2022 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE) | 978-1-6654-9246-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/MLISE57402.2022.00093

Unteady aerodynamics modeling method based on dendrite-based gated recurrent neural network model

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***Abstract*—System identification-based aerodynamic reduced-order model (ROM) is an effective method for solving nonlinear unsteady aerodynamics prediction. However, most of the ROMs are shallow neural network architecture which is difficult to capture nonlinear aerodynamic behavior with large samples and Varying Mach Numbers. This paper proposes a dendrite-based gated recurrent neural network (DD-GRU) fusion model from deep learning theory to improve the capability of system identification-based ROM in varying flow conditions. DD-GRU network can process time-series data, which is also suitable for capturing the time-delay effect of unsteady aerodynamics. Unlike other recurrent models, DD-GRU uses the dendrite method to re-extract the logic of information of GRU. The approach is evaluated by predicting NACA64A01 airfoil transonic aerodynamic loads across multiple flow conditions. The example demonstrates that the model accurately predicts the harmonic aerodynamic response in the frequency and time domains with different flow conditions.**

Keywords:* *Reduced-order model; gated recurrent neural network; Unsteady aerodynamics; Neural network.

I. Introduction

High-fidelity computational fluid dynamics (CFD) is the primary method for predicting unsteady aerodynamics. However, because of the expensive cost of time and computing resources in full-order simulations, the CFD method is inappropriate for some aeroelastic analyses, like optimization design[1] and system control. System identification-based ROM is a black-box system that can handle the balance of computational efficiency and forecast accuracy well. These approaches have low computational complexity because they only need small-scale samples instead of full-order snapshots. System identification-based ROMs can divide into two types: One is linear algorithm methods, and the other is nonlinear algorithm methods. One of the exemplary linear identification approaches is the auto-regressive with exogenous input (ARX). Zhang and Ye [2]use this method for flutter analysis at a high angle of attack, and Jiang [3] analysis frequency locking in vortex induced vibration. However, the linear ROM performs poorly in the strong aerodynamic off-line caused by transonic shock wave motion, high angle of attack flow separation, or large-scale structural motion. To solve this limitation, researchers have developed many nonlinear ROMs. Kou and Zhang [4, 5] proposed an improved recursive radial basis function neural network (RRBF), predicting the aerodynamic load of unsteady transonic flow and simulating the limit-cycle oscillation (LCO) by coupling structural equations. Glaz, Liu, and Friedmann [6] developed a surrogate-based approach for predicting pitching/plunging nonlinear unsteady aerodynamic loads. Although a large number of ROMs have been developed and studied, these studies are basically limited to the simulation of single flow conditions. This situation is because most of the current ROM uses a shallow neural network structure, making it difficult to accurately identify aerodynamic loads across multiple Mach numbers and complex flow conditions.

There are two characteristics in the aerodynamic modeling under various flow conditions: the first is that with the change of parameters, the aerodynamic nonlinearity is stronger, and the dynamic behavior is complex. The second feature is that many data sample points will be generated under multiple working conditions. For a large dataset aerodynamic identification, the existing ROM construction approaches for small sample constant flow condition is unable to capture such complex dynamic behavior. To accommodate these characteristics, Deep learning (DL) methods which have attractive potential to deal with big training samples could be used. Deep learning has recently made great progress in Natural Language Processing (NLP), which means that it has the ability to process complex information in temporal data. More recently, deep learning has received extensive attention in fluid mechanics. Ling [7] uses airfoil images to train a convolution neural network for predicting airfoil aerodynamic coefficients. Li and Kou [8] proposed a long short-term memory network to accurately predict the aerodynamic load and coupled the structural equation to simulate the LCO effect. The gated recurrent neural network (GRU) solves the vanishing gradients problem of RNN, enables it to remember long-time information, and significantly improves the prediction ability of time series data. Hu et al.[9] used GRU to predict the ship trajectory, and the results show that the simulation trajectory is consistent well with the actual trajectory. Dai, Ma, Xu [10], and Feng [11] improved the GRU network to predict traffic flow. As one of the deep neural network architectures, the GRU network performs well on time series data and large training sets. Therefore, gated recurrent

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DOI 10.1109/MLISE57402.2022.00093

neural provide an excellent thought to capture the varying flow conditions in a nonlinear aerodynamic system.

In this paper, we propose a System identification-based ROM of dendrite-based gated recurrent neural network (DD-GRU). This ROM can process a large number of datasets, with the ability to predict transonic aerodynamic loads. NACA 64A010 airfoil filtered random signals at various vibration amplitudes and frequencies are used to train the ROM. The results show a good performance of DD-GRU for predicting the aerodynamic loads with various amplitudes in a range of Mach numbers.

II. METHODS

A. DD Model And GRU Model

Gidon et al.[12]found that dendrites can classify linearly inseparable inputs and have the ability of XOR calculation. Liu and Wang [13] proposed a dendrite neural network (DD) based on the above research. Dendrite structure extracts the logical relationship of data through the Hadamard product of neurons and inputs and realizes the nonlinear mapping from input to output. Fig.1 describes the basic units of the dendrite network structure. Where A^l and A^{l-1} denote the output and input of the model, respectively. $\circ$ is the Hadamard product. X is the original input. The dendrite model can extract logical information from the data[13]. This study combines the DD network with the GRU network, where GRU is responsible for processing large quantities of complex time-series data, and DD will process the interactive information between Gru outputs.

GRU is a typical deep neural network with memory ability. As the most widely used variant of LSTM, GRU can greatly reduce training time while having considerable accuracy. Its detailed structure is shown in Fig.2. The GRU is able to use two unique gating mechanisms to store important information, which can be stored in the network for a long time without being cleared because they are irrelevant to prediction. GRU selectively remembers or forgets information through the update gate and reset gate, respectively, so that the network has memory ability. The update gate is responsible for managing the current state, accepting the original part of the information, and forgetting the new part of the information. The reset gate is responsible for selecting the original part of the information and transferring it to the candidate state.

Calculation processes of the Gru are expressed by mathematical formulas as:

1) Calculate the reset gate and candidate hidden state

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{1}$$

$$h = tanh(W \cdot [r_t \times h_{t-1}, x_t]) \tag{2}$$

Where r_t is the reset gate, $\widetilde{h}_t$ represents the candidate state, h_{t-1} denotes the state of the previous time, and x_t represents the input of the current neuron.

2) Calculate the update gate and hidden status

$$u_t = \sigma(W_u \cdot [h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1-u_t) \times h_{t-1} + u_t \times \widetilde{h}_t \tag{4}$$

Where u_t represents the update gate and h_t is the current state.

B. DD-GRU

The DD-GRU fusion model proposed in this paper and the modeling process are illustrated in Fig.3.

This study uses three datasets to train, validate and test the model. The training set is used for model training and determining the model parameters, and the validation set is used to evaluate the model performance during training and determine the best model. The test set is the sample needed to

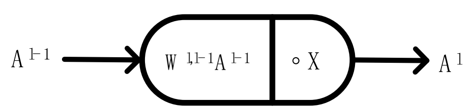


Figure 1. Typical structural unit of dendritic network.

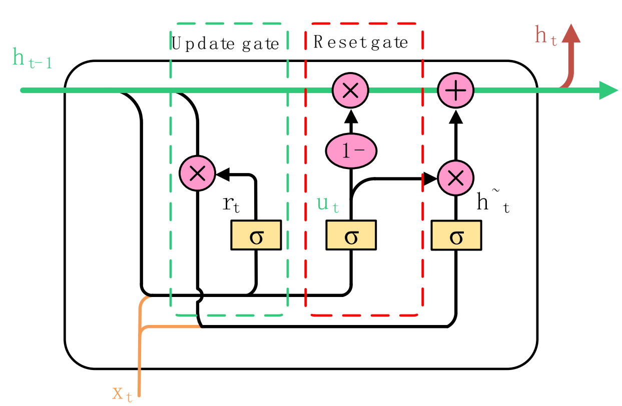


Figure 2. Basic structure diagram of gated recurrent unit network.

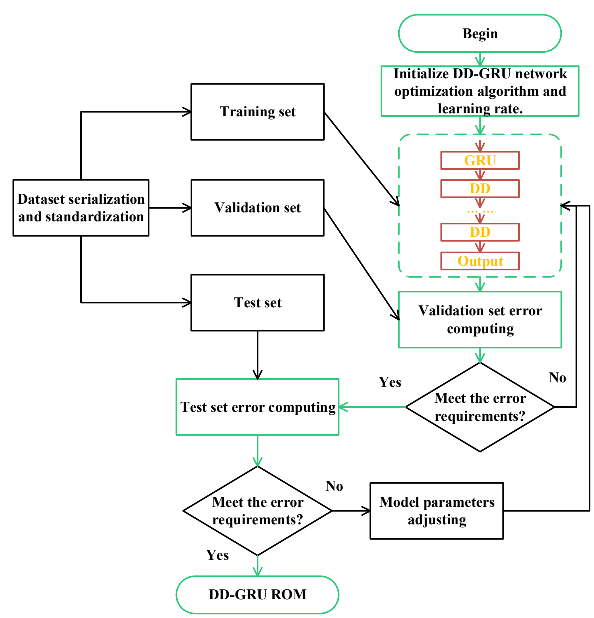


Figure 3. Flowchart of the DD-GRU aerodynamic model.

apply the model. The core training process of DD-GRU is divided into three parts. First, the data are serialized to retain the time information of the sequence, then put train data into the GRU network layer for training. Finally, the output of logical information by the GRU is further processed through the DD network, and the prediction results are output. This work uses the Keras library to build the DD-GRU network.

III. UNSTEADY AERODYNAMIC MODELING

In this paper, the System identification-based aerodynamic ROM is used to predict unsteady aerodynamic loads. Where the input variables of the ROM are transonic NACA64A010 airfoil pitching angle (α), plunging displacement (h/b), and Mach number (Ma). The output is the pitch and lift moment coefficients.

$$\begin{cases} u_t = [(h/b)_t \quad \alpha_t \quad Ma] \\ \qquad [(C_l)_t \quad (C_m)_t] \end{cases} \tag{5}$$

The ROM can be expressed by the following mathematical formula:

$$y_t = \varphi(u_t, y_{t-1}, h_{t-1}) \tag{6}$$

Where u_t and y_t are input and output of current time instant, and h_{t-1} denotes the memory state of the last moment. GRU simulates the time-delay effect of unsteady aerodynamics through hidden a state.

The DD-GRU network unit number has been set as 64 and uses one hidden layer. The model number of the DD network is set as 3, and the number of neurons is 64. The nadam optimizer is used for model optimization, avoiding the model falling into the local minimum.

In this work, the aerodynamic model of a NACA 64A010 airfoil with two degrees of freedom, pitching/plunging, was developed using DD-GRU neural network model, and the accuracy of the ROM has been verified. In order to obtain the prediction model of transonic multi Mach numbers, the training samples were selected as five transonic Mach numbers, with an interval of 0.2 from 0.74 to 0.82. The training and validation signals are filtered white Gaussian noise (FWGN) signals, consisting of 3500 and1000 time steps, respectively, as shown in Fig.4. In order to enable the model to learn a wider range of information, the training amplitude was set between 0.01 and0.7, and the validation set with smaller amplitudes was used to enhance the ability of the model to learn detailed information. The independent variable T in the figure represents the

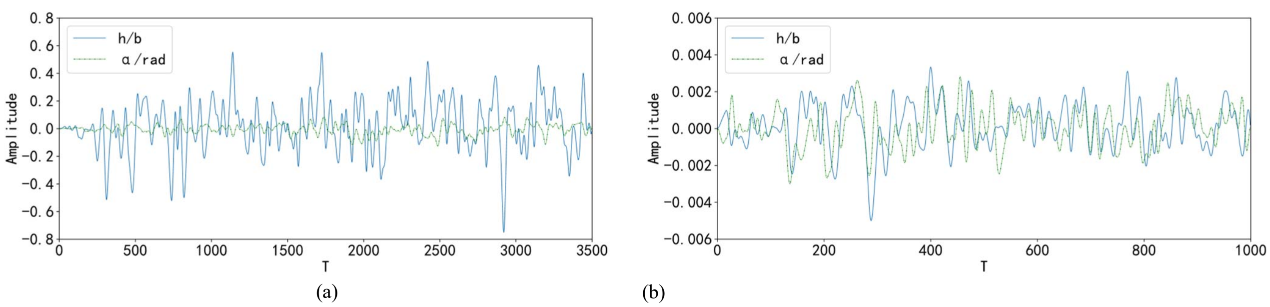


Figure 4. **a** Training inputs with 3500 time steps. **b** validation inputs with 1000 time steps

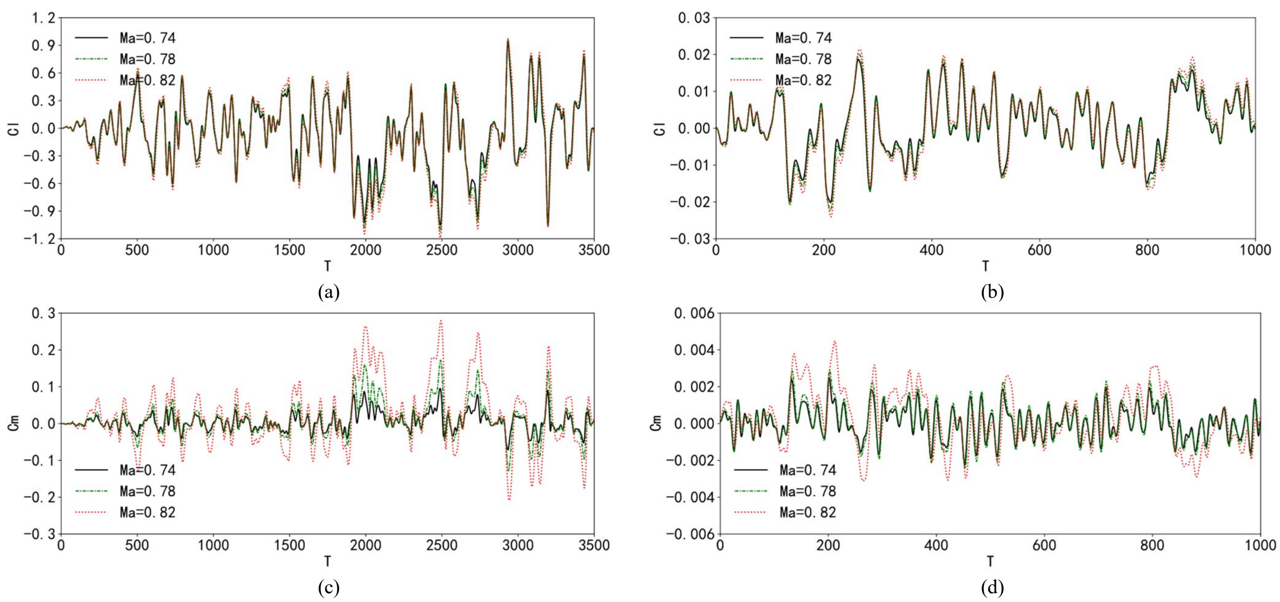


Figure 5. Aerodynamic loads calculated from CFD simulations at three Mach numbers: (a) lift coefficient of train set. (b) lift coefficient of validation set. (c) moment coefficients of train set. (d) moment coefficients of validation set.

dimensionless time. To ensure that the training signal covers sufficient frequency information, the time step D_t of ROM and CFD is set to 0.6 and 0.4, respectively. Large amplitude samples are used as training to ensure that the model learns as much information as possible, and small amplitude random movements are used as validation to verify how well the model learns detailed information. The strong nonlinear characteristics of the aerodynamic loads of the training and validation signals can be seen in Fig.5. As in (7), this study used Relative error to estimate the accuracy. The data in this paper comes from [5], and more details are given in the literature.

$$r = \frac{\left\| y_{ROM} - y_{CFD} \right\|_F}{\left\| y_{CFD} \right\|_F} \times 100\% \tag{7}$$

Where y_{CFD} is the CFD simulations, y_{ROM} is Predictive result of ROM.

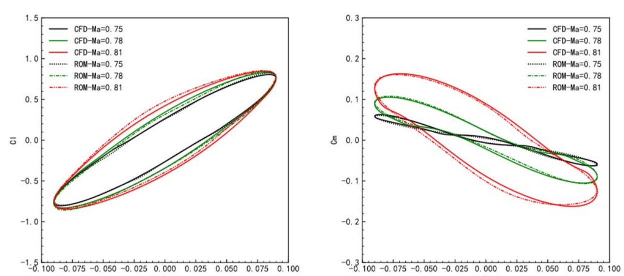
IV. Results and Discussion

In this study, the test set comprises different time steps N_t, amplitude, Mach number, and frequency. However, only four representative cases are selected to show the performance of the model in this paper. The test sets were selected from some harmonic motion signals at a different reduced frequency k, which calculate by (8) to evaluate the aerodynamic ROM of the noise environment. The equilibrium positions of these harmonic motions are at zero pitching or plunging. For each single frequency example, we calculated more than ten cycles to eliminate the influence of the transient effect on an aerodynamic force at the initial stage of simulation. The predicted hysteresis comparison results are all from the last cycle.

$$k = \frac{\omega b}{V} = \frac{\pi}{N_t \times D_t \times M} \tag{8}$$

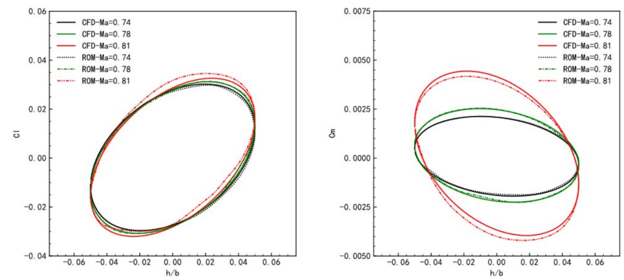
Where N_t is the number of the time steps, D_t is the aerodynamic time step, M denotes the Mach number.

From Figs.6-9, it can be seen that DD-GRU can accurately predict the hysteresis loops under different working conditions. Due to the strong nonlinear characteristics of the moment coefficient itself and the limited sample of linear kinetics, the overall prediction of the moment coefficient is not as good as



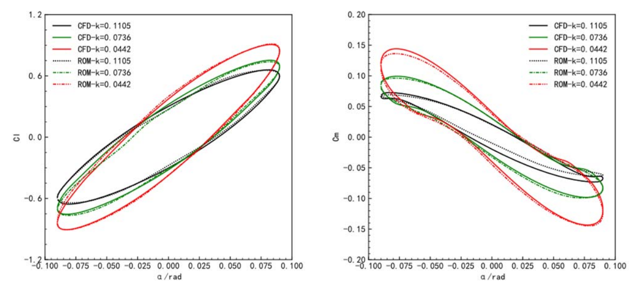
(a) (b)

Figure 6. Predictions of harmonic motions across three Mach number with $(\alpha/\mathrm{rad})_{max}$ =0.07 and 120 steps/period: (a) Lift coefficient. (b) Moment cofficient.



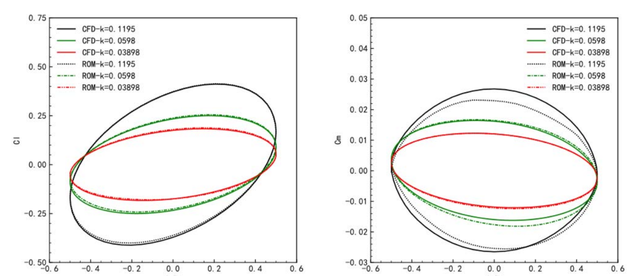
(a) (b)

Figure 7. Predictions of harmonic motions across three Mach number with $(h/b)_{max}$ =0.3 and 90 steps/period: (a) Lift coefficient. (b) Moment cofficient.



(a) (b)

Figure 8. Predictions of harmonic motions across three reduce frequencies with $(\alpha/\mathrm{rad})_{max}$ =0.09 and Ma=0.79: (a) Lift coefficient. (b) Moment cofficient.



(a) (b)

Figure 9. Predictions of harmonic motions across three reduce frequencies with $(h/b)_{max}$ =0.5 and Ma=0.73(extrapolation): (a) Lift coefficient. (b) Moment cofficient.

the lift coefficient.

It can see that the model accurately gives the pitching motion response under different amplitudes at low Mach numbers in Fig.6 and 7. When the Mach number is equal to 0.81, shock waves are generated on the wing surface, and the aerodynamic nonlinearity becomes extremely complex. however, the ROM still basically predicts the trend of the lift coefficient and moment coefficient at this time.

As shown in Fig.8 and 9, the model's performance was evaluated by using harmonic motion at the same Mach number and amplitude for different reduced frequencies. It can be seen that the amplitude of pitching motion increases

TABLE I. RELATIVE ERROR OF TEST CASE

Degree of freedom	Selected variables and results				
	Ma	$(\boldsymbol{h/b})_{max}$ ***or*** $(\boldsymbol{\alpha/rad})_{max}$	***k***	***Cl (%)***	***Cm (%)***
Pitching	0.75	0.09	0.0582	2.38	4.71
Pitching	0.78	0.09	0.0559	3.38	4.39
Pitching	0.81	0.09	0.0539	4.90	6.05
Plunging	0.74	0.05	0.0776	4.15	4.28
Plunging	0.78	0.05	0.0746	3.32	2.78
Plunging	0.81	0.05	0.0718	7.64	7.03
Pitching	0.79	0.09	0.1105	3.05	11.12
Pitching	0.79	0.09	0.0736	5.36	3.85
Pitching	0.79	0.09	0.0442	2.84	4.86
Plunging	0.73	0.5	0.1195	1.93	14.10
Plunging	0.73	0.5	0.0598	3.93	7.27
Plunging	0.73	0.5	0.0398	2.59	1.82

with the increase of reduced frequency, but the model can still accurately grasp the phase information. In Fig.9, As the extrapolation example, the ROM shows good generalization performance for the lift coefficients but fails to capture their peaks well for the strongly nonlinearly varying moment coefficients. The relative error results of fig.6-9 list in Table 1. It can be seen from the table that the relative error is within a reasonable range, and the maximum error is 14.10%, which is obtained in the extrapolation experiment.

V. CONCLUSIONS

This paper proposes a system identification-based aerodynamic ROM based on DD-GRU. By coupling the GRU network's time sequence information processing ability and the logical information extraction ability of the DD network, this deep learning approach can simulate and predict the complex aerodynamic nonlinear time-delay effect. The ROM is verified by using the two degrees of freedom motion data of a NACA 64A010 airfoil in transonic flow.

The experimental results show that the ROM successfully predicts the unsteady aerodynamic loads varying multiple Mach numbers. The ROM can accurately predict the aerodynamic moment coefficients and lift coefficients under harmonic motion. Extrapolation experiments demonstrate the excellent generalization performance and robustness of the model. In general, the DD-GRU network proposed in this paper can effectively predict the strong nonlinear characteristics in unsteady aerodynamics and is a tremendous potential system identification-based ROM.

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