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**APPLICATION OF NEURAL NETWORKS TO  
UNSTEADY AERODYNAMIC CONTROL**

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# Unsteady Fluid Dynamic Models and Control

## Problem

Understand → Predict → Control

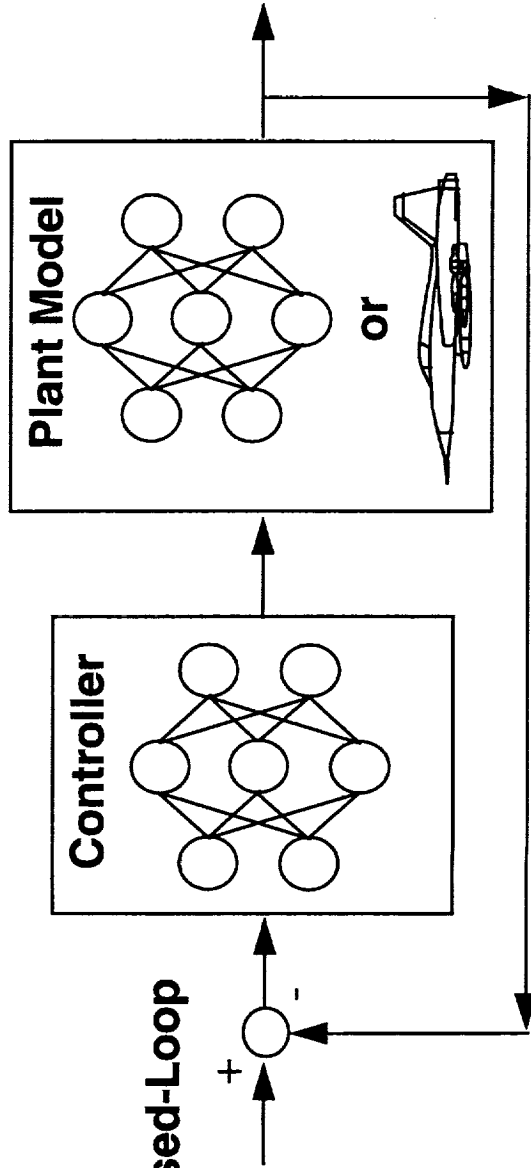
Fluid Mechanics of Dynamic Maneuvers  
Unsteady Boundary Layers  
Vortex Dominated Flows

## Potential Payoffs

Aircraft, Helicopters, Underwater Vehicles, Wind Turbines ...

## One Solution

Neural Networks:  
Demonstrate Closed-Loop  
Control



## Pitching Alters Vorticity Generation and Accumulation



**STEADY:**

**Vorticity  
generated and shed  
at equal rates**



**UNSTEADY:**

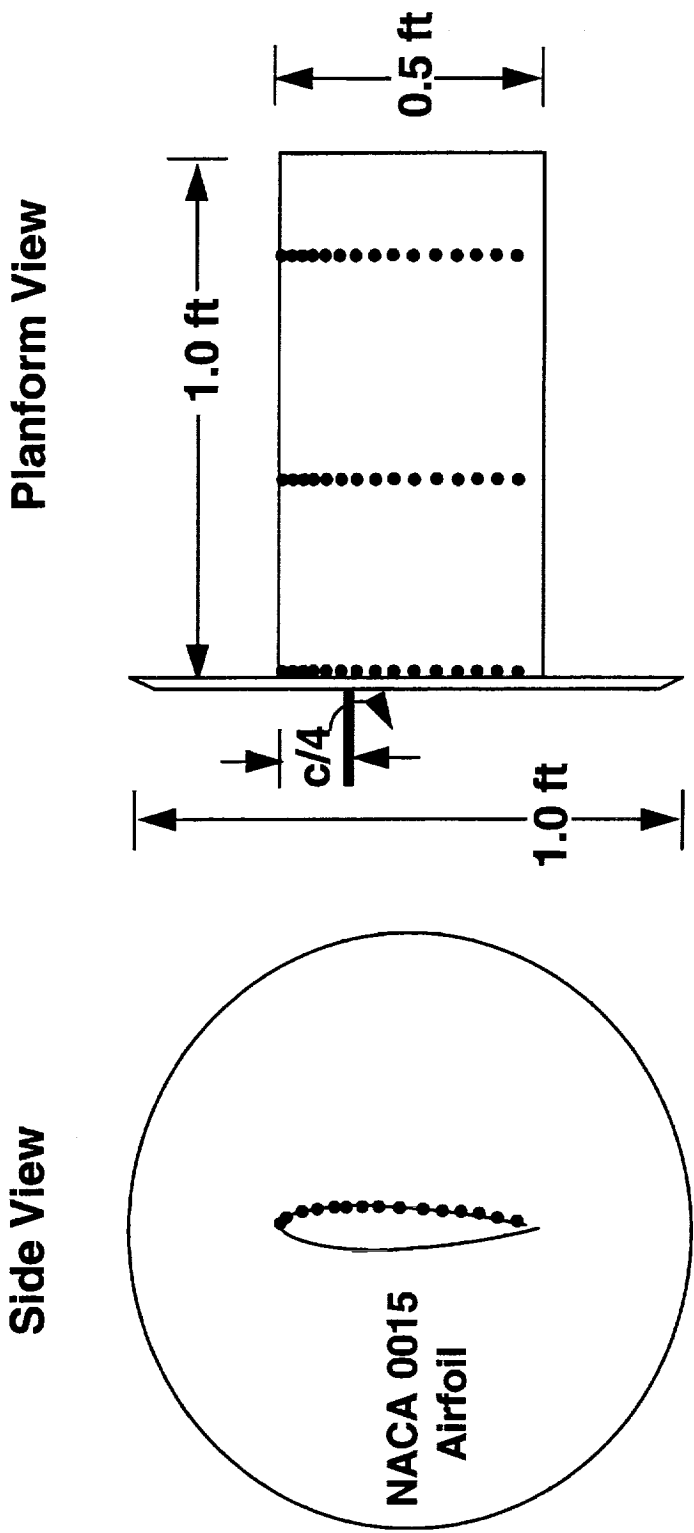
**Boundary layer  
separates,  
vortex initiated near  
leading edge**



**UNSTEADY:**

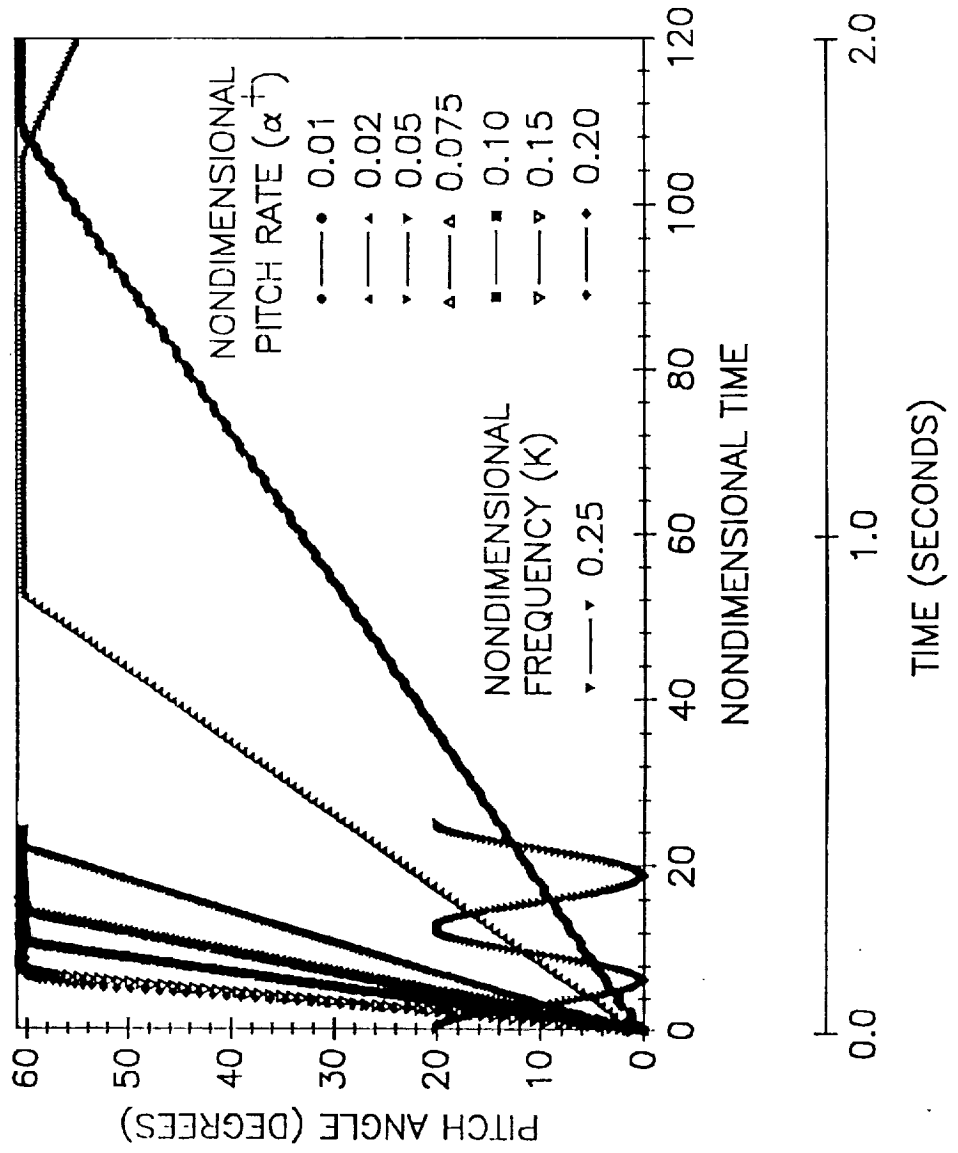
**Vorticity  
accumulates into  
large, energetic  
unsteady vortex**

# Wind Tunnel Wing Model



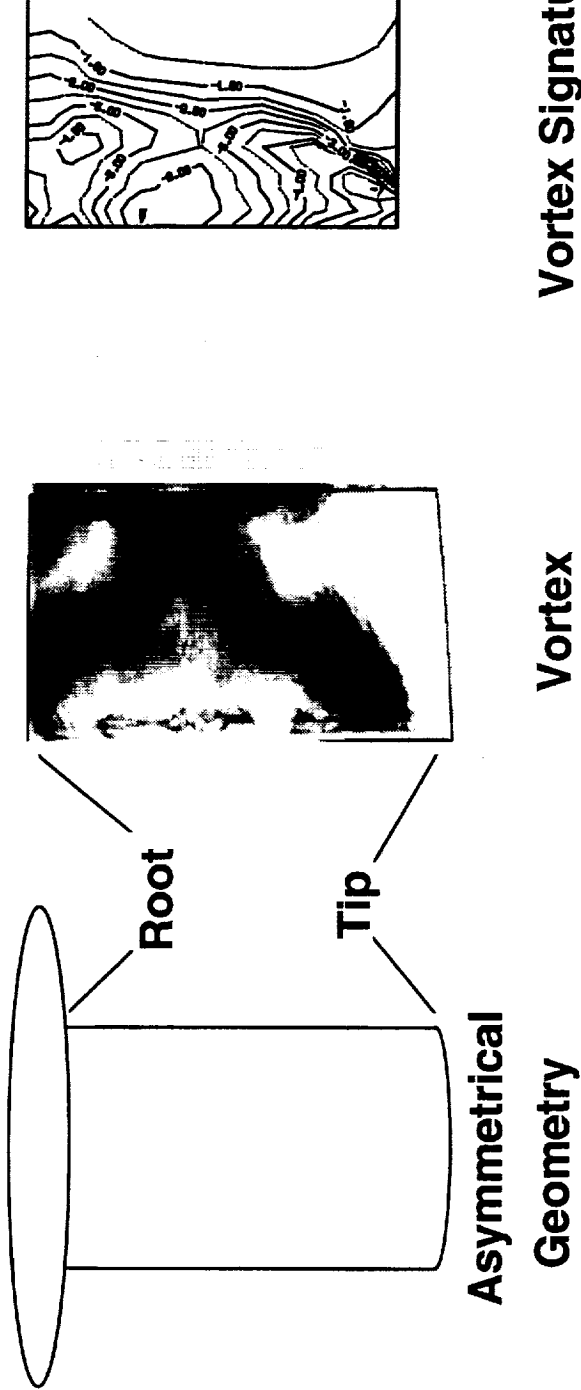
- 15 Pressure Taps (0 to 90% Chord)
- Pressure Transducers Close Coupled With Wing Surface
- 3 Span Locations (Wing Root, 37.5% Span & 80% Span)

# Wing Motion Histories



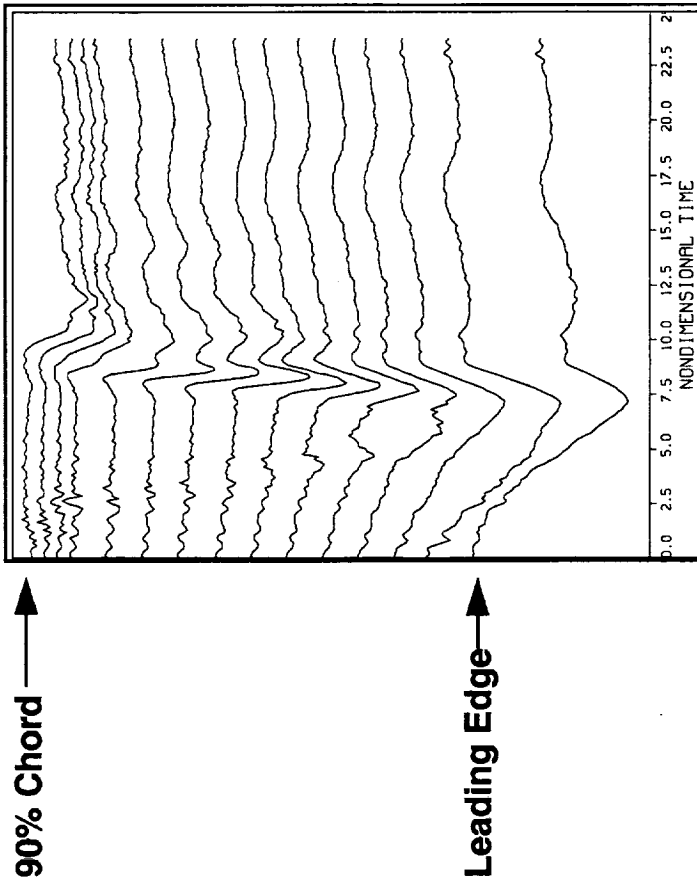
# Surface Pressure Topologies and Flow Visualization

- Free wing tip and bounded wing root give 3-D unsteady flow field



# Experimental Data Format

- Data Acquisition  
Sampling Rate 500 Hz

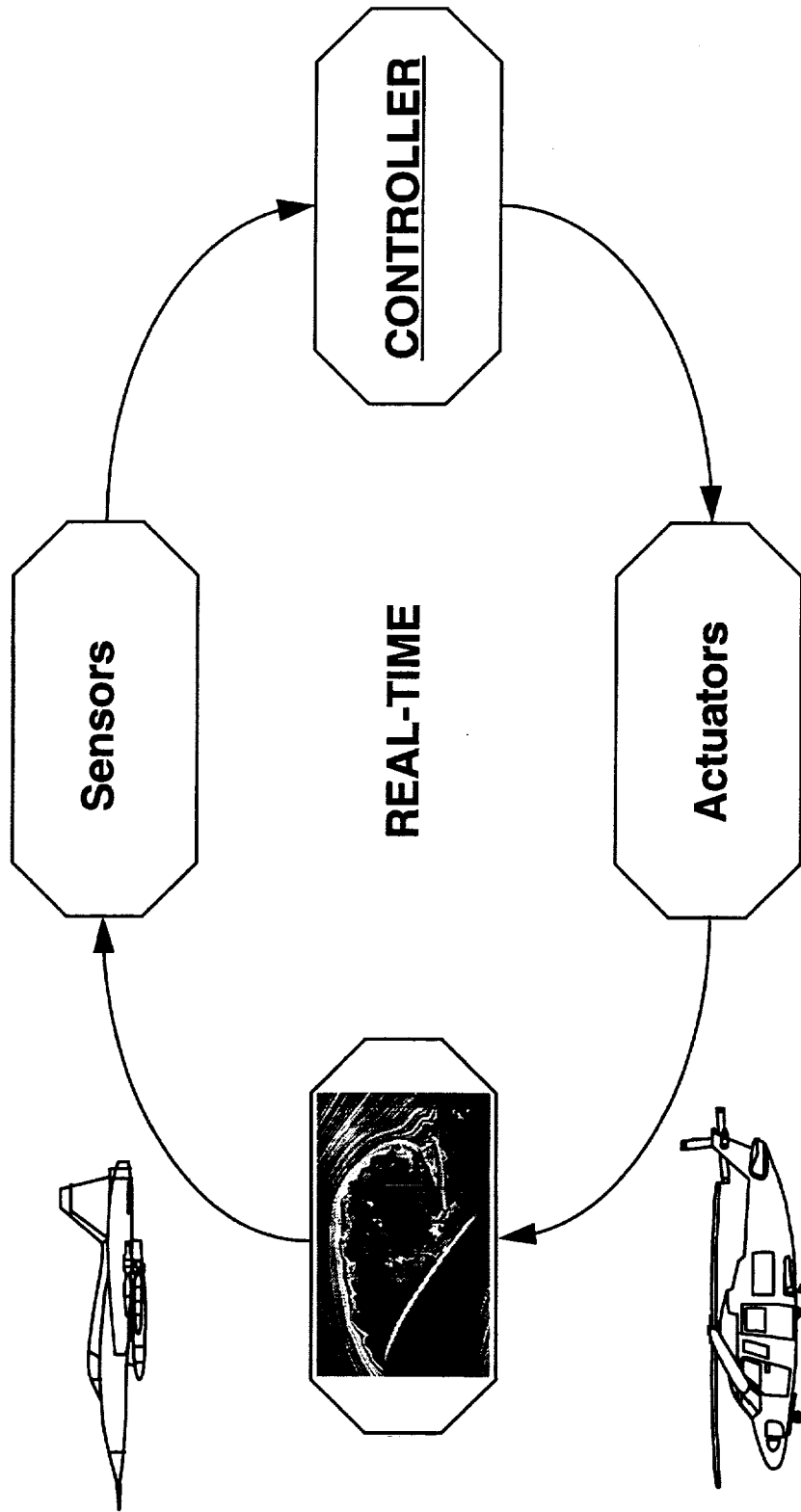


Samples

$C_{p15}(t1)$	$C_{p15}(t2)$	.....	$C_{p15}(t200)$
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
.	.	.	.
$C_{p2}(t1)$	$C_{p2}(t2)$	.....	$C_{p2}(t200)$
$C_{p1}(t1)$	$C_{p1}(t2)$	.....	$C_{p1}(t200)$

Time

# Neural Network Control Unsteady Aerodynamics





# Control System Requirements

## Constraints

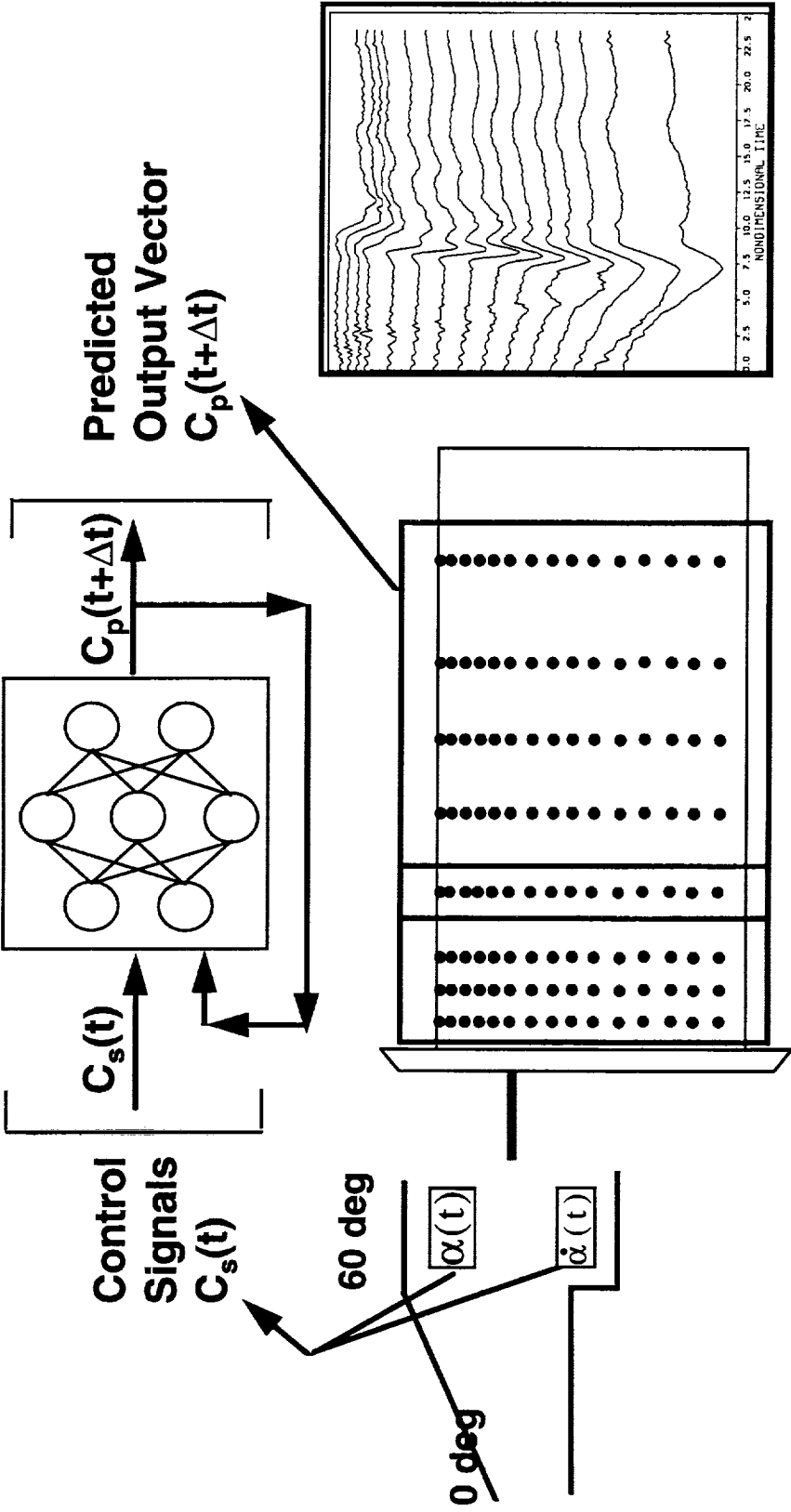
- Plant Output Can Be Highly Nonlinear
- Significant Time Lags Inherent to the System (Mechanical, Viscous and Convective)
- System Integration (Sensors, Actuators, Controllers, Flow Field Dynamics and the Time-Lags Associated with Each)

## Requirements

- Controller for Both Linear and Nonlinear Responses
- Predict the Future State of the Plant / Generate Control Signals with the Required Lead Times
- Many Inputs and Many Outputs in Parallel
- Integrate Multivariate Signals (Sensors, Actuators and Controller)
- Handle Temporal Mismatches (Time-Lags) Automatically

# Neural Network Control

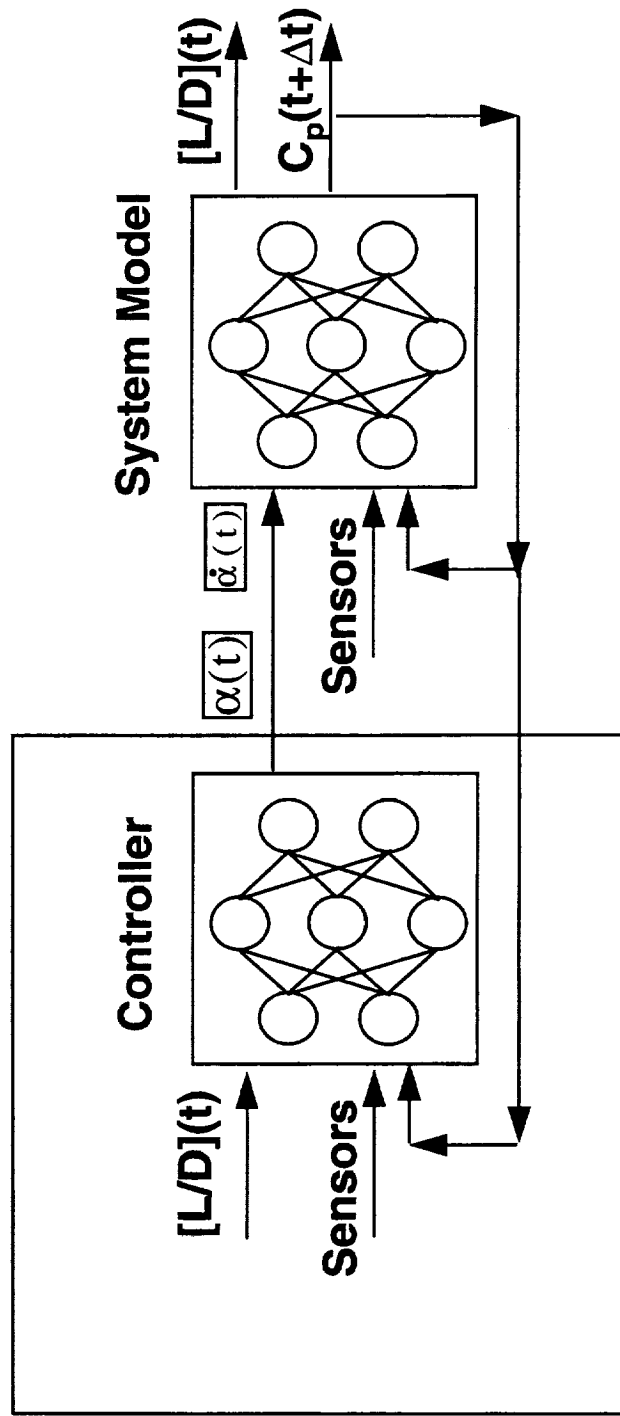
- Develop Neural Network Model of the Plant



- Inputs: Wing Motion History and Recurrent Feedback
- Outputs: Time-Dependent Unsteady Surface Pressures & Forces/Moments

# Neural Network Control

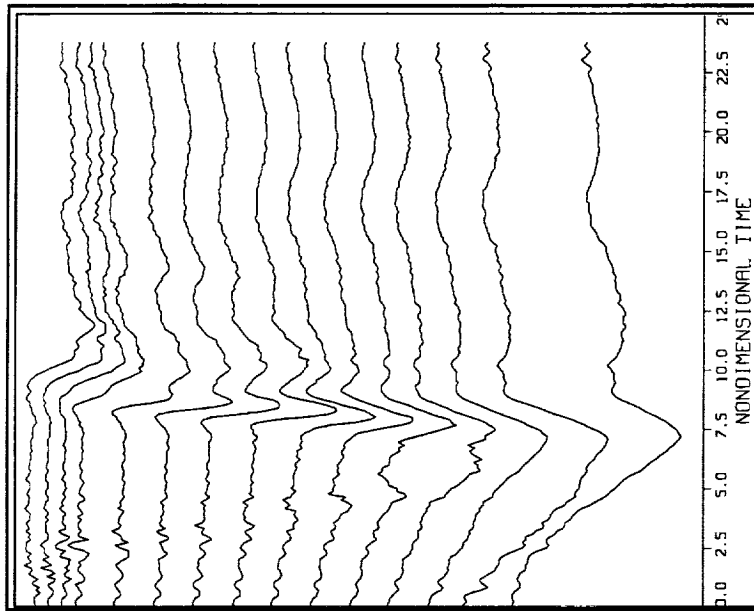
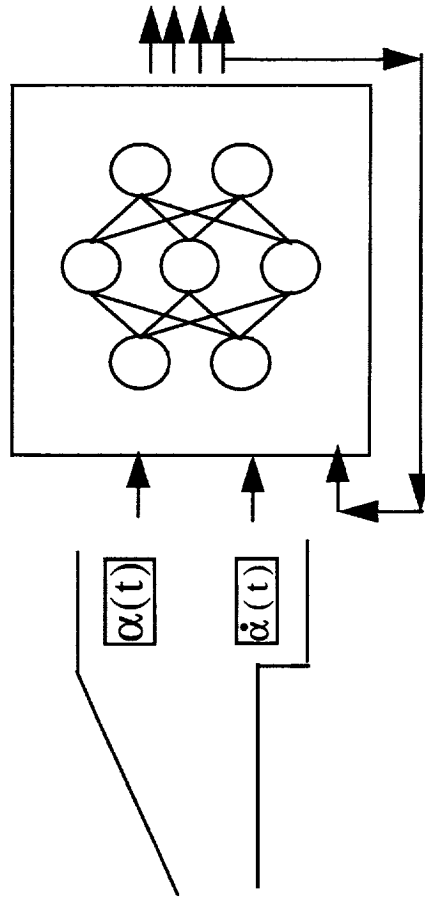
- Closed-Loop Control



- Actual system would include sensor inputs to both the plant & controller

# Neural Network Model of Unsteady Flow Field Wing Interactions

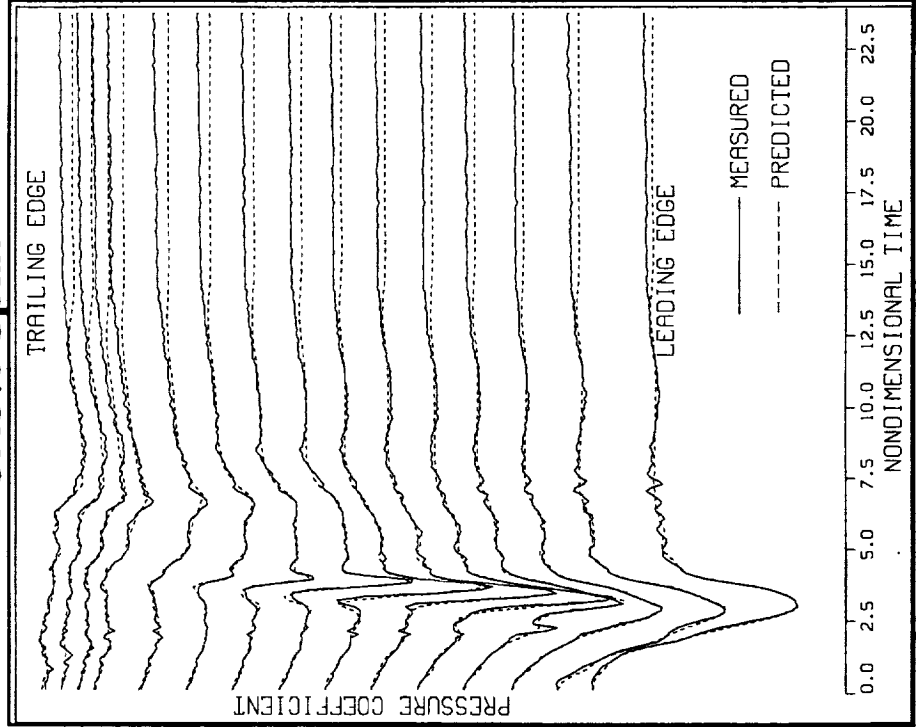
Time-Dependent Plant Model



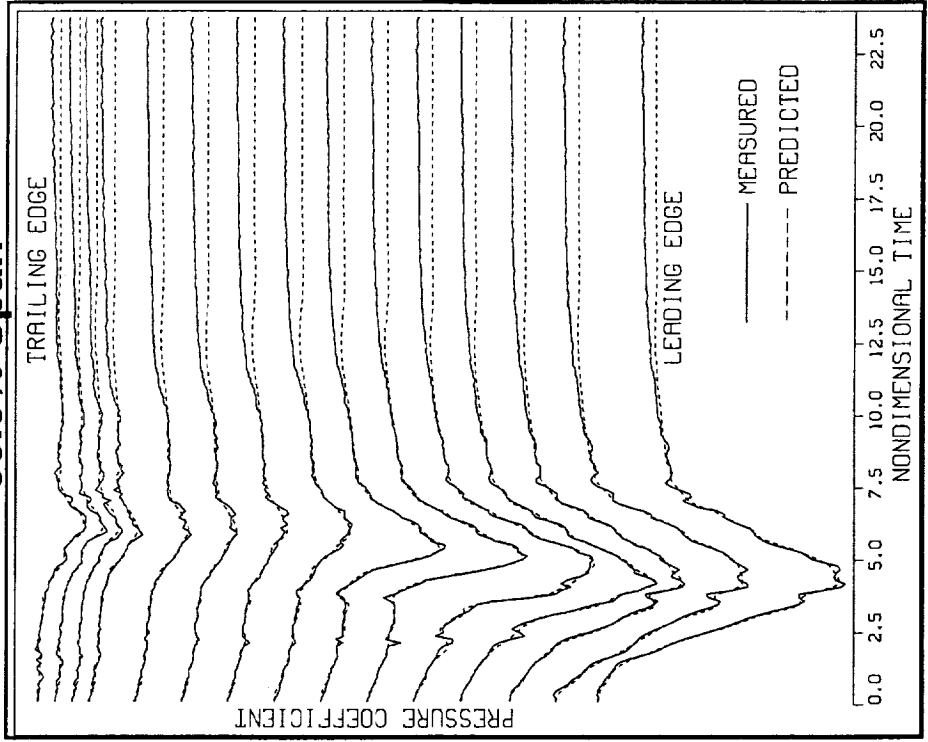
# Model Replicates 3-Dimensionality

- Constant rate pitch motion,  $\alpha^+ = 0.20$

**37.5% Span**

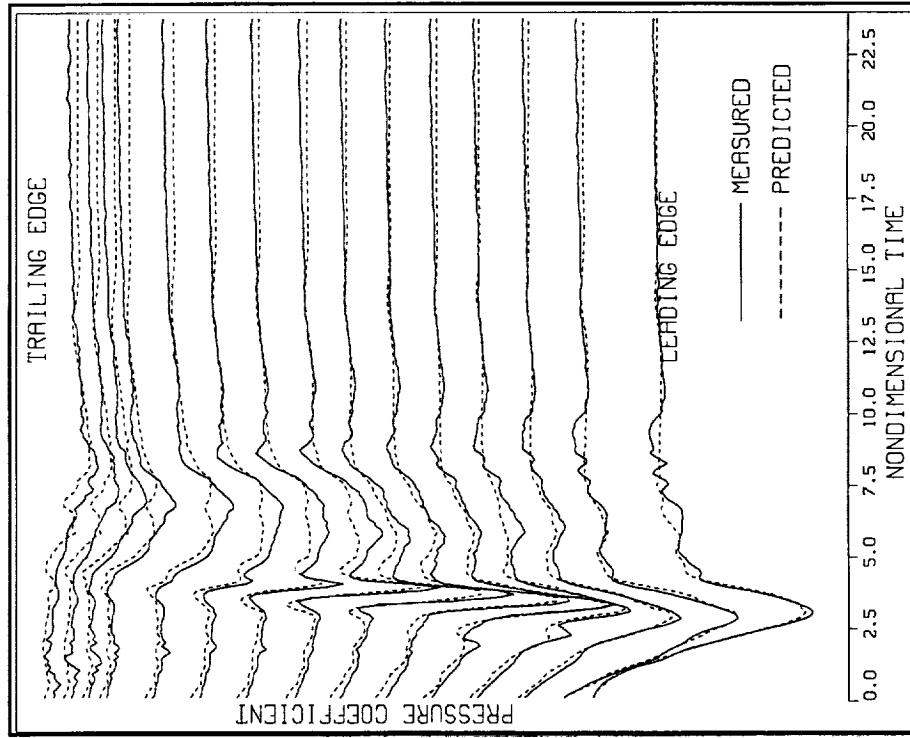


**80.0% Span**

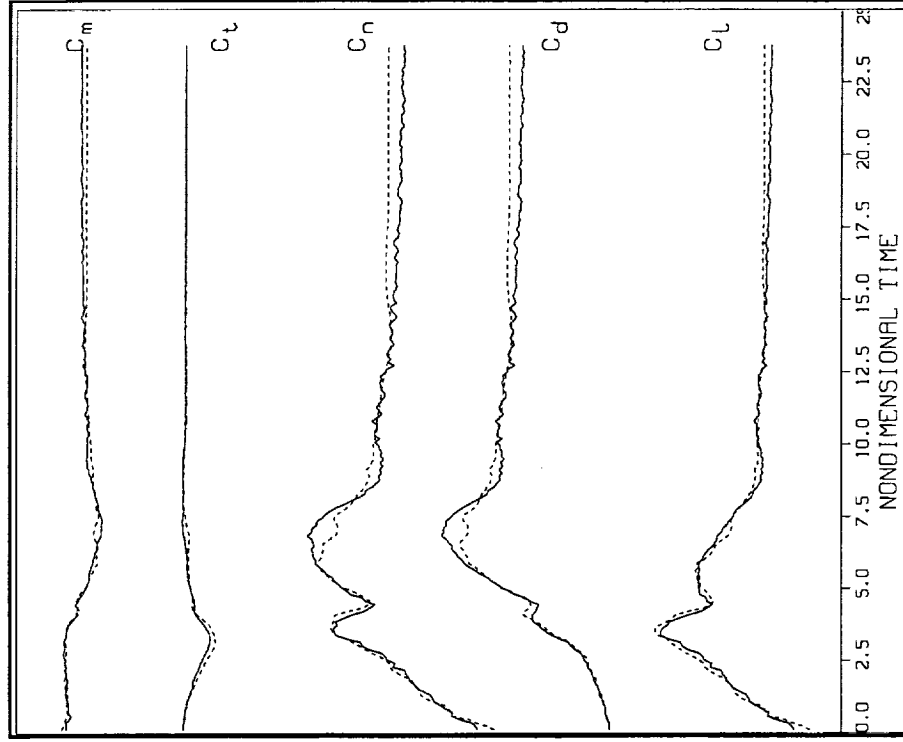


# Model Interpolates to Novel Cases

- Constant rate pitch motion,  $\alpha^* = 0.15$



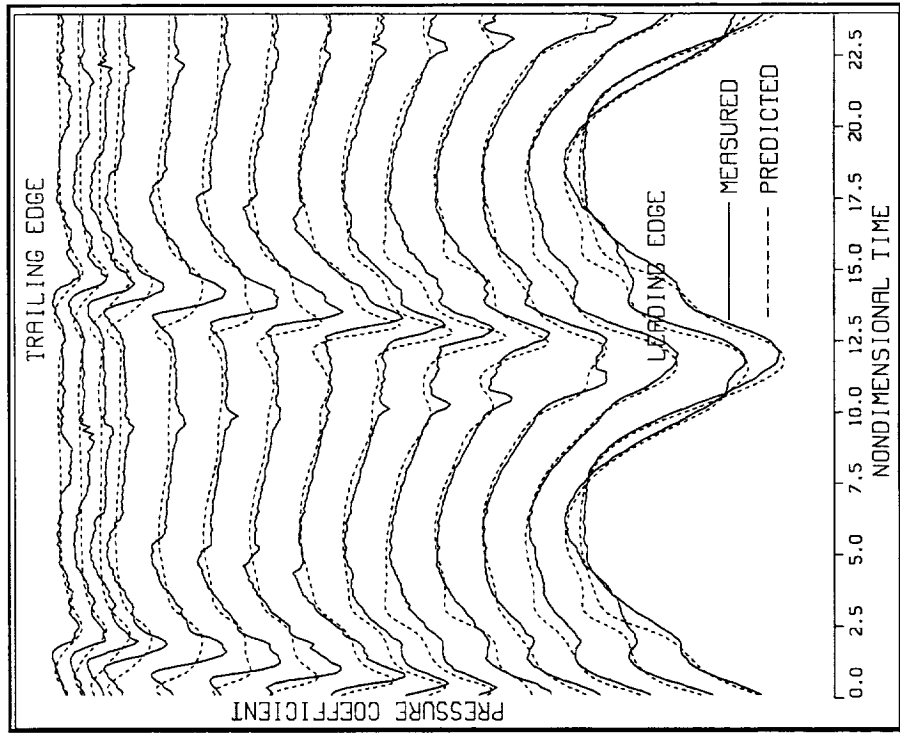
**Surface Pressures**



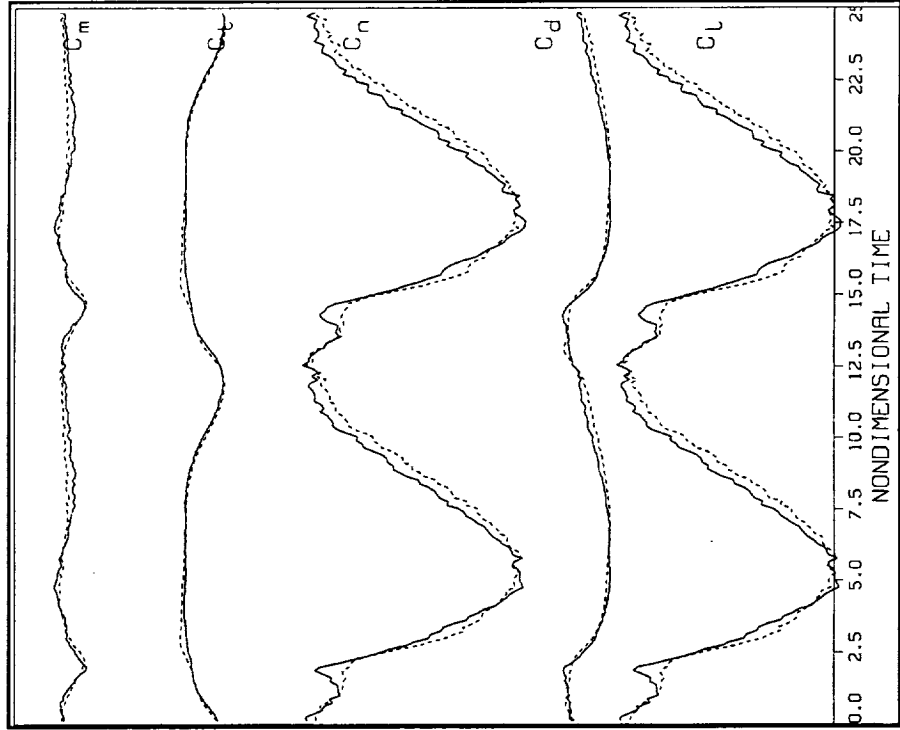
**Aerodynamic Coefficients**

# Model Extrapolates to Novel Cases

- Harmonic motion history,  $K = 0.25$

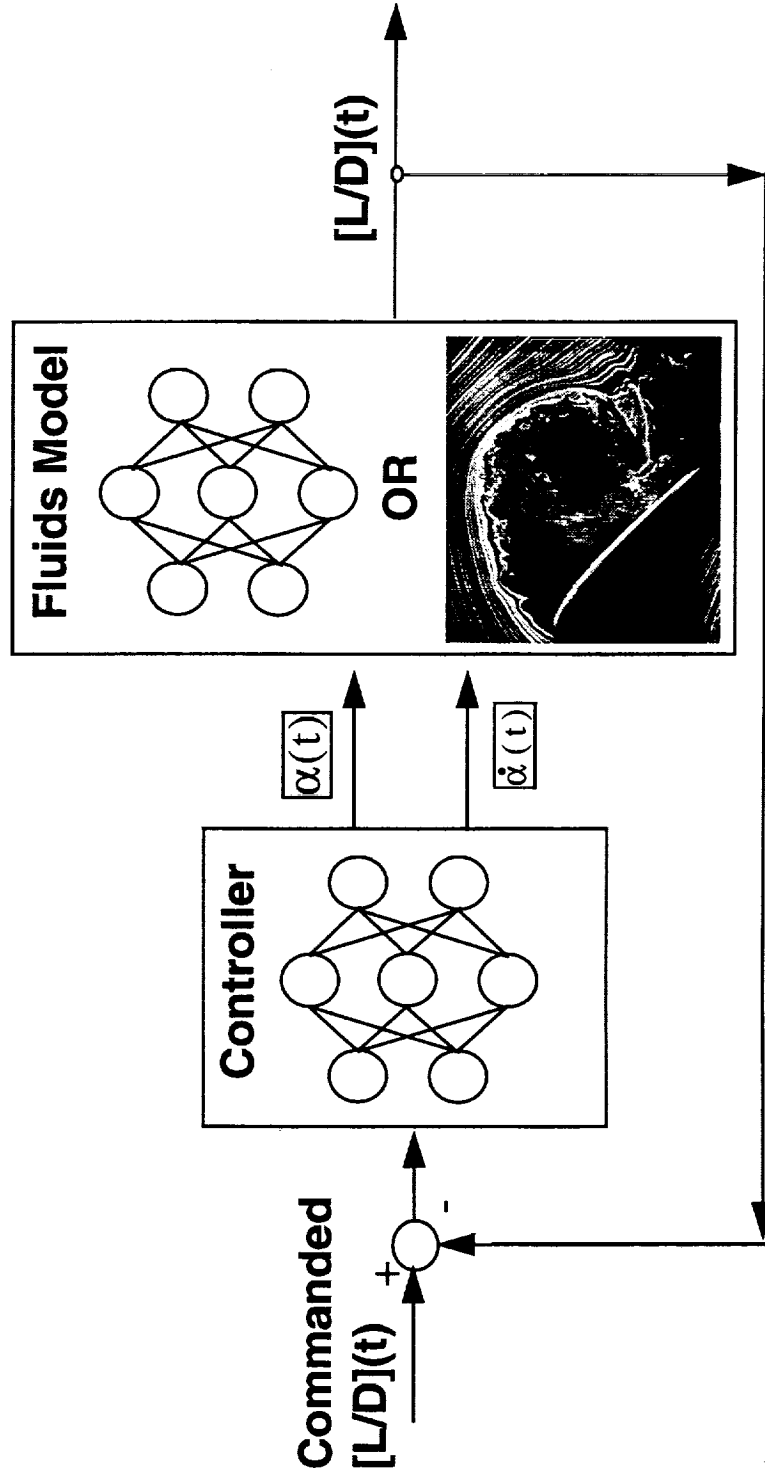


Surface Pressures



Aerodynamic Coefficients

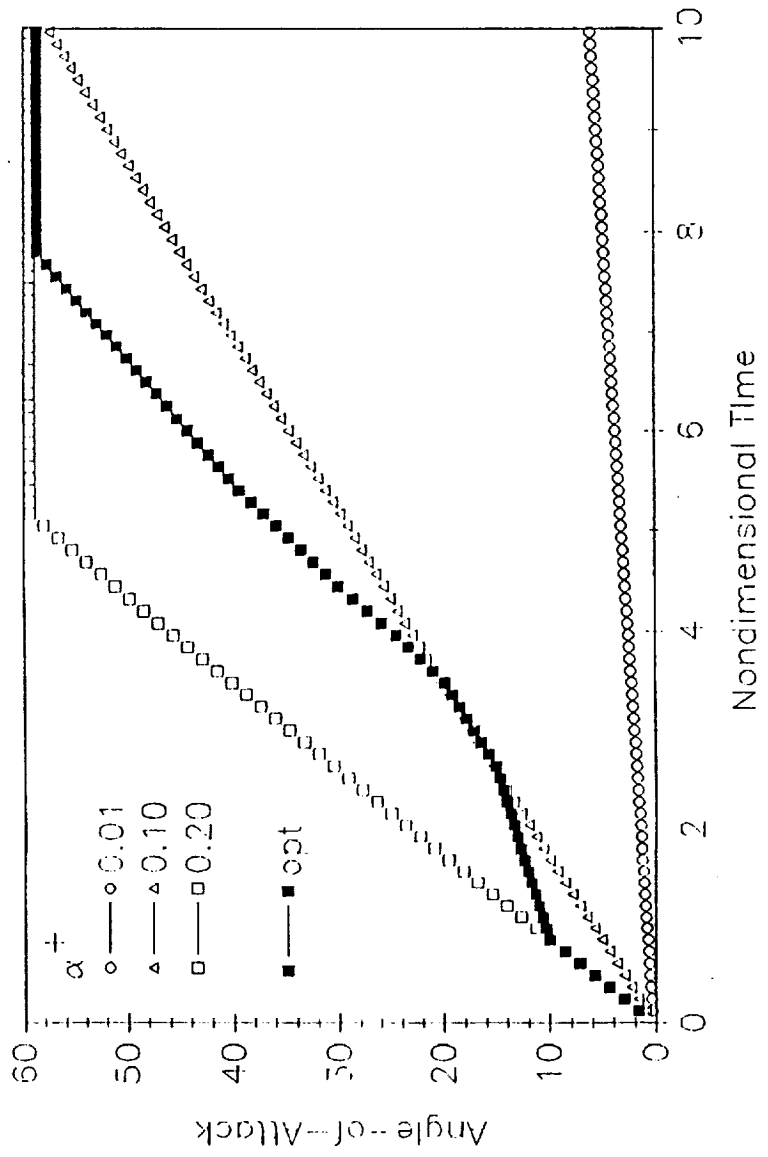
# Closed-Loop Neural Network Control of Unsteady Separated Flows



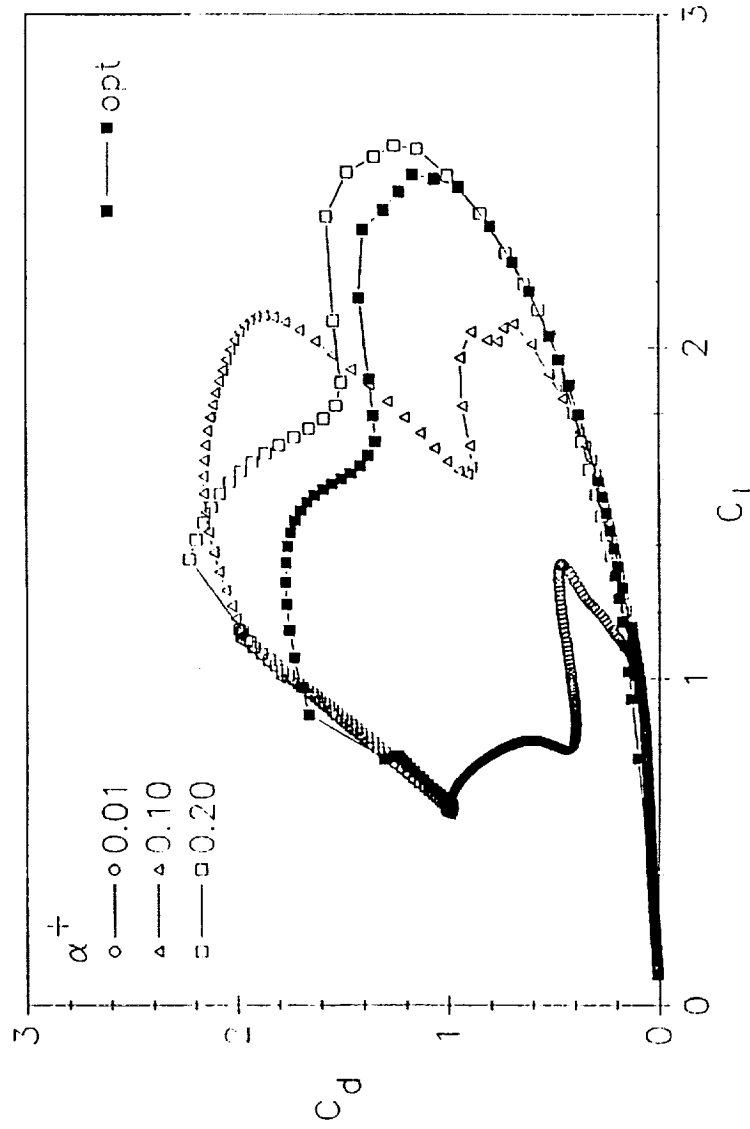
- Demonstrate Optimization and Control of Time-Dependent  $[L/D]$



# Neural Network Optimized Wing Motion History for [L/D](t)

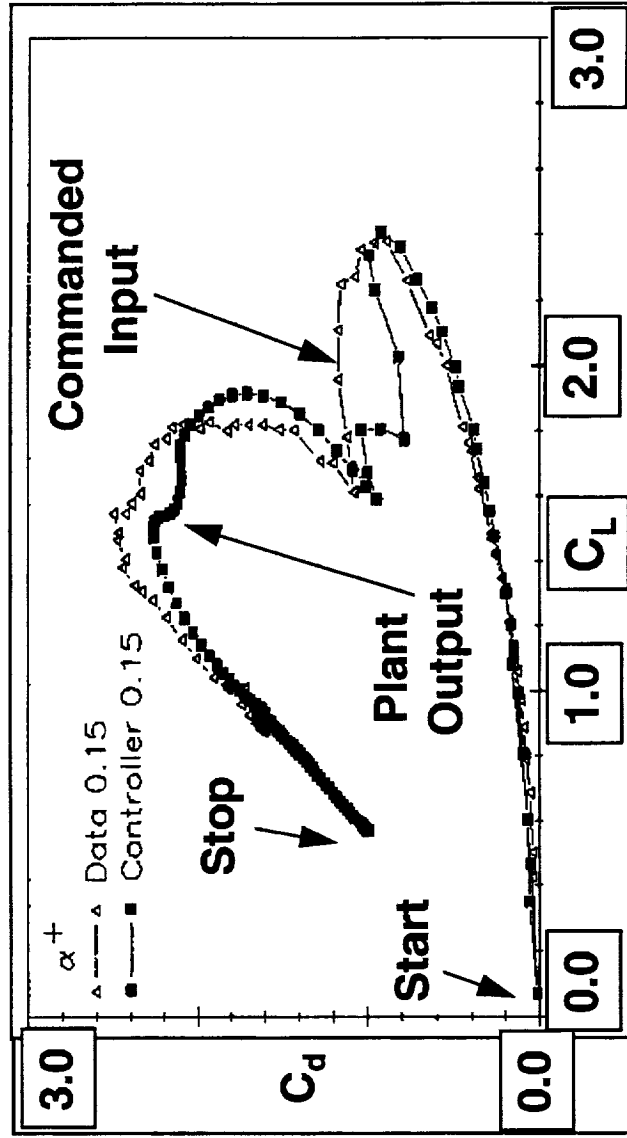


# Neural Network Optimized Drag Polar



- Less Than 10% Loss in Lift
- 20% to 40% Decrease in Drag

## Neural Network Controller Yields Commanded $[L/D](t)$ for Novel Cases



- Neural Network Controller Trained on Limited Experimental Data
- Neural Network Controller Accurately Interpolates to Novel Cases

# CONCLUSION

- **Alternative (State-of-the-Art) Solutions**

## **Computational Fluid Dynamics**

**Two-Dimensional Solutions (No 3-Dimensionality)  
Computationally Intensive (10's of Hours of Cray Time)**

**To Date Control Of Unsteady Aerodynamics Has Not Been Demonstrated**

- **Neural Networks Offer Unique Opportunities:**

**Simplify Modeling of Three-Dimensional, Vortex Dominated, Unsteady Separated Flow Fields (Practical Geometries & Applications 3-D)**

**Effective Means for Controlling Unsteady Aerodynamics**

**Address Integration of Sensors, Actuators, Controllers and Time Lags Into Adaptive Control Systems**