Active flow control using Synthetic jets and Neural Network

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ABSTRACT

Delay of stall using active flow control technique is an active area of research. The present study deals with active flow control technique using synthetic jets. Neural Network has been used to design the control system for active flow control and arrive at optimal flow rates and angle of synthetic jets. The optimization considers only angle of attack as the objective function and tries to increase it i.e., to delay the stall. The study considers NACA 0012 aerofoil with Mach number of 0.15 and Reynolds number of 3 million. Using both suction and blowing synthetic jets along with neural networks it has been shown that flow filed becomes favorable and stall angle is delayed.

INTRODUCTION

Stall is an aerodynamic phenomenon resulting in loss of lift. As the angle of attack of increased, the lift increases correspondingly. However upon reaching a peak value, for a particular angle of attack, the lift begins to plummet and for greater angles, the lift goes on decreasing at an alarming rate. This decrease in lift results in loss of control of the pilot over the aerodynamic surfaces of an airplane and eventually leading to catastrophic fatalities [1]. Since the safety of people is of paramount importance, a number of aviation and research organizations are pursuing to mitigate the stall and to avert/prevent the aerial disasters stemming out because of stall [2][3]. A number of methods have been devised to control stall phenomenon and they all can be grouped into two broad categories viz., active flow control methods and passive flow control methods [4]. In passive flow control, flow around the aerodynamic surfaces is monitored without the expense of external energy. Active flow control modifies a flow with external energy. A predetermined method of control involves the introduction of steady or unsteady energy inputs without consideration for the state of flow field. In interactive methods of flow control, the power input to the actuator (controller) is continuously adjusted based on some form of measuring element (a sensor). The control loop for interactive control can be either a feed forward or feedback. In the feed forward control loop, the sensor is placed upstream of the actuator. In the feedback control loop a sensor is placed downstream of the actuator to measure the control flow field parameter and is compared with upstream reference variable [5].

METHODOLOGY

The problem consists of designing a control system to delay stall using both suction and mass ejection simultaneously. As a first stage, k-ω SST turbulence model [6] is employed to carry out simulations over a NACA0012 aerofoil at subsonic flows for Mach number of 0.15 and for the corresponding Reynolds number of 3 million. An inlet velocity of 50 m/s is imposed on the inlet boundary and outflow condition is used since the turbulence parameters at the outlet are unknown. as shown in figure 2.2(a) and C_f graph at the trailing edge is as shown in figure 2.2(b).. The simulations so carried out are validated with the data obtained from NASA [7] and further the critical angle of attack is determined and the same is found to be around 16°. One of the active flow control methods; Synthetic jets, involving slits over the aerofoil for suction and blowing at 0.4c and 0.7c respectively is used to delay the stall phenomenon. The pressure along the aerofoil with the ones obtained from the CFD simulations are used to train a neural network based on back propagation algorithm. The whole control system model was implemented in Simulink so as to facilitate the implementation of controller on a microprocessor.

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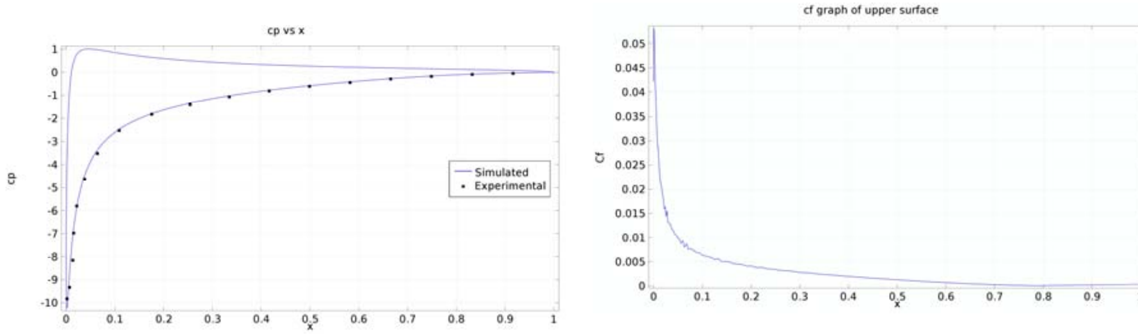
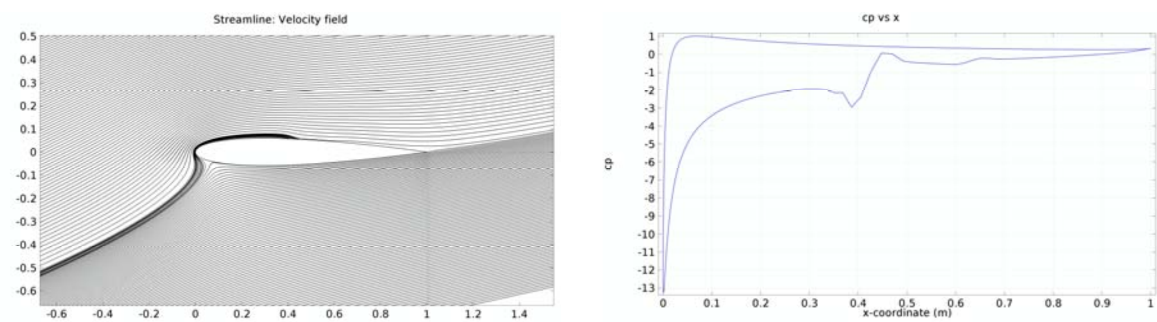


Figure 2.2 (a) Pressure coefficient graph (b) Wall shear stress graph.

To energize the flow over the aerofoil synthetic jets are used, also suction method is used to enhance the delay of separation of flow over the aerofoil to higher angle of attack. Two slits, each of length 0.05c is created over the aerofoil. The first slit created at 0.4c is used for suction and the other created at 0.7c is used for blowing [8]. Using Bernoulli's energy equation for dynamic fluids, the angles of suction and blowing along with the velocity of blowing is calculated and used as reference. Since neither of slit is perfectly horizontal with respect to chord line of the foil, their respective inclinations is considered while calculating β, γ and *r*. Where β is the angle of suction at the leading edge, γ is the angle of mass ejection at trailing edge and *r* is ratio expressed as velocity of mass ejection and free stream velocity. The simulation of synthetic jet actuators, involving the angle of attack 16.5° angle of suction(β) of -27°; angle of jet(γ) of 0°, -2° and -4° and jet ratio(*r)* of 1 and 1.5 is carried out (Figure 2.3(a)). The kinks in the Cp graph are due to presence of the slits (figure 2.3(b)).

2.3(a) Stream lines with active flow control, (b) Pressure coefficient with active flow control for AoA=16.5



deg.

The change of C_f sign towards the trailing edge suggests that the flow is not attached to the aerofoil, in other words the flow separation has taken indicating the onset of stall. But in figure 2.4(b) due to active flow control the flow remains attacked to the aerofoil, which is indicated by C_f number at the trailing edge (figure2.4(c)). This clearly shows that the active flow control method is affective in advancing the stall. The discontinuity in the graph indicates the presence of slit on the aerofoil for active flow control. Using active flow control simulations are carried out for angles beyond the stall and modified C_l vs. alpha graph is drawn which evidently shows the improved lift and the postponement of stall to a higher degree of 19° (figure 24(a)).

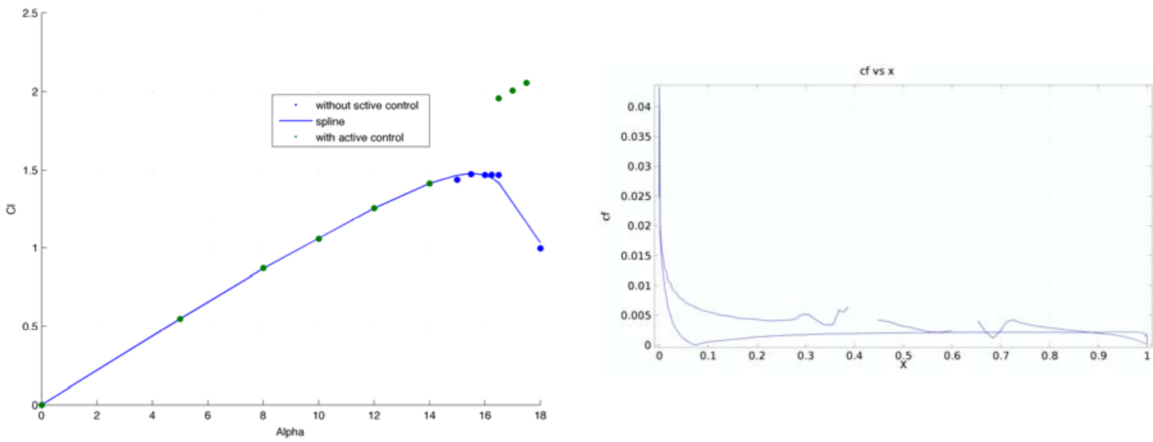


Figure 2.4 (a) Modified Cp graph with active flow control (b) Cf graph with active flow control.

A piezoresistive sensor can be used to convert the stall pressure into voltage signal which is directly used by the control system. The sensor for control system picks up the instantaneous values of pressure existing over the aerofoil. These values are used by the control system. The instantaneous pressure is checked against the stalling pressure. If the former is found to be greater and/or equal to the latter, the synthetic jets involving suction and blowing at the respective slits are actuated. The parameters involved in suction and blowing like □ and *r* are monitored by the control system so as to optimize lift and to eventually delay stall.

A control system is an interconnection of components forming a system configuration that will provide a desired system response. The basis for analysis of a system is the foundation provided by linear system, which assumes a cause-effect relationship for the components of a system.
To implement the control system Artificial neural networks [9] (Figure 2.6 shows the basic structure if neural network) is used because of the adaptive nature and ability to fit complex nonlinear functions. Feed forward neural network is non-parametrical statistical model for extracting non-linear relations in the data. A common NN model configuration is to place between the input and output variables, hidden layers or neurons. In this problem sinusoidal function is used as a transfer function since the output varies from -1 to +1 so that both negative and positive values can be mapped. The transfer function in the output layer is modified in order to map the out value from +∞ to —∞.

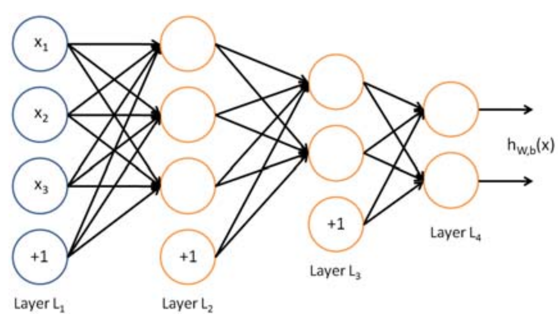


Figure 2.6 Neural networks with neurons, Input layer, Hidden and output layer.

The Neural Network with two hidden layer was constructed in Simulink. The hidden layer consisted of two layers with three neurons in each layer. Input layer consisted of one neuron and output layer contained two neurons. Pressure picked up by the pies-resistive sensor was used as independent input or feature set to predict the dependent synthetic generation velocity and angle of ejection. Since the neural networks are computationally expensive and their deployment in Simulink [10] is very difficult. Back-propagation algorithm [11] was not directly implemented in Simulink. Instead the neural network was trained offline using MATLAB® codes and the updated weights were directly used in the Simulink model to predict the output. Hence the Neural Network cannot update its weight online; as a result the network has limited range of output and accuracy. The Simulink model for feed-forward neural network is as shown in figure 2.7.

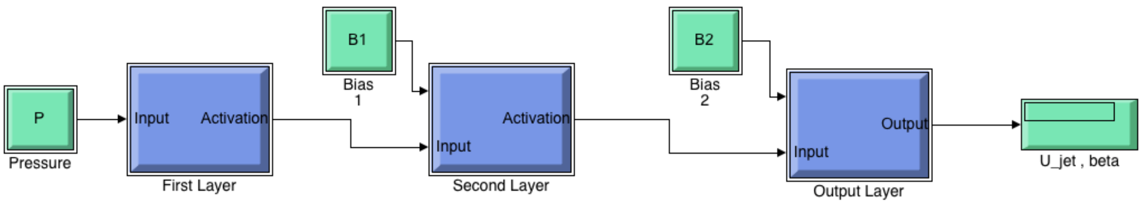


Figure 2.7 feed forward neural network in Simulink.

A motor Simulink model was constructed to connect the synthetic jet velocity (Figure 2.5) given by the neural network into a motor actuator that can pump desired velocity of synthetic jet. Calibration should be done in order to synchronize the motor speed and the jet velocity a PID controller can be used to control the motor, there by making it a closed loop actuator. Since all the simulations in Simulink are time dependent, we need to collect the data online through a data acquisition system for the performance characteristics of motor actuator. On the similar grounds an actuator to control for angle of the synthetic jet is contracted. In the model instead of using the speed of the motor, the angular position of the motor is used as an actuator to control the angle. Since a Continues speed motor is used, the angular position is not accurate. The output from the motor can be connected to other mechanisms through micro controller such that desired angle of incidence of the jet is obtained

IMPLEMENTATION OF NEURAL NETWORL FOR FLOWCONTTROL

The neural is trained by splitting the given data into training set and test set. In this case there were 18 data sets available. Hence 15 sets were used as training set and 3 were used as test set. This procedure is followed to determine the performance of the neural network and also to avoid the over fitting on the given test data. A neural network of two hidden layers each consisting of three neurons excluding the bias neuron. The output layer has two neurons corresponding to jet velocity and jet inclination and input neuron consists of two neurons corresponding to angle of attack and pressure at the trailing edge. Thus trained neural network was tested for generalization using the test and very good results were obtained. “fmincg" was used to minimize the error of the cost function, which an advanced line search algorithm for minimization.

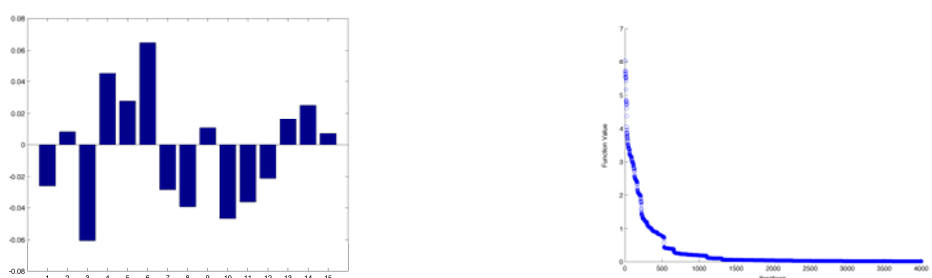


Figure 2.9 Error in the output layer and the value of the cost function.

Figure 2.9 shows the trained neural network error, it is evident that error is low and the network has learnt effectively. Thus using the trained neural network, CFD simulation and piezoresistive sensor are put together and simulated for over control effect and the results are as shown.

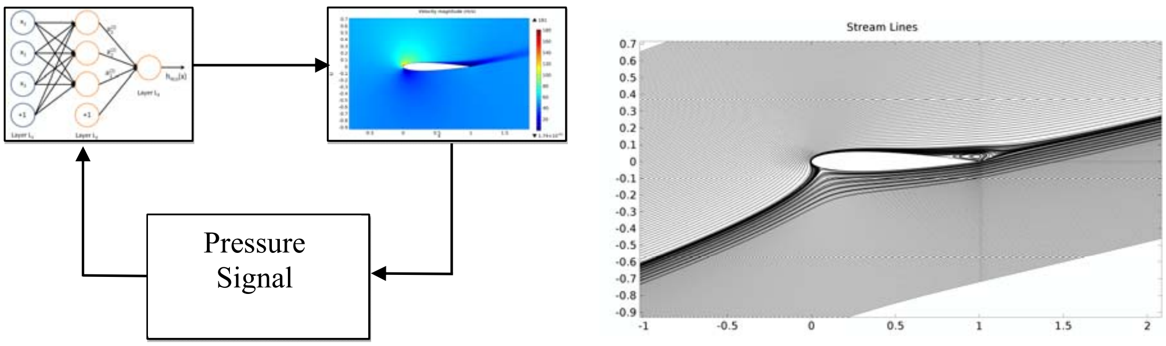


Figure 2.10 (a) The overall simulation (b) Velocity field without active flow control.

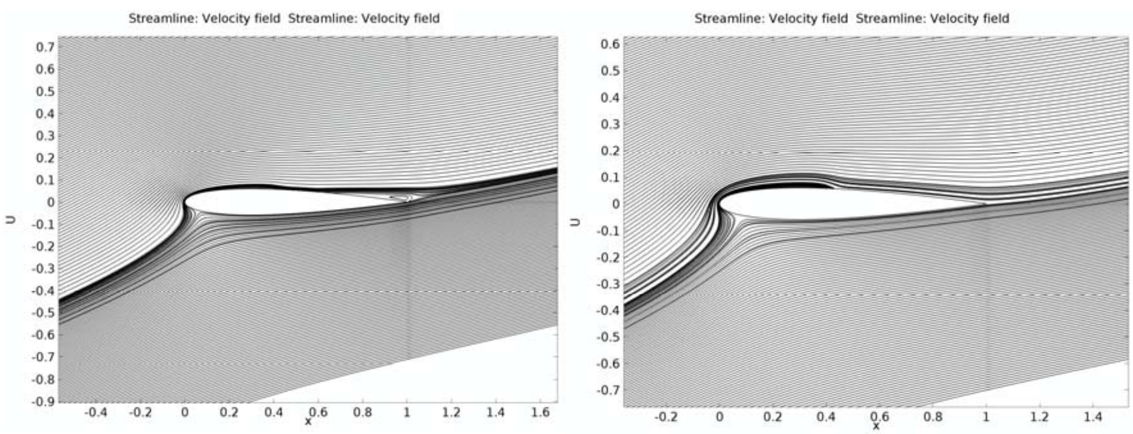


Figure 2.11 (a) Velocity field after one loop of controller (b) Velocity field after three loop of controller.

The overall implementation of neural network based control system is demonstrated by figure 2.10(a). The controller works in a loop (A loop can devices as the sequence of operation of the controller when actuated by the sensor) with the input from the piezoresistive sensor picking up the stall signal from the aerofoil. When the sensor picks up the signal the controller is actuated to generate synthetic jets by controlling the speed of the jet and the angle of inclination of the jet with respect to the chord line of the aerofoil. When the jet is actuated fluid flow on the aerofoil changes. Figure 2.10(b) shows the velocity profile after one loop of actuation. After actuating the jets a new pressure profile is generated, the sensor and feeder again pick this new pressure to the controller depending upon the new input, controller generates new values of jet velocity and angle of incidence (Figure 2.11(a)). This process is continued until the pressure profile settles to a stable Value and the output from the controller changes no more. Thus the optimized controlling action is achieved.

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CONCLUSIONS

The study aimed at developing a control system to delay stall to higher angle of attack in four stages as explained in the methodology. The four modules of the project, i.e., Validation of the turbulent CFD model on NACA0012 aerofoil; Synthetic jet generation; Design of control system are successfully completed. The following conclusions are drawn:

- The turbulent CFD model on NACA0012 aerofoil is successfully validated. Data obtained from various simulations carried out for some standard angles of attack are compared with the experimental data obtained from NASA [6].
- Synthetic jet actuation method is used as a type of active flow control to delay stall. Two slits are created, one for suction and the other for blowing.
- The pressure signals captured along with the stalling pressure are sent to the control system. The values of pressure sensed are decisive in activating the control system at the right moment for the right duration.
- A control system is designed to monitor the active flow process. Data obtained from the sensors and the turbulent CFD simulations involving synthetic jets are used to train the neural network offline so that appropriate values of r and □ are predicted using back propagation algorithm.
- Data on which the neural networks are trained may be insufficient for transient behavior. Hence training the neural network online will increase its reliability for transient solutions.
- The current study includes only stall angle as objective function for optimization, for better performance other factors like lift, drag and design constraints can be considered.

REFERENCE

[1] Crane and Dale. 1997, Dictionary of Aeronautical Terms, third edition, page 486. Aviation supplies & academics.

[2] National transportation safety board. 2002, Annual Review of Aircraft Accident Data U.S. General Aviation.

[3] Michael Braukus, John M. Foley and Daryl Stephenson. 2013, from http://www.nasa.gov/press/2013/november/nasa-boeing-finish-tests-of-757-vertical-tail-with-advanced-technology/#.U7yl4lbIR4U.

[4] Mohsen Jahanmiri. 2010:12, Active Flow Control: A Review, Division of Fluid Dynamics, Department of Applied Mechanics, CHALMERS UNIVERSITY OF TECHNOLOGY.

[5] Ari Glezer and Michael Amitay. 2002, George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Annu. Rev. Fluid Mech. 2002. 34:503–29.

[6] Menter, F. R., Kuntz, M., and Langtry, R., 2003, pp. 625 - 632, "Ten Years of Industrial Experience with the SST Turbulence Model," Turbulence, Heat and Mass Transfer 4, Ed: K. Hanjalic, Y. Nagano, and M. Tummers, Begell House.

[7] 2013, http://turbmodels.larc.nasa.gov/naca0012_val.html

[8] R. Duvigneau, A. Hay & M. Visonneau. 2004, Optimal location of a synthetic jet on an airfoil for stall control, Laboratoire de Mécanique des Fluides CNRS UMR6598 Equipe Modélisation Numérique Ecole Centrale de Nantes, rue de la Noé, 44321 Nantes, FRANCE.

[9] (2014), from http://en.wikipedia.org/wiki/Artificial_neural_network.

[10] Simulink® User manual. 2013, from http://www.matworks.com

[11] Andrew Ng., 2013, from http://www.coursera.com/machine_learning