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Aerodynamic Prediction and Optimization of Vortex Generator for 600km/h Maglev Train Based on Deep Learning

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Abstract

As high-speed maglev trains target operational speeds of 600 km/h, the complex wake flow and flow separation at the tail car significantly contribute to aerodynamic drag and stability challenges. This study proposes an integrated framework combining Computational Fluid Dynamics (CFD) and deep learning for the rapid prediction and optimization of the tail flow field. Passive flow control is implemented via vortex generators (VGs) installed on the tail car. A high-fidelity dataset was constructed using CFD simulations based on the Shear Stress Transport turbulence model, covering speeds from 400 to 600 km/h and various VG deflection angles. Subsequently, a U-Net convolutional neural network was developed to map the relationship between geometric/boundary parameters and the resulting wake vorticity contours and aerodynamic coefficients. Results indicate that the U-Net model achieves high accuracy in predicting complex wake topologies with a significant reduction in computational cost compared to traditional solvers. Specifically, an optimal deflection angle of 10° was identified, yielding maximum drag reduction. The findings demonstrate that the proposed deep-learning-based approach effectively accelerates the design and evaluation of bionic-inspired passive flow control structures for ultra-high-speed maglev systems.

Keywords: maglev trains, aerodynamic force, vortex generator, drag reduction, deep learning, U-net.

1 Introduction

Maglev trains represents the frontier of ground vehicle technology, with proposed operational speeds reaching 600 km/h [1]. At such ultra-high velocities, aerodynamic performance becomes the primary determinant of energy efficiency and operational safety [2,3]. While significant research has focused on the streamlining of the lead car, the aerodynamic characteristics of the tail car—characterized by intense wake turbulence and massive flow separation—remain a critical bottleneck. The complex vortex shedding in the wake region not only contributes substantially to the total pressure drag but also induces undesirable aerodynamic lift fluctuations.

To mitigate these effects, passive flow control surfaces, such as vortex generators (VGs), have emerged as a promising solution. Unlike active control systems, these surface-mounted structures require no external energy input and operate by re-energizing the boundary layer through the introduction of streamwise vortices [4]. The effectiveness of such passive measures depends heavily on the precise mapping between the bionic-inspired structural parameters and the local flow field topology [5,6,7]. However, traditional optimization processes relying solely on Computational Fluid Dynamics (CFD) are computationally prohibitive, particularly when exploring a vast multi-dimensional design space involving varied speeds and geometric configurations.

In recent years, deep learning has revolutionized fluid mechanics by providing a surrogate modeling approach that bypasses the iterative convergence process of Navier-Stokes solvers. Specifically, the U-Net architecture, with its symmetrical encoder-decoder structure and skip connections, has shown remarkable potential in preserving high-resolution spatial features of flow fields. By leveraging the mapping capabilities of U-Net, researchers can transition from point-wise aerodynamic coefficient estimation to full-field flow topology prediction.

This paper establishes a rapid flow-field prediction framework for a 600 km/h maglev train equipped with VGs. Utilizing a CFD-generated dataset validated against grid independence tests, we train a U-Net model to predict tail vorticity contours and aerodynamic forces. The study aims to elucidate the influence of VG deflection angles on wake suppression and to demonstrate the feasibility of deep-learning-assisted design in high-speed rail aerodynamics.

2 Methods

The high-fidelity flow field data required for training the deep learning model were generated using steady-state Computational Fluid Dynamics (CFD). The aerodynamic model is based on a 1:10 scaled three-car grouping of a high-speed maglev train, the model details are shown in Figure 1. To investigate passive flow control, vortex generators (VGs) were symmetrically mounted on both sides of the tail car's nose section, as shown in Figure 2. Based on previous research experience, the width of the vortex generator is 20mm, the angle is 30 °, and the length is 300mm.

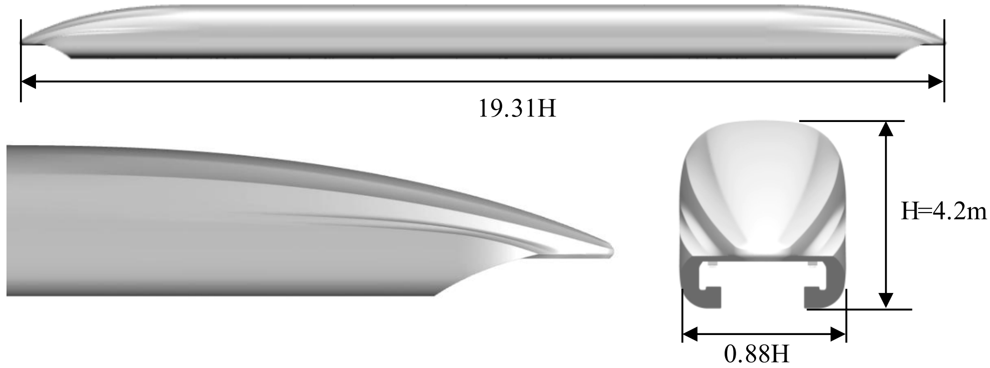
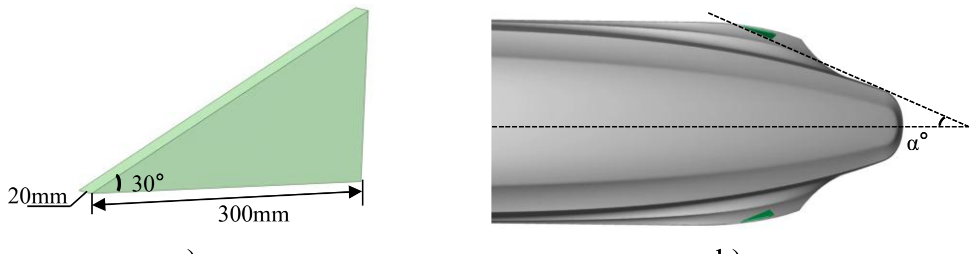


Figure 1: The train model details.

The computational domain was discretized using a hybrid meshing strategy. To ensure the capture of complex separation flow and vortex shedding in the wake region, a multi-level grid refinement approach was employed. Grid independence was rigorously verified by comparing three mesh densities. The "Fine Mesh" configuration, consisting of approximately 67.62 million cells, was selected for the final production runs. This mesh achieved a relative error of only 1.30% in the drag coefficient compared to the extrapolated grid-independent value, demonstrating a high degree of numerical convergence and spatial resolution.

Numerical simulations were performed using a density-based solver. The Shear Stress Transport (SST) k-ω turbulence model was adopted to accurately predict the flow separation under high Reynolds number conditions. The boundary conditions were prescribed as follows: a velocity inlet to simulate varying operating speeds (400–600 km/h), a pressure outlet with ambient static pressure, slip wall conditions for the ground and far-field boundaries, and a symmetry plane for the longitudinal cross-section to reduce computational overhead.



a) b)
Figure 2: Dimensional parameters and installation position of vortex generator.

To accelerate the evaluation of VG design parameters, a deep learning surrogate model based on the U-Net architecture was developed. The U-Net was designed to capture the high-dimensional nonlinear mapping between the train's operating conditions and the resulting aerodynamic features. The input to the network consists of the tail car’s initial state parameters and flow field information at various speeds, while the output yields the predicted vorticity contours and aerodynamic force coefficients (drag and lift) corresponding to specific VG deflection angles α.

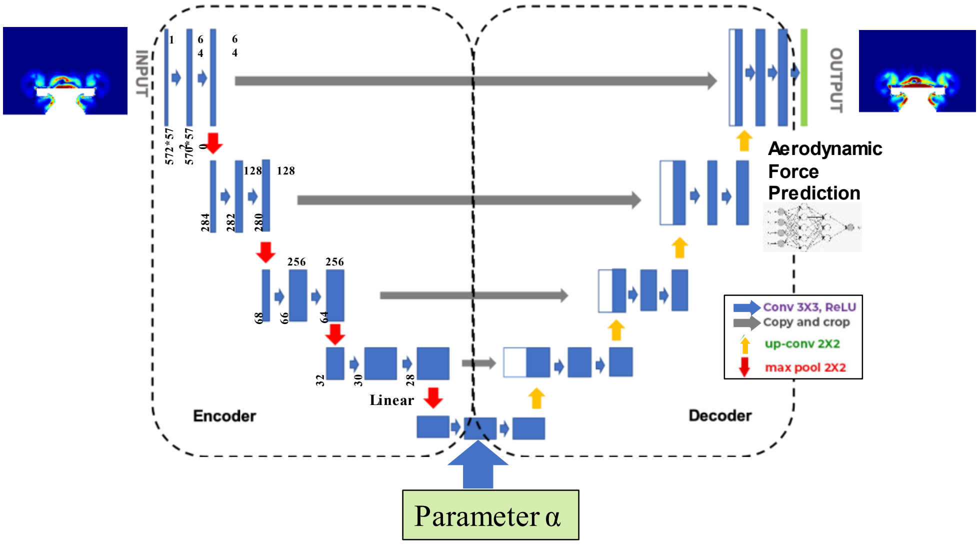


Figure 3: Details of U-net network model.

The architecture features a symmetrical encoder-decoder path with skip connections, which facilitates the preservation of multi-scale spatial features essential for reconstructing intricate vortex structures. The architecture features a symmetrical structure comprising a contracting path (encoder) and an expansive path (decoder). The encoder progressively extracts hierarchical flow features and reduces spatial dimensions via different convolutional layers coupled with downsampling operations. Conversely, the decoder employs up-convolutions to restore the spatial resolution.

A critical component of this architecture is the implementation of skip connections. These connections concatenate the high-resolution feature maps from the encoder directly with the upsampled feature maps in the decoder at the same hierarchical level:

$$F_{out}^{(l)} = Concat(F_{up}^{(l)}, F_{encoder}^{(l)}) \tag{1}$$

where $F_{up}^{(l)}$ denotes the upsampled feature map at layer l, and $F_{encoder}^{(l)}$ represents the corresponding feature map from the contracting path. This mechanism effectively mitigates the loss of fine-grained spatial information during downsampling.

The model was trained on a structured dataset comprising 64 unique operating cases, encompassing a parametric sweep of flow velocities and deflection angles.The training process was governed by the following key hyperparameters to ensure stability and accuracy:

- Loss Function: Mean Squared Error (MSE), optimized for minimizing pixel-wise deviations in flow field contours.
- Activation Function: Hyperbolic tangent ($tanh$), chosen for its gradient properties in normalizing flow field variables.
- Learning Rate: Fixed at 5e-5, ensuring stable convergence of the loss curve.
- Batch Size: 32, balancing computational efficiency and stochastic gradient performance.

By integrating the physics-based accuracy of CFD with the inferential speed of U-Net, this framework enables a rapid transition from geometric configuration to performance evaluation.

3 Results

From the numerical simulation results, it can be seen that a prominent flow separation region, designated as Region 1, is observed near the tail nose, characterized by a large low-pressure zone and intense vortex shedding. In region 2, there is a transition from low pressure to high pressure. When the airflow reaches the nose tip of the tail car, due to the severe contraction of the body geometry (from a wide body to a sharp or rounded nose tip), the airflow undergoes significant deceleration here, forming a high-pressure zone at the nose tip. In this study, the function of the vortex generator is to delay flow separation, therefore the vortex generator was selected to be arranged in region 1.

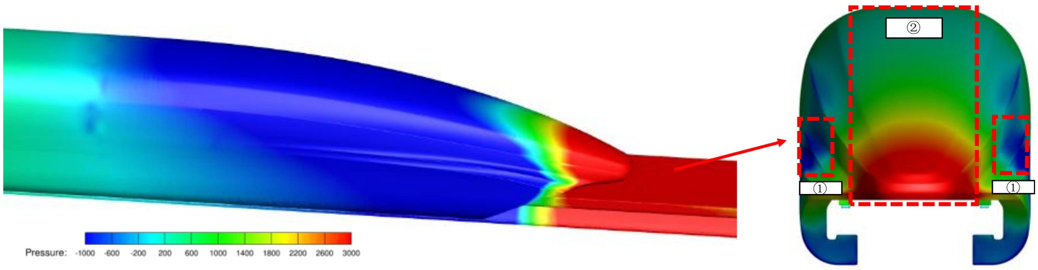


Figure 4: Details of U-net network model.

Speed(km/h)	α=5°	α=10°	α=15°	α=20°
400	1.12%	1.46%	1.19%	0.51%
450	0.81%	1.06%	0.98%	0.27%
500	0.63%	1.06%	0.80%	0.42%
550	0.66%	0.89%	0.62%	0.24%
600	0.50%	0.80%	0.52%	0.11%

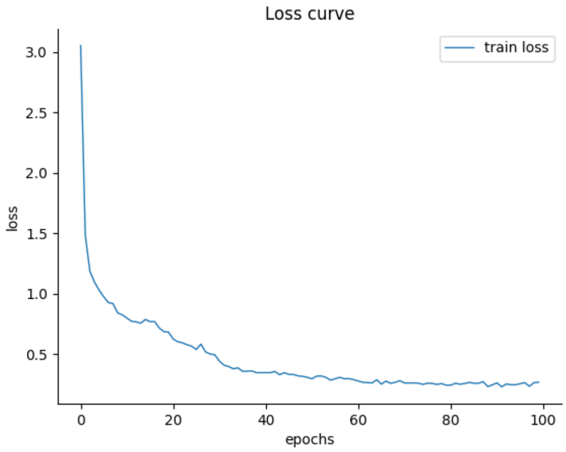
Table 1: Drag reduction rate of vortex generator at different deflection angles(%).

Table 1 shows the changes in drag reduction rate of the tail car of the train at different speeds (400–600 km/h) and different deflection angles ($\alpha = 5°, 10°, 15°, 20°$) of the vortex generator. The results indicate that the drag-reduction performance is highly dependent on the deflection angle. While all tested angles provided some level of benefit, the optimum drag-reduction efficiency was consistently achieved at $\alpha = 10°$. Beyond this threshold, the parasitic drag of the VGs themselves begins to offset the gains from wake suppression. Table 2 shows the lift characteristics, the lift-reduction effect (downforce enhancement) exhibited a monotonic increase with the deflection angle, indicating that larger angles are more effective at suppressing the upward flow at the tail nose, thereby improving the vertical stability of the vehicle at ultra-high speeds.

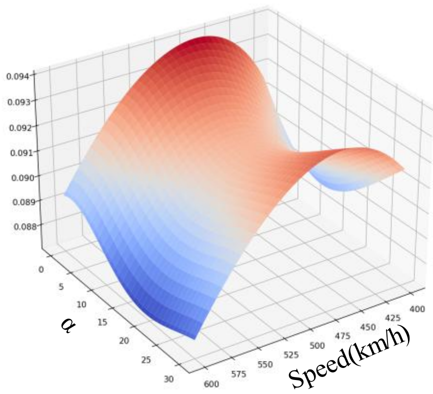
Speed(km/h)	α=5°	α=10°	α=15°	α=20°
400	7.72	7.66	16.4	20.8%
450	4.24	6.99	16.7	29.2%
500	8.82	11.7	21.9	27.3%
550	10.0	14.8	24.4	29.5%
600	9.65	14.5	25.2	28.9%

Table 2: Lift reduction rate of vortex generator at different deflection angles(%).

The U-Net model's performance was assessed through loss curve analysis and direct flow-field comparison. As shown in Figure 5, the loss curve demonstrated rapid convergence and stabilized at a low MSE value, indicating a robust learning process. Qualitatively, the vorticity contours predicted by the U-Net framework show exceptional agreement with the high-fidelity CFD simulation results, accurately capturing the spatial distribution and intensity of the wake vortices. Quantitatively, the model yields high-precision aerodynamic force coefficients. Crucially, while traditional CFD solvers require significant temporal and computational resources for each design iteration, the trained U-Net model provides near-instantaneous flow-field predictions, enabling rapid design space exploration and optimization of passive flow control devices.



a)



b)

Figure 5: U-net training loss and prediction results.

The model exhibits high precision in predicting integrated aerodynamic coefficients. The relative errors for the drag coefficient and lift coefficient across the test cases were maintained prediction error within 2%. This suggests that the latent features extracted by the encoder are sufficient to represent the global pressure distribution on the train surface, even when the local flow field undergoes complex separation under different VG deflection angles.

4 Conclusions and Contributions

This study investigated the effectiveness of vortex generators for the aerodynamic control of a 600 km/h maglev train using an integrated CFD and deep-learning approach. The main conclusions are as follows:

- Effectiveness of Passive Control: Installing vortex generators on both sides of the tail car's nose section effectively mitigates flow separation and reduces the vortex intensity in the wake region, leading to improved aerodynamic performance.
- Optimal Design Parameters: Within the speed range of 400–600 km/h, the drag-reduction performance reaches its optimum at a deflection angle of 10°.

Meanwhile, the aerodynamic lift-reduction effect scales positively with the increase in deflection angle.

- Surrogate Modeling Advantage: The U-Net architecture demonstrates high fidelity in predicting complex three-dimensional vorticity contours and aerodynamic forces. This deep-learning-based framework significantly accelerates the design and optimization cycle of vortex generators.

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