

# Neural Network Based Adaptive Control of Synthetic Jet Actuator

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**Abstract** A synthetic jet actuator (SJA) is a zero-net-mass-flux device that imparts fluid momentum and is useful for active flow control (AFC). In many applications, SJAs are either used to suppress unwanted flow separation or control the flow directions. However, due to the delay and unsteadiness of the SJA influence and non-linearity of flow dynamics, it could be rather difficult to model the overall system and optimize the SJA controller to achieve desired effect. In this paper, in an attempt to resolve these problems, an Artificial Neural Network (ANN) has been used to model the airfoil system. Accordingly, in order for all points of the output to approximate the trajectory, a Model Predictive Controller was used. According to the results achieved, it can be said that the ANN Model Predictive Controller achieved online adaptive learning based on the response of the rough exterior controller and successfully reduced the errors and fluctuations of system output.

**Keywords** Neural Network Predictive Controller, Aerodynamic Control, Synthetic Jet Actuator

## 1 Introduction

A synthetic jet actuator transfers momentum to the surroundings by alternately ingesting and expelling fluid through a cavity containing and oscillating diaphragm and has been shown to be a useful AFC device [1, 2]. Compared with continuous jets, synthetic jet actuators (SJAs) are low-weight, compact and do not require internal fluid supply lines [3, 4]. A schematic diagram of a typical synthetic jet actuator is shown in Fig. 1, which also illustrates the primary structure and shows vortex pairs emanating from a nozzle while the SJA is in operation. An SJA typically has a nozzle or slot connected to a cavity in which a piezoelectric membrane oscillates. By oscillating the diaphragm, the working fluid is alternately ingested and expelled through the nozzle exit, forming a train of discrete vortical structures that impart linear momentum to the flow without net mass injection [5]. The ability of the vortex pairs to overcome the suction velocity during the ingestion stroke depends on its self-induced velocity, which in turn is a function of the vortex strength. The fact that no external fluid source is required combined with the availability of increasingly small vibrating diaphragms, e.g.

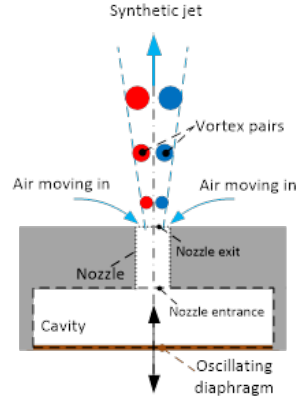


Fig. 1: Schematic diagram of a synthetic jet actuator.

piezo-electric disks, allows the design of extremely compact devices. [6, 7]. In the presence of cross flow, the vortex structure convects downstream, which creates a favorable pressure gradient and momentum exchange for separation suppression.

Neural networks are capable of identifying non-linear and complex systems, making them capable modeling tools. The gradient descent algorithms utilized for ANN training, such as Adam and Adadelata provide optimization of neural network weights to reduce the error of prediction and constantly updates the model when system behavior changes. A neural network is a black box in the sense that it can approximate any function and establish the underlying correlations, even though studying its structure won't give us any insights on the system. Therefore, the intricate design of equations and variables with physical meaning is required, and the model could improve on its own provided with a rough exterior controller to provide the initial training and the robustness of controller.

## 2 Numerical Models and Methods

### 2.1 Neural Network Structure

The structure of the NN used in the model predictive controller is given in Fig. 3. The purpose of the NN is to predict the future states of error with inputs obtained from the past.  $ewin[t+i]$  and  $Q[t+i]$  corresponds to the window averaged error and the jet amplitude over the nearest working cycle of SJA.  $i > 0$  corresponds to the future time step in the output layer, while  $i \leq 0$  corresponds to the past time step in the input layer. In addition, the angle of attack  $\alpha[t]$  and its first derivative  $\dot{\alpha}[t]$  are also directed to the input layer for better prediction.

### 2.2 Model Predictive Controller

The Model Predictive Controller (MPC) operates on the future prediction of data points from the NN based system model. In order for the output to track the desired trajectory, the MPC algorithm works to minimized the cost function based on these future points.

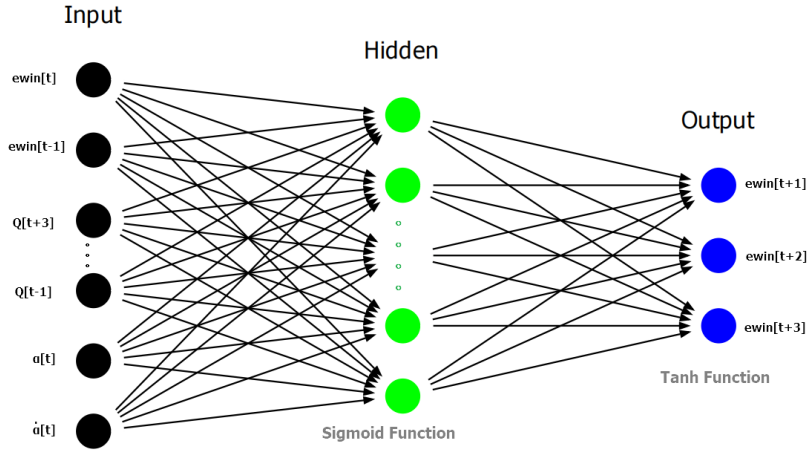


Fig. 2: Structure Diagram of the feedforward Neural Network.

The controller, at any time step, predicts the output signal in the prediction horizon  $y[t+i], i = 1, 2, \dots, N_p$ , and compares them with the reference trajectory. The controller performs the optimization of control inputs  $u[t+i], i = 1, 2, \dots, N_u (N_u < N_p)$  in the control signal domain to minimize the cost function  $J(u)$ . The controller then applies the optimal control input signal  $u[t]$  to the system afterwards.

$$J(u) = \sum_{i=1}^{N_p} \text{abs}(\hat{y}[t+i] - y_s[t+i])^3 w[i]$$

where  $w[i]$  is the control weighting defined for each time step in the future.

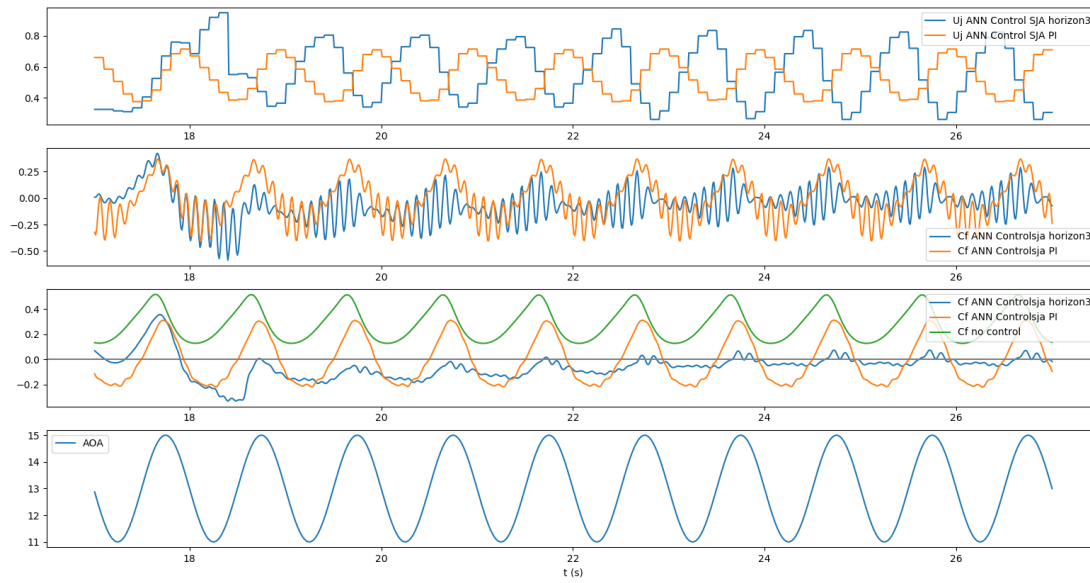


Fig. 3: Wall Friction Output.

## Declarations

### Availability of supporting data

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

### Competing interests

The authors declare that they have no competing interests.

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### Authors' contributions

XS implemented the model, checked the results, wrote the first draft and revised the manuscript. PS was responsible for funding and revision of the manuscript.

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