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Aerodynamic Function Learner (AFL): Data-based autonomy discovering framework for nonlinear form aerodynamic equations

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SUMMARY:
An accurate and concise aerodynamic force expression is significant for wind-induced vibration analysis. The existing semi-empirical data-driven model try to find out the best model can fit aerodynamic nonlinearity, which leads to the large model with too many parameters. This work proposes a novel neural network to find the nonlinear form expression for aerodynamic from data autonomously, which called Aerodynamic Function Learner(AFL). Compared with traditional "blackbox" neural network, AFL can produce interpretable and generalizable results. First step is dataset collection by forced motion wind tunnel test. Secondly, the full-connective aerodynamic function learner network is trained by fitting experimental data. After training, the connection in network becomes sparsity. At last, the function can be discovered from the explanation of network. It is worth mentioning that this algorithm can find expression which is not obey superposition rule. The effectiveness of the framework is verified by a experimental dataset, which is collected by force motion wind tunnel test.

Keywords: Nonlinear aerodynamic, Equation learner, Neural network

1. INTRODUCTION

An accurate and concise aerodynamic force expression is significant for wind-induced vibration analysis, including aeroelastic stability analysis and structural shape optimization(Curtiss Jr et al., 2013). Since 1920s, the foundation of linear unsteady aerodynamic theory was created and divided into three basic problem: simple harmonic oscillation lift frequency response, impulsively started lift step response and gust problem. In order to solve engineering problem in real world, the semi-empirical modeling becomes popular. since the failure of Old Narrow Tacoma Bridge, a classical example is flutter derivatives(Scanlan and Tomko, 1971), which is the most widely used theory in bridge wind-resistant design. The aerodynamic force expression format with undetermined parameters is sufficient and more effective for engineering practice.

Semi-empirical expression format is from understanding of aerodynamic force, like linear-relation between aerodynamic force and motion from Theodorson's research. During several decades research, more and more nonlinear aeroelastic phenomenons of wind-induced vibration have been found, like limit-cycle oscillation, multi-frequency effect, hysteretic phenomenon and motion dependence features. The existing semi-empirical data-driven model does not focus on what causes aerodynamic nonlinearity, only try to find out the best model can fit aerodynamic nonlinearity.

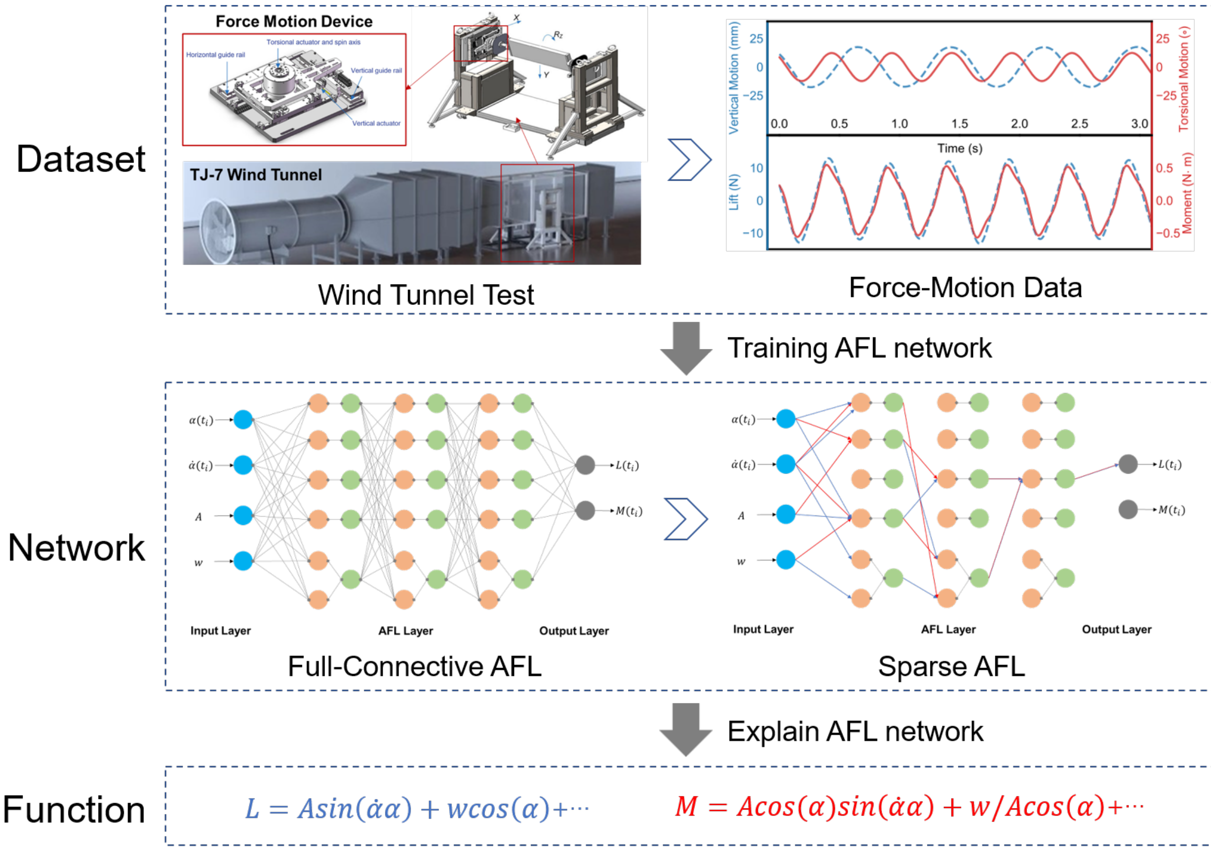

Figure 1. Schematic of nonlinear aerodynamic function discovering method. First step is dataset collection by forced motion wind tunnel test. Secondly, the full-connective aerodynamic function learner network is trained by fitting experimental data. After training, the connection in network becomes sparsity. At last, the function can be discovered from the explanation of network.

In order to discover a concise and fitted expression for nonlinear aerodynamic force autonomously, this study propose a data-based autonomy discovering method(Ma et al., 2023). The unknown nonlinear aerodynamic function $F = f(x)$ can be transferred to a concise combination of several symbolic operation. The most effective items are chosen by algorithm and used to rebuild nonlinear aerodynamic system. The previous work can find accuracy and concise superposition equations for aerodynamic, which means the target nonlinear expression (f) is a linear combination of nonlinear functions:

$$f(x) = \sum_j \theta_j g_j(x) \tag{1}$$

This work tries to build a novel data-based autonomy discovering framework, which can find aerodynamic equations that have nonlinear expression form and do not necessarily obey superposition rule. The nonlinear expression form can be written as:

$$f(x) = f(W \cdot x + b) \tag{2}$$

In this work, a neural network architecture named aerodynamic function learner(AFL) is proposed to fit the aerodynamic motion-force data. Compared with traditional "blackbox" neural network, AEL can produce interpretable and generalizable results. The training data is collected by forced motion wind tunnel test. Schematic of nonlinear aerodynamic function discovering method is shown in Figure 1.

2. AERODYNAMIC FUNCTION LEARNER NETWORK ARCHITECTURE

The aerodynamic function learner (AFL) neural network is based on fully-connected neural network, which is shown in Figure. 2. The activation function of each layer, rather than being the usual choices in neural networks such as ReLU or tanh, may consist of several functions (such as sine or the square function). It makes the AEL might be written as a physically meaningful explicit formula.

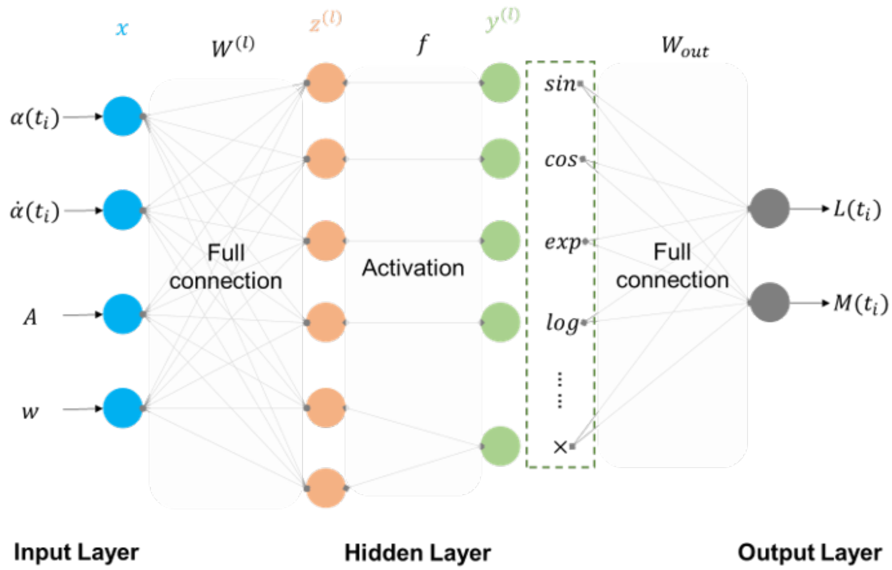

Figure 2. Example of the Aerodynamic Function Learner(AFL) neural network. The number of hidden layer can be increased as needed.

For a L-layer network, there are $L-2$ hidden layers, each consisting of a linear mapping followed by non-linear transformations. The output of layer l can be written as follow:

$$y^{(l)} = \sum_j f_j(W^{(l)} y^{(l-1)} + b^{(l)}) \tag{3}$$

where f_j is activation functions, $W^{(l)}, b^{(l)}$ is the weight and bias of layer l.

In order to find the most concise function that fits the relationship between motion to aerodynamic loads, the neural network should enforce sparsity. In this work, a L_0 regularization term is added to the loss function. It can set as many weight parameters to 0 as possible such that those parameters can be removed from the final expression.

3. AERODYNAMIC MOTION-FORCE DATASET

The data considered in this work are the force and motion measurement of quasi-flat plate in coupled vertical-torsional harmonic motion. These measurements originate from physical experiments. An aerodynamic force-motion dataset is a group of time series data, which records aerodynamic forces (Lift and Moment) and displacements (Vertical and Torsional) of a motioned object at each time step.

Forced vibration wind tunnel test is used to create the dataset, which can make the model move as pre-defined motion in time domain. All forced motion tests were implemented in TJ-7 boundary layer wind tunnel, which is a simple straight-flow wind tunnel with a test section of 0.65m wide, 3.2m long, and 1.2m high.

4. MODEL TRAINING

The AFL is fully differentiable, which allows us to train it by using back-propagation. A stochastic gradient descent algorithm with mini-batches and Adam is applied to calculate the weight updating. The mean square error (MSE) is used to quantify the accurate performance and the length of equation represents the concise metric. Limit to space, the detail of training results will be shown in full text.

5. CONCLUSIONS

This work proposes a novel neural network to find the nonlinear form expression for aerodynamic from data autonomously, which is called Aerodynamic Function Learner(AFL). The effectiveness of the framework is verified by a experimental dataset, which is collected by force motion wind tunnel test.

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