

Efficient Prediction of Automotive Surface Aerodynamic Fields via Transfer Learning with Graph Neural Networks

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Conventional CFD analysis requires high computational cost, motivating machine-learning surrogate models that learn from CFD results to rapidly predict aerodynamic fields [1,2]. Among these, graph neural networks (GNNs), which candirectly handle complex unstructured meshes, are well suited to automotive aerodynamic prediction [3]. However, achieving high accuracy for new vehicle shapes often requires large-scale retraining with abundant CFD data, a practical challenge in terms of cost. Transfer learning, which adapts a model pre-trained on existing data to new data, is an effective approach to this problem [4]. This study applies transfer learning to GNN-based prediction of vehicle surface aerodynamic fields, comparing it with training from scratch under limited CFD data, and examines how differences in shape/CFD conditions and training data size affect its effectiveness.

Five datasets were used: DrivAerNet++ [5] (NotchBack, FastBack, EstateBack), DrivAerML [6], and CX-5 [7] (Table 1). The DrivAerNet++ subsets share CFD conditions and differ only in shape; DrivAerML and CX-5 differ from the pre-training dataset in both shape and CFD conditions. The GNN model X-MeshGraphNet [3] predicts nodal pressure and wall shear stress on the vehicle surface, represented as an unstructured graph with geometric node/edge features.

Table 1 Comparison of datasets used in this study

Dataset	Shape	Solver	Mesh Size	Reynolds Number
DrivAerNet++	NotchBack, FastBack, EstateBack	RANS	24M	$8.37 \times 10^6 \sim 1.01 \times 10^7$
DrivAerML	Notch	DDES	160M	7.19×10^6
CX-5	SUV	LES	200M	5.83×10^6

Table 2 Transfer Learning Setup

Case	Pre-training Dataset	Target Dataset	Dataset Differences
A	NotchBack	FastBack	Shape
B	NotchBack	EstateBack	Shape
C	NotchBack	DrivAerML	Shape CFD conditions
D	NotchBack	CX-5	Shape CFD conditions

The model was pre-trained on DrivAerNet++ NotchBack (300 samples) and fine-tuned (full fine-tuning) on four target datasets (Table 2): Cases A/B differ only in shape, Cases C/D differ in both shape and CFD conditions. Each target used 100 training samples, with the rest for validation/testing; Case A was also tested with 25 samples. Validation loss (MSE of pressure and wall shear stress vs. CFD) was tracked, and the epoch at minimum loss defined the best model and training efficiency.

Transfer learning outperformed scratch training in all cases (Fig. 1): improvements in minimum validation loss/epochs were ~15%/99% (Case A), 15%/98% (Case B), 9.6%/9% (Case C), and 1.1%/34.7% (Case D). Gains were larger when only shape differed (A, B) and markedly smaller when CFD conditions also differed (C, D). For Case A, training data was reduced from 100 to 50 and 25 samples (Fig. 2, mean of three repeated trials per size). Minimum validation loss increased substantially for scratch training ($0.165 \rightarrow 0.183 \rightarrow 0.202$) but remained nearly stable for transfer learning ($0.140 \rightarrow 0.142 \rightarrow 0.144$). Epochs to reach the best model stayed around 600–730 for scratch training and 7–10 for transfer learning, with little dependence on data size. This shows that transfer learning retains its accuracy even as training data is reduced, while scratch training degrades substantially, further widening the performance gap between the two approaches.

These results show transfer learning improves both accuracy and training efficiency for GNN-based aerodynamic prediction. When only shape differs, pre-trained knowledge transfers effectively, enabling fast adaptation with limited data; this advantage persists even as data is reduced, while larger CFD-condition differences limit its benefit. These findings support the practical use of transfer learning for new but similar designs and highlight both its potential and its limits in automotive aerodynamic prediction.

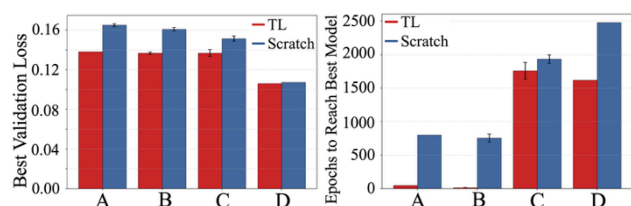


Fig. 1 Comparison of Transfer Learning and Scratch Learning: best validation loss and epochs required to reach the best model for each case. A: FastBack, B: EstateBack, C: DrivAerML, D: CX-5.

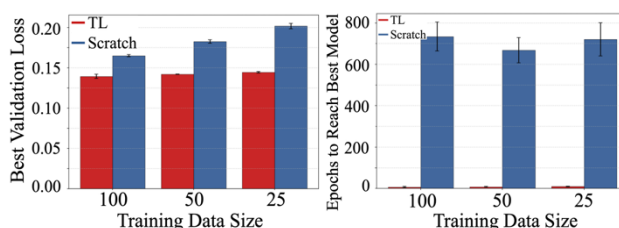


Fig. 2 Training Data Size Dependency of Transfer Learning : Case A (FastBack)