

A RESIDUAL LEARNING FRAMEWORK FOR IMPROVED AERODYNAMIC LOAD PREDICTION

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ABSTRACT

This paper will describe the evaluation of the effectiveness of a residual learning framework for aerodynamic load prediction, with a focus on predicting nonlinear and unsteady aerodynamic loads. Initially exercised on two-dimensional airfoils, the approach augments classical low-order airfoil theories with modular residual learning models that correct specific aerodynamic effects not accurately captured by baseline formulations. The objective is to improve aerodynamic load prediction accuracy while retaining physical structure, interpretability, and computational efficiency.

The proposed framework integrates a baseline aerodynamic model based on linear steady (thin-airfoil) theory with a sequence of data-driven residual corrections. Rather than modeling the total aerodynamic response directly from nonlinear unsteady aerodynamic data, the framework decomposes the aerodynamic loads into a physics-based baseline contribution and a set of effect-specific residual corrections,

$$F_{total} = F_{baseline}^{f_0} + \sum_{i=1}^N g_i \Delta F_i^{f_i}, \quad g_i \in [0, 1]$$

$$\Delta F_i^{f_i} = NN_i^{f_i}(x_i)$$

where F_{total} denotes the total aerodynamic output of interest (e.g., aerodynamic force or moment components), and $F_{baseline}^{f_0}$ represents output of a physics-based low-order aerodynamic model evaluated at fidelity level f_0 . The term $\Delta F_i^{f_i}$ denotes the residual correction associated with the i th aerodynamic effect, with $i = 1, \dots, N$ where N is the total number of effects. Each residual correction is represented by a neural-network-based model $NN_i^{f_i}$ trained using data of fidelity f_i and evaluated using a minimal set of input variables x_i relevant to that effect. The parameters g_i enables adaptive control of different aerodynamic effect. Separate residual models are introduced to account for steady nonlinear effects, acceleration-dependent and quasi-steady contributions, and unsteady time-history effects. Figure 1 illustrates the proposed modeling workflow, highlighting the modular structure of the residual corrections and their combination with the baseline physics model. Each residual component is trained using aerodynamic datasets of appropriate fidelity, which may differ across residual components depending on the physical effect being modeled, enabling targeted correction and reducing the need to model the full response directly. Within this framework, instantaneous and quasi-steady aerodynamic effects are modeled

using instantaneous input–output pairs evaluated at each time step, whereas history-dependent residual corrections are modeled using input–output time histories.

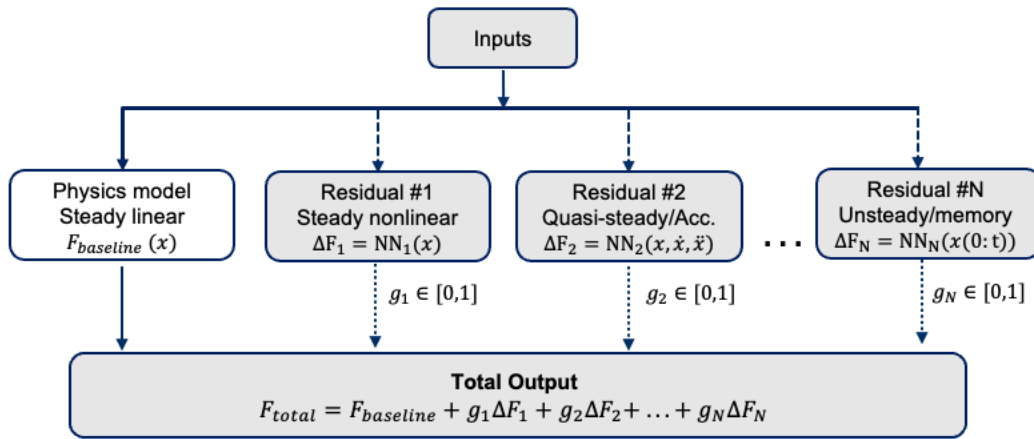


Fig 1. Modular residual learning framework for aerodynamic load prediction.

The study considers the NLR 7301 airfoil test case, consistent with previous neural-network-based aerodynamic modeling studies by Wang et al¹⁻². These prior studies demonstrated the feasibility of learning nonlinear and unsteady aerodynamic behavior from high-fidelity CFD data for this airfoil and provide a foundation for the present effort. In parallel, recent studies³⁻⁶ have highlighted the potential of residual learning approaches for modeling nonlinear and unsteady aerodynamics. Motivated by these developments, the present work focuses on extending residual learning formulations by explicitly separating distinct aerodynamic effects into multiple residual learning modules, rather than representing all corrections through a single residual model. Leveraging the existing high-fidelity CFD results from Wang et al., the proposed framework further incorporates complementary lower-fidelity datasets generated under similar flow conditions. Different neural network architectures are employed depending on the nature of the residual being modeled, with feedforward neural networks used to learn steady nonlinear residuals and recurrent architectures, including long short-term memory (LSTM) networks, used to capture unsteady and history-dependent aerodynamic behavior.

Comparisons are performed between baseline-only aerodynamic predictions, direct data-driven models trained on total aerodynamic loads, and the proposed residual learning framework. These comparisons are used to assess the effectiveness of modular residual learning formulations in improving nonlinear and unsteady aerodynamic load prediction relative to baseline linear models and direct data-driven approaches, and to examine the role of residual decomposition in accuracy, interpretability, and computational efficiency.

The novel contribution of this paper lies in the systematic decomposition and evaluation of multiple residual learning modules; each associated with a specific aerodynamic effect and trained using data of appropriate fidelity. Unlike existing data-driven airfoil models that focus on learning total aerodynamic forces or single residual corrections, the proposed approach isolates nonlinear, quasi-steady, and unsteady contributions and corrects them individually. This structure enables

selective activation of residual corrections and provides a flexible foundation for multi-fidelity learning when high-fidelity data are limited⁵⁻⁷.

By combining established aerodynamic theory with targeted residual corrections, the proposed framework offers a practical methodology for improving nonlinear and unsteady aerodynamic predictions while reducing training cost and preserving interpretability. The results of this study will inform future developments in reduced-order aerodynamic modeling for aeroelastic analysis, control-oriented applications, and multi-fidelity simulation frameworks.

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