AI-DRIVEN FLOW PREDICTION AROUND AN AIRFOIL

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Introduction

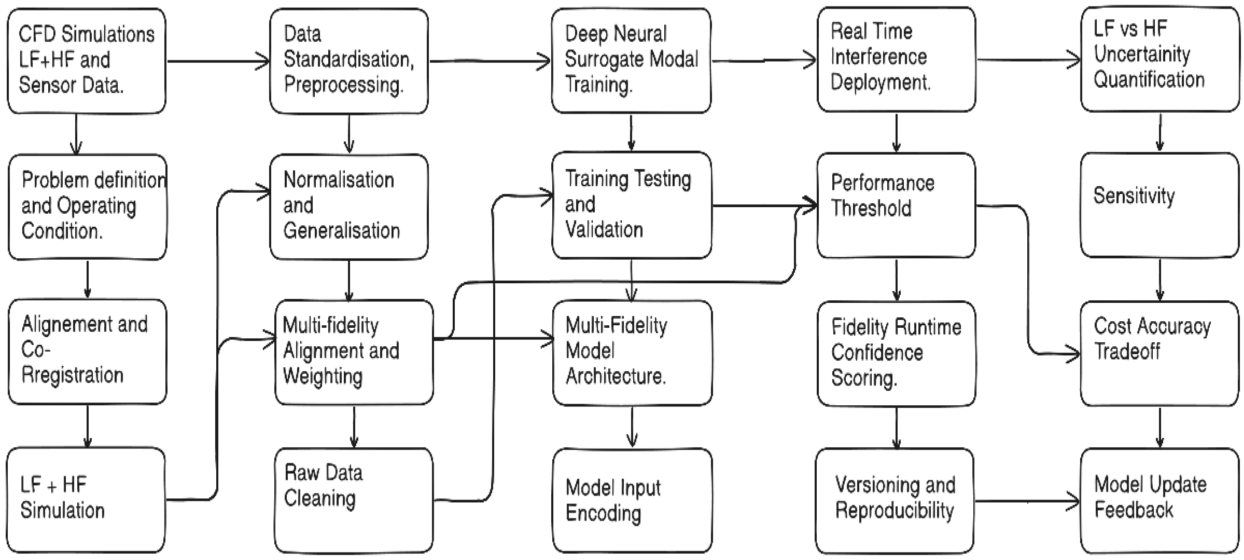
The emergence of data-driven modeling and neural networks offers a transformative alternative for studying aerodynamic behavior. Deep learning techniques are capable of learning mappings between aerodynamic input variables and response outputs directly from data, enabling instantaneous prediction once trained. Neural networks have demonstrated strong performance in predicting aerodynamic coefficients, reconstructing pressure and velocity fields, and approximating turbulent flow behavior. Convolutional Neural Networks (CNNs), in particular, leverage spatial information and local feature extraction, making them effective for aerodynamic modeling where flow structures exhibit spatial coherence.

This research adopts a hybrid evaluation strategy combining both Low Fidelity Data + High Fidelity Data. The physical wind tunnel generates high-fidelity experimental measurements through pressure sensors, load cells, and flow visualization systems. In parallel, CFD predicts aerodynamic performance in real time, reducing the number of physical testing iterations. This hybrid approach enables scalable testing, supports rapid aerodynamic design optimization

Objectives:

1. To develop a hybrid aerodynamic analysis framework integrating wind tunnel experimentation and computational fluid dynamics for accurate data generation.
2. To design and train a multi-fidelity neural network surrogate model capable of predicting aerodynamic coefficients with high accuracy and reduced computational cost.
3. To enable real-time aerodynamic prediction and optimization by combining experimental data, simulation results, and machine learning techniques.

Methodology:



- Data Acquisition:
  Aerodynamic data is obtained from CFD simulations (low-fidelity) and experimental sensor measurements (high-fidelity) under defined operating conditions.
- Data Preprocessing:
  The collected data is normalized, cleaned, and aligned to ensure consistency, followed by multi-fidelity alignment and appropriate weighting of LF and HF datasets.
- Model Development:
  A deep neural network surrogate model is designed using a multi-fidelity architecture, with proper input encoding of aerodynamic parameters.
- Model Training and Validation:
  The dataset is split into training, testing, and validation sets to evaluate model performance and ensure generalization.
- Deployment and Evaluation:
  The trained model is deployed for real-time inference with performance thresholds and confidence scoring based on fidelity.
- Uncertainty and Optimization:
  Sensitivity analysis and cost–accuracy trade-off are performed, followed by model updates through a feedback loop for continuous improvement.

Result and conclusion:

The proposed hybrid aerodynamic framework successfully integrates experimental wind tunnel data, CFD simulations, and deep learning–based surrogate modeling. Results demonstrate that multi-fidelity data significantly improves prediction accuracy compared to single-fidelity approaches. The neural network model achieves rapid convergence and enables real-time prediction of aerodynamic coefficients with minimal computational cost. Analysis shows that a small proportion of high-fidelity data substantially enhances model performance, while excessive high-fidelity data yields diminishing returns. The framework effectively captures key aerodynamic trends, including lift, drag, and moment variations with angle of attack. However, deviations at higher angles highlight limitations in modeling complex flow phenomena such as separation. The cost–accuracy trade-off analysis confirms the existence of an optimal fidelity balance. Overall, the study establishes that combining physics-based methods with data-driven models provides an efficient and scalable approach for aerodynamic analysis and design optimization.

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Future Scope:

- Train the model with more airfoils and wider operating conditions to improve accuracy.
- Use the experimental data to retrain and validate the model, making it more realistic.
- Extend from 2D airfoils to full 3D wings or aircraft geometries.
- Develop a user interface or software tool where users input parameters and instantly get results.
- Integrate with optimization algorithms to automatically generate best-performing airfoil shapes.
- Improve the model to handle complex turbulent and unsteady flows.
- Apply in aerospace, automotive, drones (UAVs) for faster design cycles.
- Create a virtual wind tunnel (digital twin) for continuous testing and simulation.