August 27-31, 2023
FLORENCE - ITALY
ICWE 16
16th International Conference on Wind Engineering

Data-driven rapid prediction model for aerodynamic force of high-speed train with arbitrary streamlined head

Zhenxu Sun [1], Shuanbao Yao [2], Renfang Huang [3], Dilong Guo [4], Guowei Yang [5]

[1] *Institute of Mechanics, Chinese Academy of Sciences, Beijing, China, sunzhenxu@imech.ac.cn*
[2] *CRRC Qingdao Sifang Co. Ltd., Qingdao, China, yaoshuanbao@cqsf.com*
[3] *Institute of Mechanics, Chinese Academy of Sciences, Beijing, China, hrenfang@imech.ac.cn*
[4] *Institute of Mechanics, Chinese Academy of Sciences, Beijing, China, guodilong@imech.ac.cn*
[5] *Institute of Mechanics, Chinese Academy of Sciences, Beijing, China, gwyang@imech.ac.cn*

SUMMARY: (10 pt)

Due to the complicated geometric shape, it's difficult to precisely obtain the aerodynamic force of high-speed trains. The main approaches, numerical simulations and wind tunnel tests, both suffer the issues of long assessment period and prohibitive cost. Taking numerical and experimental data as the training data, the present work proposed a data-driven rapid prediction model to solve this problem, which utilized the Support Vector Machine (SVM) model to construct a nonlinear implicit mapping between design variables and aerodynamic forces of high-speed train. Within this framework, it is a key issue to achieve the consistency and auto-extraction of design variables for any given streamlined shape. A general parameterization method for the streamlined shape which adopted the idea of step-by-step modeling has been proposed, so that the rapid extraction of the values of design variables could be realized. Taking aerodynamic drag as the prediction objective, the effectiveness of the model was verified. The results show that the proposed model can be successfully used for performance evaluation of high-speed trains. Under the condition that the prediction accuracy is comparable with numerical simulations, the efficiency of the rapid prediction model can be improved by more than 90%. With the enrichment of data for the training set, the prediction accuracy of the rapid prediction model can be continuously improved. Current study provides a new approach for aerodynamic evaluation of high-speed trains and can be beneficial to corresponding engineering design departments.
Keywords: Aerodynamic force, Inverse design, High-speed train

1. INTRODUCTION

As a near-ground rail transport tool with large slender ratio, the high-speed train usually experiences complex three-dimensional turbulent flow at high Reynolds number (Baker, 2010; Raghunathan et al., 2002; Schetz, 2001). The complex geometric shapes of key exposed components such as pantographs, bogies, and windshields have a great impact on the aerodynamic performance of trains. During the engineering design process, it's unbearable to perform high-fidelity numerical simulations for practical high-speed trains with multiple carriages. Therefore, most researches on the flow field characteristics of high-speed trains commonly consider simplified shapes (Hemida & Baker, 2010), for instance, ignoring the influence of bogies, pantographs and windshields, reducing the number of carriages(Wang et al., 2008), and scaling down the size of the model. Aiming at precisely and efficiently predicting aerodynamic force of high-speed train with arbitrary streamlined shape, a data-driven rapid prediction model was proposed in current study, which could make full use of existing data from numerical simulations and wind tunnel tests. With use of this model, a nonlinear implicit mapping between design variables and aerodynamic forces of high-speed train could be constructed. More importantly, within this framework, it is a key issue to achieve the consistency and auto-extraction of design variables for any given streamlined shape. A general parameterization method for the streamlined shape which adopted the idea of step-by-step modeling has been proposed, so that the rapid extraction of the values of design variables could be realized.

2. INVERSE DESIGN OF THE STREAMLINED HEAD

The inverse design of the head shape of high-speed train is to obtain the values of the design variables according to the three-dimensional geometric data of the existing head shape, then input the values into the head shape parametric design model to implement the reconstruction of the three-dimensional shape. The specific process for the inverse design of a streamlined head is shown in Figure 1：

① Determine the streamlined head that needs to be inversely designed, and perform grid discretization on it.

② Use the self-developed data processing code to automatically obtain the discrete data of each profile according to their location characteristics.

③ Adopt PSO algorithm to optimize and obtain the optimal value of each design variable for the key control profiles by taking minimizing the average fitting error as the optimization goal.

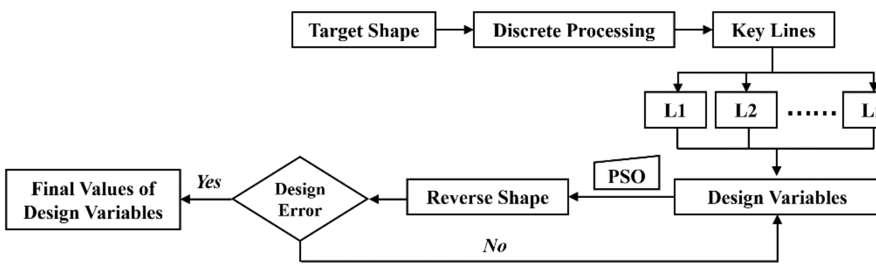

Figure 1. Flow chart for the inverse design of the streamlined head.

As seen in Figure 1, the single-objective PSO algorithm was adopted herein for the inverse design of the streamlined head. The specific coefficients for PSO are listed as follows: the population of particle swarm is 200, the total number of iterations is 500, the value of acceleration factor is 2, the inertia factor gradually changes from 1.2 to 0.8 as the number of iterations increases, and the maximum flight speed of the particles: the value for the cowcatcher is 2 and the value for the other key control profiles is 5.

The inverse design objective of each control profile is the average error between the inverse design profile and the target profile, and the objective function is shown below:

$$f_r = \frac{1}{n}\sum_{i=1}^{n} d_i \qquad (1)$$

Where f_r is the value of the objective function in inverse design, n is the number of discrete points of the control profile, and d_i is the minimum distance between each discrete point and the target line.

3. CONSTRUCTION OF THE RAPID PREDICTION MODEL

Current study adopts the algorithm ε-TSVR (ε-twin support vector regression) proposed by Shao et al. (2013) compared with standard SVM algorithm, ε-TSVR owns higher prediction ability and requires less training time.

Figure 2 shows the flow chart of optimizing free coefficients of the SVM model. The whole process is as follows:

1) For a given training sample set, determine the number of sampling groups, randomly group each training sample, and ensure that the number of training samples in each group is the same.

2) Determine the initial coefficients of PSO, such as the number of particle swarms, the number of iterations. The number of particles and the number of iterations have a great influence on the optimization efficiency, and should neither be too large nor too small.

3) Select a group of training samples sequentially as the test samples and use the other groups of training samples to construct the sub-SVM model, then obtain the prediction error of the test samples.

4) Obtain the optimal value of free coefficients after iteration. When using SVM to predict the target value, the average of the predicted values of each sub-SVM model is used as the final predicted value.

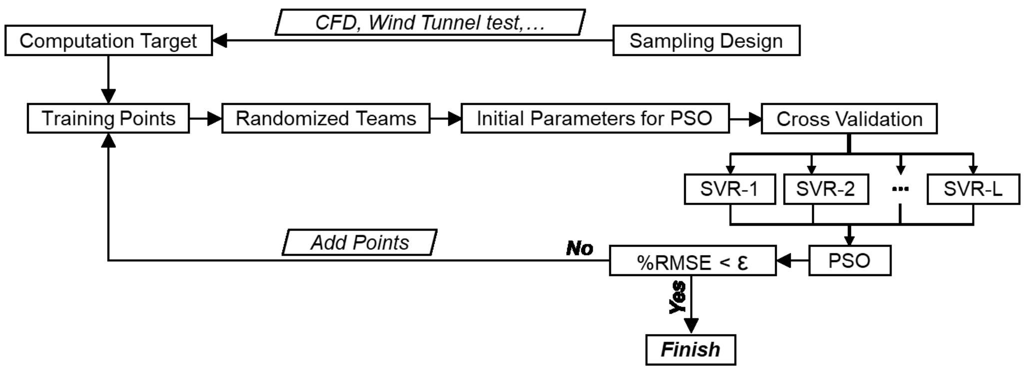

Figure 2 Construction flow chart of the SVM model.

4. RESULTS AND DISCUSSIONS

The effectiveness of the rapid prediction model is validated by taking the aerodynamic drag coefficient as the objective in current study. The distribution of the drag coefficient of the initial sample set is shown in Figure 3. The design objective is obtained ether from numerical simulations, as the black dots show, or from wind tunnel tests, as the blue dots show in Figure 3. It can be seen that samples from the numerical simulations are uniformly distributed while that from wind tunnel tests are distributed in area with larger value ranging from 0.32 to 0.39, which is because samples tested in wind tunnels are designed specifically under engineering design requirements with plenty engineering constraints such as vehicle gauge, cab space, and head length.

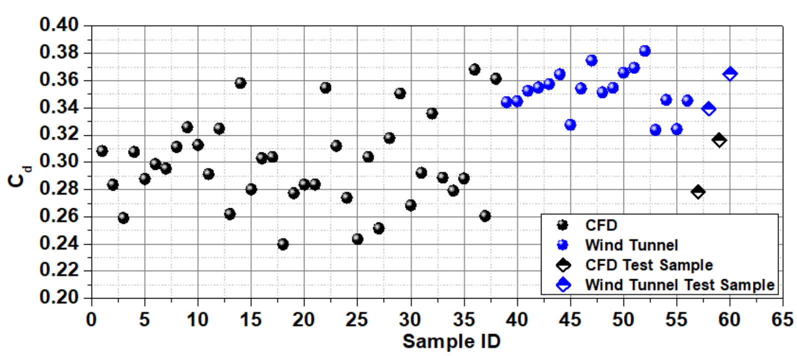

Figure 3 Target value distribution of the sample set.

Taking the wind tunnel test data as benchmark data, there is little difference between CFD calculation error and that of rapid prediction model, indicating that when the training samples reaches a certain number, the accuracy of the rapid prediction model is basically the same as the CFD simulation.

Table 1 Comparison of results from three different approaches.

	T1	T2	T3	T4
Wind Tunnel Test	/	/	**0.3394**	**0.3650**
Numerical Simulation	**0.2783**	**0.3163**	0.3375	0.3536
Rapid Prediction	0.2849	0.3021	0.3485	0.3685
Relative Error	2.37%	4.49%	2.61%	0.96%

5. CONCLUSION

The emphasis of this study is to present a framework of data-driven rapid prediction model and demonstrate its promising potential in predicting aerodynamic forces of high-speed trains. Using the proposed model, the prediction efficiency and accuracy could be both achieved. As demonstrated in this work, we adopted the idea of step-by-step modeling, and proposed a general three-dimensional parameterization method for head shape. Combining with the inverse design concept, the rapid extraction of the values of the design variables were realized. Using data from numerical simulations and wind tunnel tests as the initial training data, and adopting the SVM model to construct a nonlinear implicit function between design variables and aerodynamic forces of high-speed train, the data-driven rapid prediction model was finally proposed. Taking aerodynamic drag as the prediction objective, the effectiveness of the model was verified. When the number of training samples reaches a certain amount, the accuracy of the rapid prediction model can be basically the same as numerical simulations. Remarkably, although only aerodynamic drag is used to verify the effectiveness of the prediction model, by changing the objective of the training samples, it can be directly applied to the rapid prediction of other aerodynamic indicators such as aerodynamic lift, aerodynamic noise, and tunnel pressure waves.

6. REFERENCES

Baker, C. (2010). The flow around high speed trains. *Journal of Wind Engineering and Industrial Aerodynamics*, *98*(6-7), 277-298.

Raghunathan, R. S., Kim, H.-D., & Setoguchi, T. (2002). Aerodynamics of high-speed railway train. *Progress in Aerospace sciences*, *38*(6-7), 469-514.

Schetz, J. A. (2001). Aerodynamics of high-speed trains. *Annual Review of fluid mechanics*, *33*, 371.

Hemida, H., & Baker, C. (2010). Large-eddy simulation of the flow around a freight wagon subjected to a crosswind. *Computers & Fluids*, *39*(10), 1944-1956.

Wang, Y., Wang, Y., An, Y., & Chen, Y. (2008). Aerodynamic simulation of high-speed trains based on the Lattice Boltzmann Method (LBM). *Science in China Series E: Technological Sciences*, *51*(6), 773-783.

Shao, Y.-H., Zhang, C.-H., Yang, Z.-M., Jing, L., & Deng, N.-Y. (2013). An ε-twin support vector machine for regression. *Neural Computing and Applications*, *23*(1), 175-185.