80% training subset and a 20% testing subset. The performance of the predictive model is assessed by evaluating its accuracy on the test data. This evaluation involves calculating the mean squared error (MSE), which quantifies the average squared difference between the predicted and actual values. Table 1 provides an evaluation of how shallow and deep neural networks perform in predicting take off distance, summarizing accuracy in the optimization method and learning rate context.

Table 1: Summary of Prediction Performance of Shallow and Deep Networks for Take Off Distance

Shallow Network				Deep Network			
Method	LR=0.001	LR=0.01	LR=0.1	Method	LR=0.001	LR=0.01	LR=0.1
SGD	0.07491	0.02189	0.00713	SGD	0.05661	0.00715	0.00357
Adam	0.00259	0.00210	0.00200	Adam	0.00093	0.00063	0.00252
Adagrad	0.09878	0.00862	0.00261	Adagrad	0.00689	0.00141	0.00174
Adadelta	0.23178	0.02305	0.01193	Adadelta	0.09033	0.00841	0.00539
AdamW	0.00337	0.00216	0.00239	AdamW	0.00103	0.00102	0.00223
Nadam	0.00347	0.00340	0.01152	Nadam	0.00146	0.00332	0.98257
RMSprop	0.00333	0.00731	0.06012	RMSprop	0.00355	0.00479	0.98257

Figure 7 and Figure 8 compares true and predicted data across various airport altitudes, it is evident that both the predictive models demonstrate strong performance, particularly at lower operational take off weights where the relationship between variables tends to be linear. Under these conditions, the models accurately reflect the true data, indicating effective learning and generalization. However, as the takeoff weights increase and the data relationships become more nonlinear, the shallow neural network exhibits a slight decline in accuracy, suggesting limitations in capturing complex patterns at higher weights. Conversely, the deep neural network consistently maintains high accuracy across all scenarios, effectively modelling the nonlinearities inherent in the data. This robustness underscores the superiority of deep learning architectures in handling complex, nonlinear relationships.

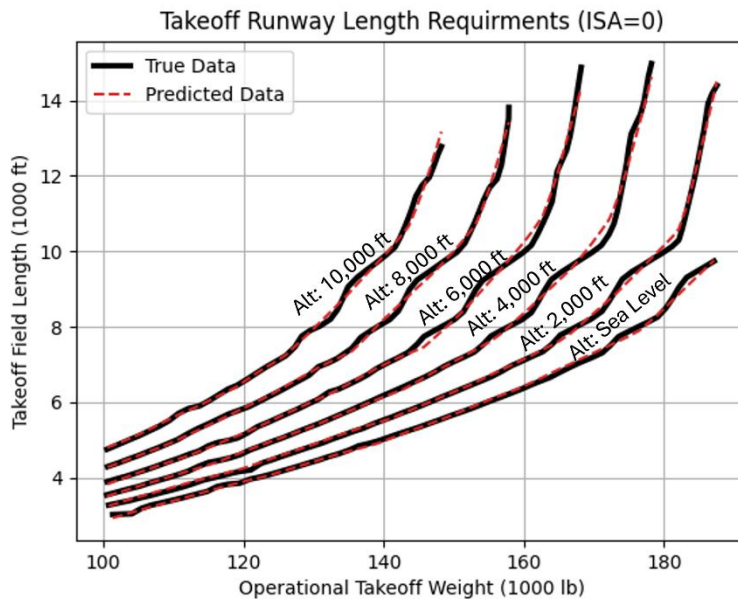


Figure 7: Model Prediction for 737-900 Takeoff Data Set with *Shallow Network*

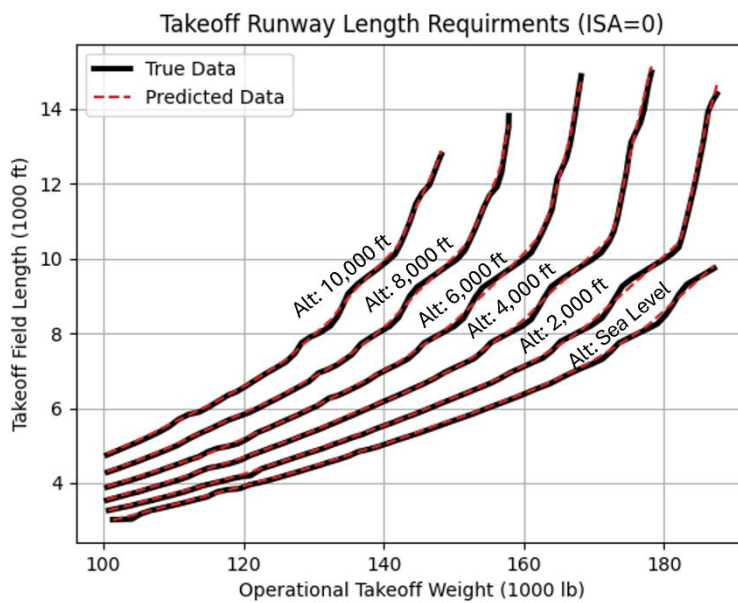


Figure 8: Model Prediction for 737-900 Takeoff Data Set with *Deep Network*

In the analysis of the landing distance scenario, a methodology similar to that used for the takeoff case is employed. Both shallow and deep neural networks are trained utilizing identical optimization algorithms and learning rates to ensure consistency in the training process. A critical factor in the landing distance is braking performance, which necessitates the inclusion of runway condition as an additional input parameter. Therefore, the surface conditions (dry vs. wet) is entered as an input in an encoded way to allow the model to account for variations in that can significantly influence landing performance. Furthermore, due to the limited availability of data across different air temperatures, the study considers three specific flap configurations: 15°, 30°, and 40° to evaluate their impact on landing distance under varying operational conditions.

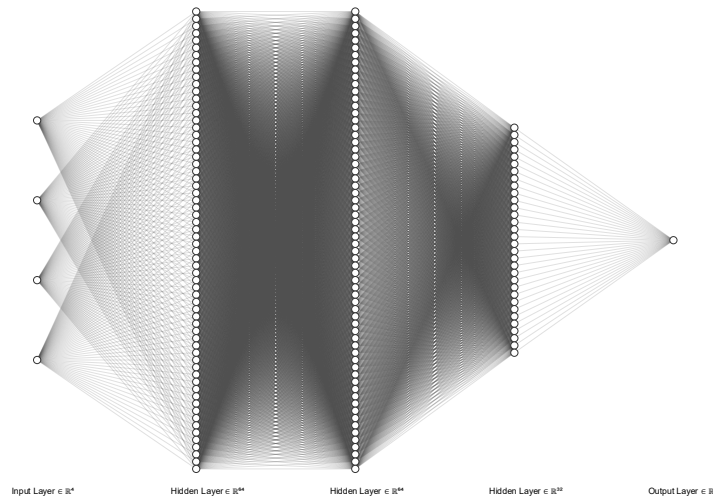


Figure 9: Deep Network Diagram for 737-500 Landing Data Set

Similar to the takeoff distance case, Figure 10 and Figure 11 show the convergence patterns of different optimization algorithms employed in training shallow and deep neural networks. It is evident that optimizers functioning with low learning rates generally exhibit slower convergence. On the other hand, again, algorithms like Adam and AdamW show strong performance low learning rates, providing stable, and smooth convergence.

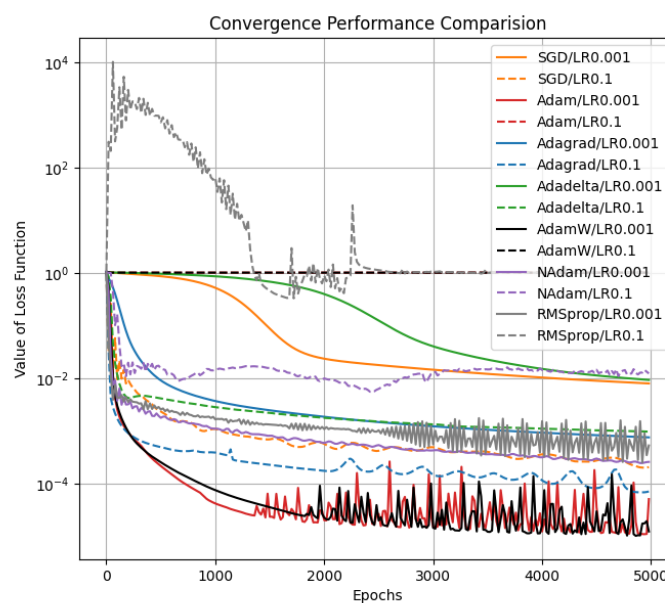


Figure 10: Convergence Performance for 737-500 Landing Data Set with Shallow Network

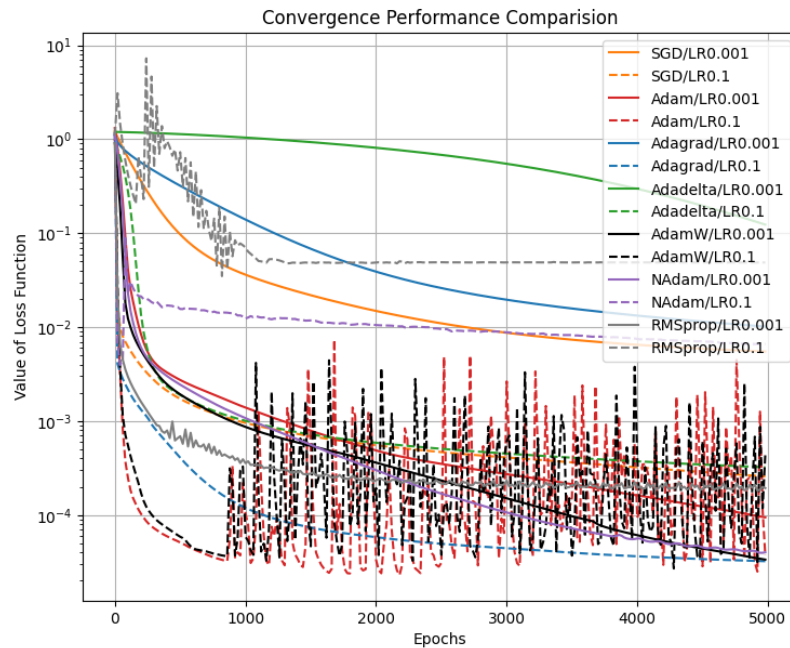


Figure 11: Convergence Performance for 737-500 Landing Data Set with Deep Network

The summary of the model's prediction performance is presented in a manner similar to the takeoff case outlined in Table 2. To provide a clear overview of the model's accuracy, the landing runway length distances measured at both flap settings of 15° and 40° are plotted in a parametric format. These plots consider various runway conditions and airport altitudes, demonstrating the capability of deep neural networks to handle such parametric datasets. This comprehensive analysis highlights the effectiveness of DNNs in predicting runway lengths across different operational scenarios, emphasizing their potential utility in aviation safety and planning.

Table 2: Summary of Prediction Performance of Shallow and Deep Networks for Landing Distance

Shallow Network				Deep Network			
Method	LR=0.001	LR=0.01	LR=0.1	Method	LR=0.001	LR=0.01	LR=0.1
SGD	0.00353	0.00251	0.00031	SGD	0.00811	0.00133	0.00036
Adam	0.00012	0.00011	0.00127	Adam	0.00014	0.00008	0.901663
Adagrad	0.00671	0.00050	0.00018	Adagrad	0.00075	0.00013	0.00026
Adadelta	0.09845	0.00281	0.00054	Adadelta	0.00721	0.00104	0.00103
AdamW	0.00017	0.00069	0.00024	AdamW	0.00010	0.00010	0.901663
Nadam	0.00012	0.00026	0.00623	Nadam	0.00035	0.00082	0.013614
RMSprop	0.00027	0.00103	0.04362	RMSprop	0.00096	0.00320	0.906401

It can also be observed that, due to the nature of braking, a relatively constant deceleration is expected. This results in landing distances that tend to be almost linear. Consequently, there is generally no need for a highly complex neural network; shallow networks tend to perform adequately in this context.

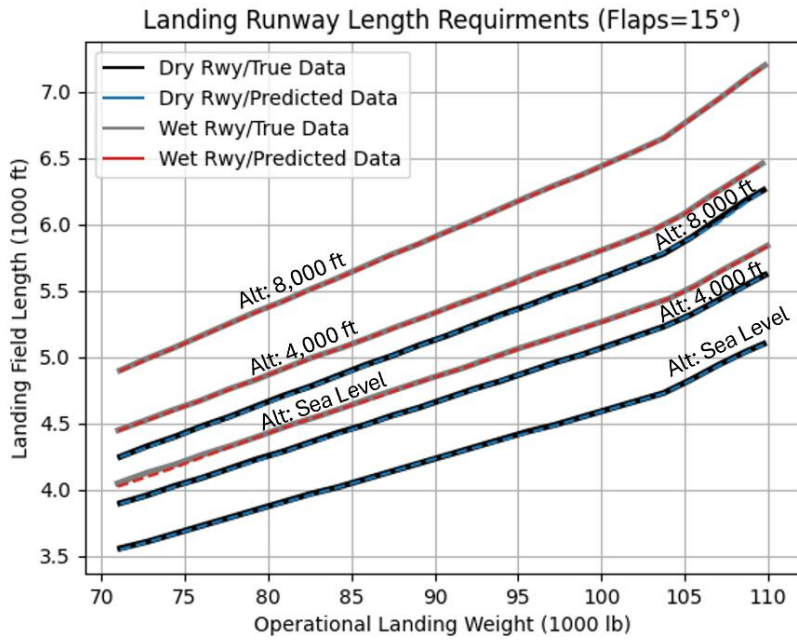


Figure 12: Model Prediction for 737-500 Landing Data Set with Deep Network

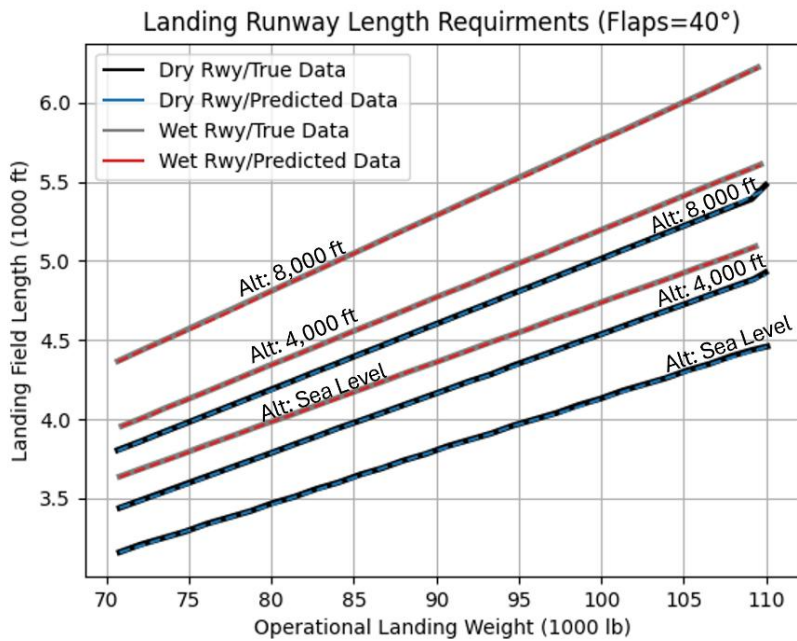


Figure 13: Model Prediction for 737-500 Landing Data Set with Deep Network

4 Conclusion

This study presented an examination of neural network based surrogate modelling for aircraft performance and aerospace related test cases. A practical investigation was conducted using a real-world dataset derived from Boeing 737 takeoff and landing performance charts. A surrogate model was developed to predict these performance metrics using only a minimal set of input features, such as aircraft weight, atmospheric conditions, and airport elevation. Despite the absence of detailed aerodynamic or propulsion data, the model successfully captured key relationships inherent in the dataset, demonstrating the capability of deep learning approaches to approximate complex physical phenomena based purely on empirical information.

Overall, the findings underscore the potential of deep neural networks and modern optimization techniques in aerospace engineering applications. By leveraging data-driven methods, it is possible to develop efficient surrogate models that complement traditional physics-based analyses, reducing computational complexity while maintaining acceptable accuracy. Future work could extend this approach by incorporating additional aircraft types, exploring transfer learning between datasets, and integrating hybrid models that combine physical insight with machine learning to further enhance predictive performance.

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