Reconfigurable Flight Control Design using a Robust Servo LQR and Radial Basis Function Neural Networks

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Reconfiguration

Presentation Outline

- Purpose
- Background
- Design Methods Used for Paper
  - Background on Model Reference Adaptive Control (MRAC)
  - Background on Robust Servomechanism LQR
  - Radial Basis Function Neural Networks
- Control Failure Survivability Results
- Results / Time Histories
- Conclusions
  - Remarks
  - Lessons Learned

Control Reconfiguration

General Background / Concepts

- **Purpose of Reconfigurable Control / Why ?**
  - **Handle Failures & Land Safely**
  - **Continue on with Mission**
  - **Buy More Time to Terminate Flight at a Better Location (UAV)**

- **Overall Controller Objective.**
  - **Maintain consistent stable performance in the presence uncertainties and unmodeled dynamics.**

Control Reconfiguration

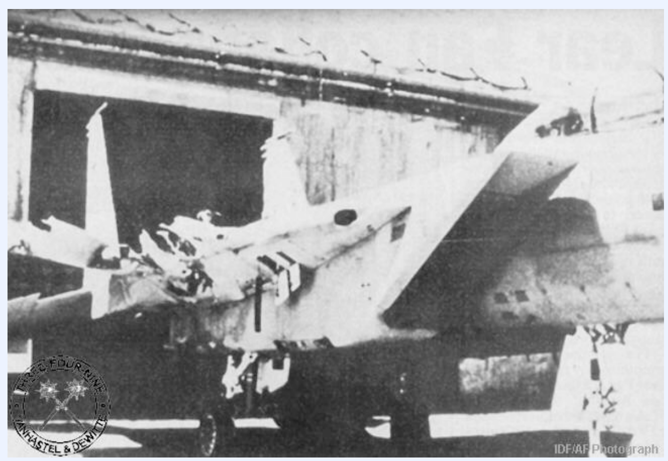
General Background / Concepts

- **Why Adaptive Control.**
  - **Handles Uncertainties and unpredicted parameter deviations.**
  - **Adaptive control is better than Robust Control w.r.t. slow varying parameters.**
- **Why Robust Control (Such as Robust LQR servo design)**
  - **Handles fast varying parameters and unmodeled dynamics.**
  - **Has good flight experience.**
- **Solution to Adaptive & Robust control issues.**
  - **Merge Adaptive augmentation into a Robust Baseline Controller.**

Reconfiguration Flight Control Systems

- **<u>Motivation / Problem Statement</u> {The Big Picture}**
  - **Land a damaged airplane or, return to a safe ejection site.**
  - **Or continue with mission**

- **General Goals & Objectives**
  - **Flight evaluation of neural net software.**
  - **Increased survivability in the presence of failures or aircraft damage.**
    - **Increase your boundary of a flyable airplane.**
    - **Increase your chances to see another day.**
    - **Increase your chances to continue the mission.**



Motivation, cont

- Airplanes in the Past Have Landed with Major Failures.

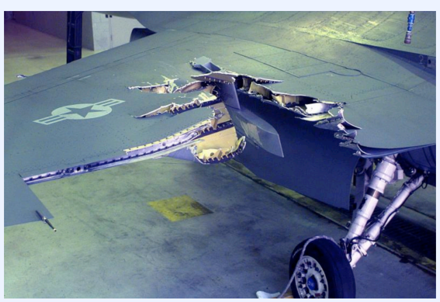
- But possibly not as many safe landings as could have, with adaptive control methods.

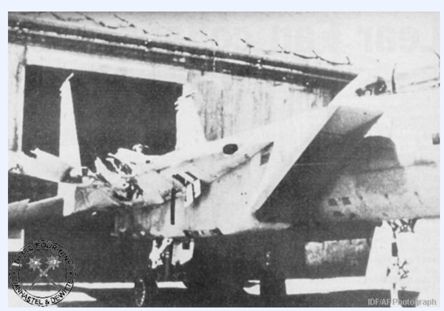
- Our Goal is to Increase the Survivability Region for the Pilot without luck or high skill levels or when the pilot is injured.

Flight Control??

- **How do we Reconfigure the Controller (called H or K)**

- **Many ways to adapt to a failure or unknown Plant (G) parameters:**
  - → **Adaptation Methods:**
    - → **Non-Learning Methods:**
      - → **Robust Reconfiguration Methods.**
      - → **Fault detection & isolation.**
      - → **Use of smart actuators (Handles only B matrix failures).**
      - → **Reconfigurable Retrofit Architecture methods.**
    - → **Learning Methods:**
      - → **Use of Neural networks**
      - → **To many to list (such as RBF Radial Basis Function)**





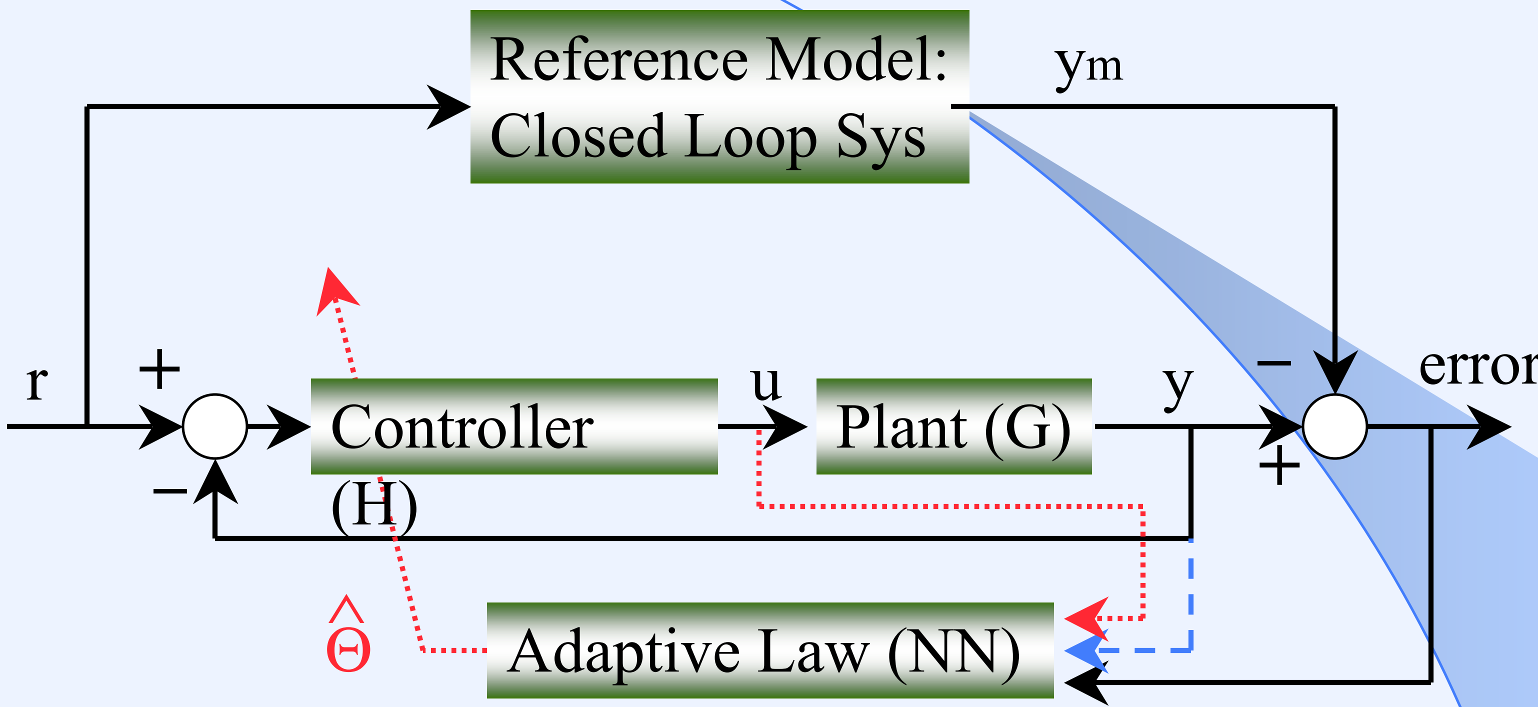
General Statements on Adaptive Controller

- Two Types of Adaptive controllers
  1. Direct Adaptive
  2. Indirect Adaptive

- The Direct Adaptive Controller Works on the Errors.
  - Needs a Reference Model to Generate P_err = (P_cmd-Psensor)
  - The Neural Network "Directly" Adapts to P_err.
  - Does not need to know the source of error.
    - No Aero Parameter Estimation Needed
    - No need for persistently exciting signals

- The Indirect Adaptive Works on Identifying the source of Error.
  - Does Not Need a Reference Model.
  - Needs to Identify the Aerodynamics that have changed! (PID)
    - PID is Time Consuming and *may not* be correct.
    - Needs persistently exciting inputs.

Model Reference Adaptive Control (MRAC)



- **Plant: Actual Plant parameters (G) are unknown.**
- **Reference Model: Ideal response (y_m) to cmd r (Use a Stable Reference Model).**
- **Adaptation Law: Is used to adjust controller (H): can be NNs.**

Servomechanism Design Methodology

Consider a MIMO system

$$\dot{X} = Ax + Bu + Ew \qquad \text{where } x \in R^n,\ u \in R^m, y \in R^p$$

$$Y = Cx + Du + Fw$$

$w =$ the disturbance (failed surface)

The dynamic controller is

$$\dot{x}_c = A_c x_c + B_c(r - y)$$

The open loop augmented system is

$$\begin{bmatrix} \dot{x} \\ \dot{x}_c \end{bmatrix} = \begin{bmatrix} A & 0 \\ -B_c C & A_c \end{bmatrix} \begin{bmatrix} x \\ x_c \end{bmatrix} + \begin{bmatrix} B \\ -B_c D \end{bmatrix} U$$

Suppose the following condition is satisfied

$$\text{rank} \begin{bmatrix} \ddot{e}_i I - A & B \\ -C & D \end{bmatrix} = n + p$$

The system is controllable and there exist a control law

$$u = kx + k_c x_c$$

If this statement is true there exist a closed-loop system that is stable.

Note :

① LQR Servo = LQR PI

①Jammed or failed surface is treated as a disturbance to the system.

② Approach is simple to implement.

Servomechanism Design Methodology (cont.)

- Remarks:
- For any such control law, asymptotic tracking and disturbance rejection are achieved; that is, the error goes to zero.
- If the augmented system is controllable, the control law can be conveniently found by applying the linear quadratic regulator (LQR) approach to the augmented system.
- After setting up the augmentation we now need to solve for the gain (k, kc)
  - ➢ Just use LQR.
  - ➢ This setup allows for a LQR tracker solution.

Control Law

$$u = kx + k_c x_c$$

$$e = r - y \to 0$$

The augmented system is

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\mathbf{x}}_c \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ -\mathbf{B}_c\mathbf{C} & \mathbf{A}_c \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{x}_c \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ -\mathbf{B}_c\mathbf{D} \end{bmatrix} \mathbf{U}$$

Servomechanism Design Methodology (cont.)

- Optimize the following cost function.

  Optimal linear-quadratic-regulator (LQR) problem.

  $$J = \int_0^T (x' Q x + u' R u) dt$$

- The algebraic Riccati equation

  $$0 = A' P + PA + Q - PBR^{-1} B' P$$

- And the optimal control is given by:

  $$u(t) = -R^{-1} B' P x(t) = K x(t)$$

Why Neural Networks?

–**Neural Networks are Universal Approximators.**

–**Minimizes a H^2 norm.**

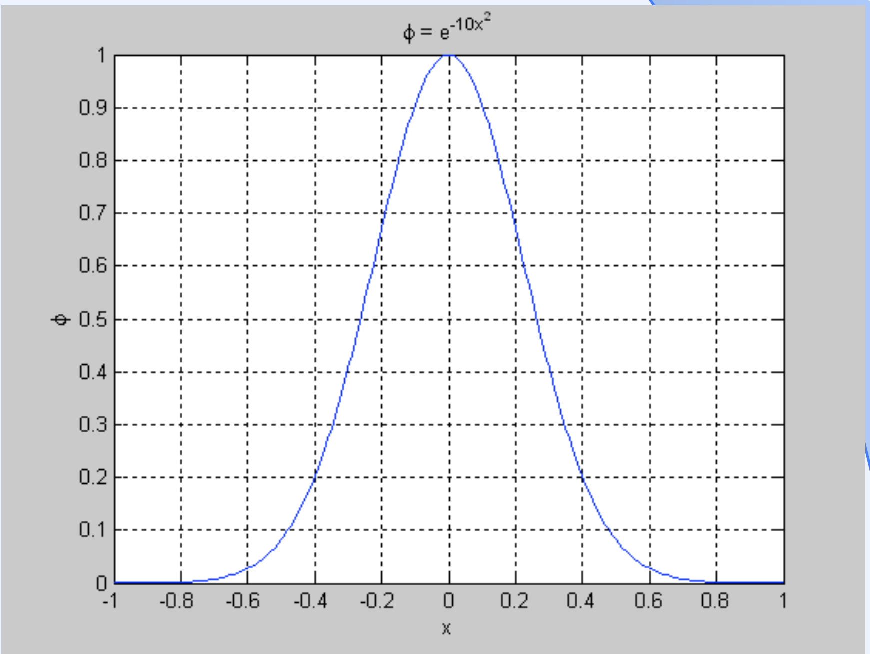
–**They permit a nonlinear parameterization of uncertainty.**

–**Why Radial Basis Functions (RBF):**

 –**RBFs will de-activate when signal is outside "neighborhood".**

Activation function

$$\phi(x) = e^{-\left[\frac{\|x-r\|^2}{2\sigma}\right]}$$

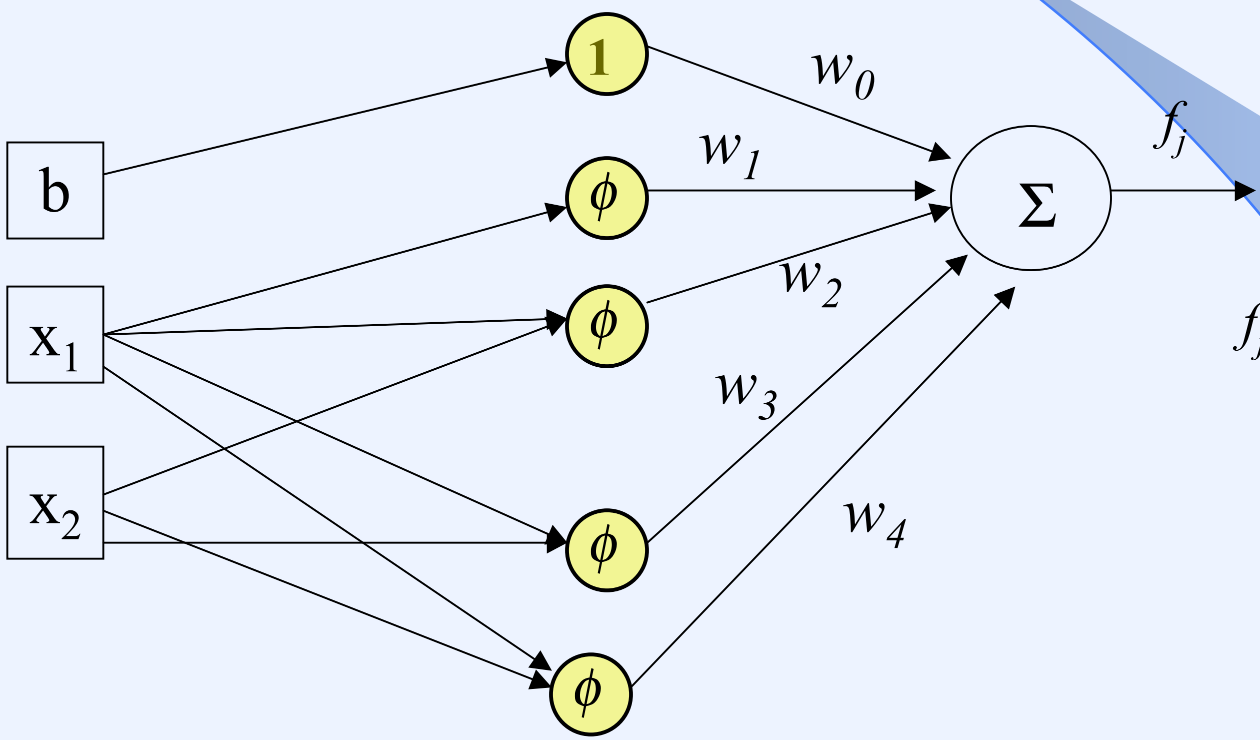


RBF Network Outputs

- The output of a RBF network with K neurons:
  - $\phi_k(x)$ is the response of the kth hidden neuron for input vector x.
  - w_k is the connecting weight of the output neuron.

$$f(x) = NN(x) = \sum_{k=1}^{K} w_k \phi_k(x) + b$$

Neurons
1 Hidden layer with 4 Neurons and 2 Inputs



$$f_j = w_0\,\mathrm{b} + w_1 \mathrm{x}_1 + w_2 \mathrm{x}_2 + w_3\, \mathrm{x}_3 + w_4\, \mathrm{x}_1 \mathrm{x}_2 +$$

ϕ means activation function

Failures Investigated

2 groups of failures are "common" among aircraft mishaps/crashes.

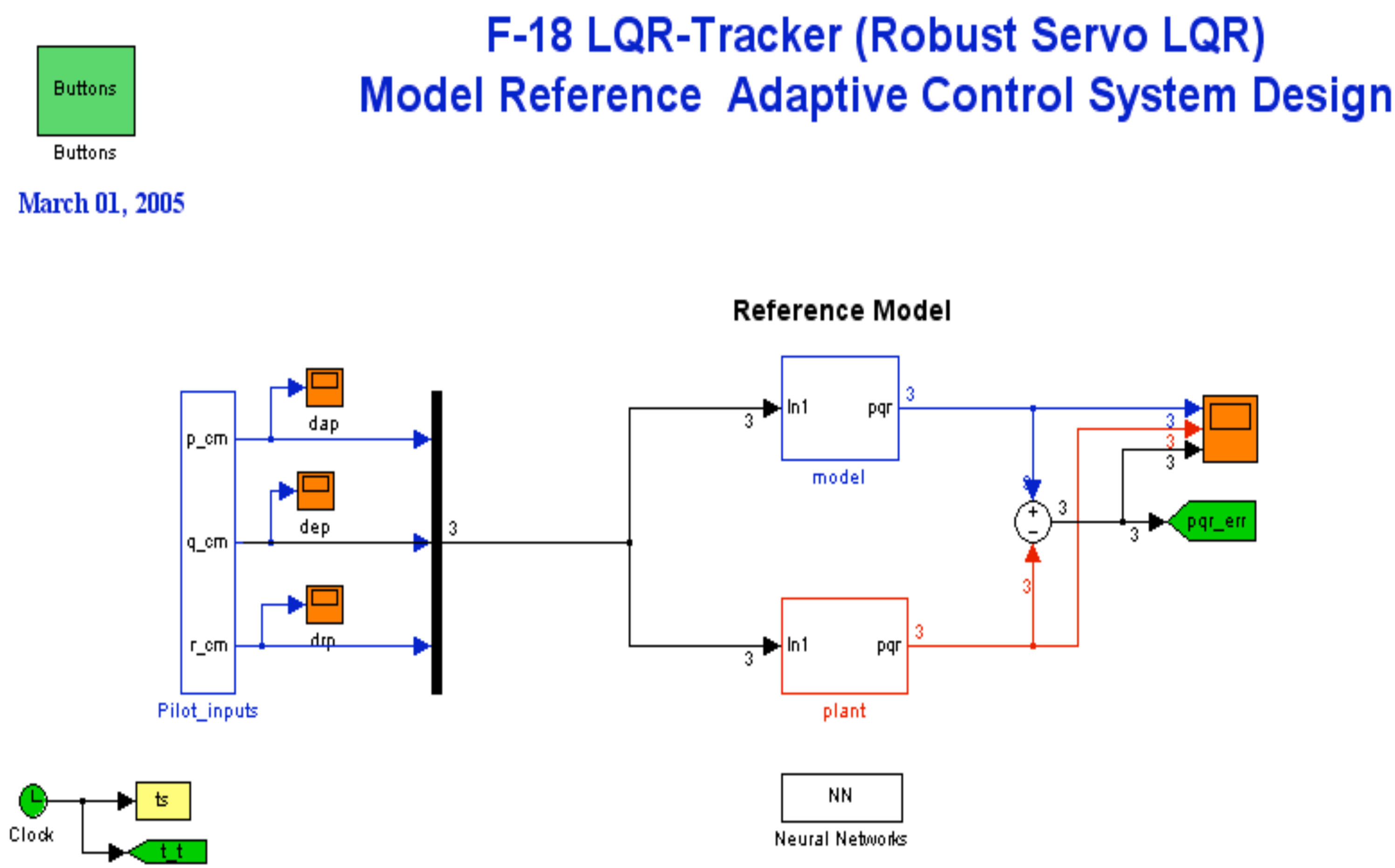
- Aerodynamic Failures or uncertainties (A Matrix problems / lost aero surfaces, bent wings)
  - Or Not well known aero terms due to modelling errors.

- Control Failures (B Matrix problems / jammed control surfaces)
  - Right stab jammed at 8. deg from trim

Control Reconfiguration Results

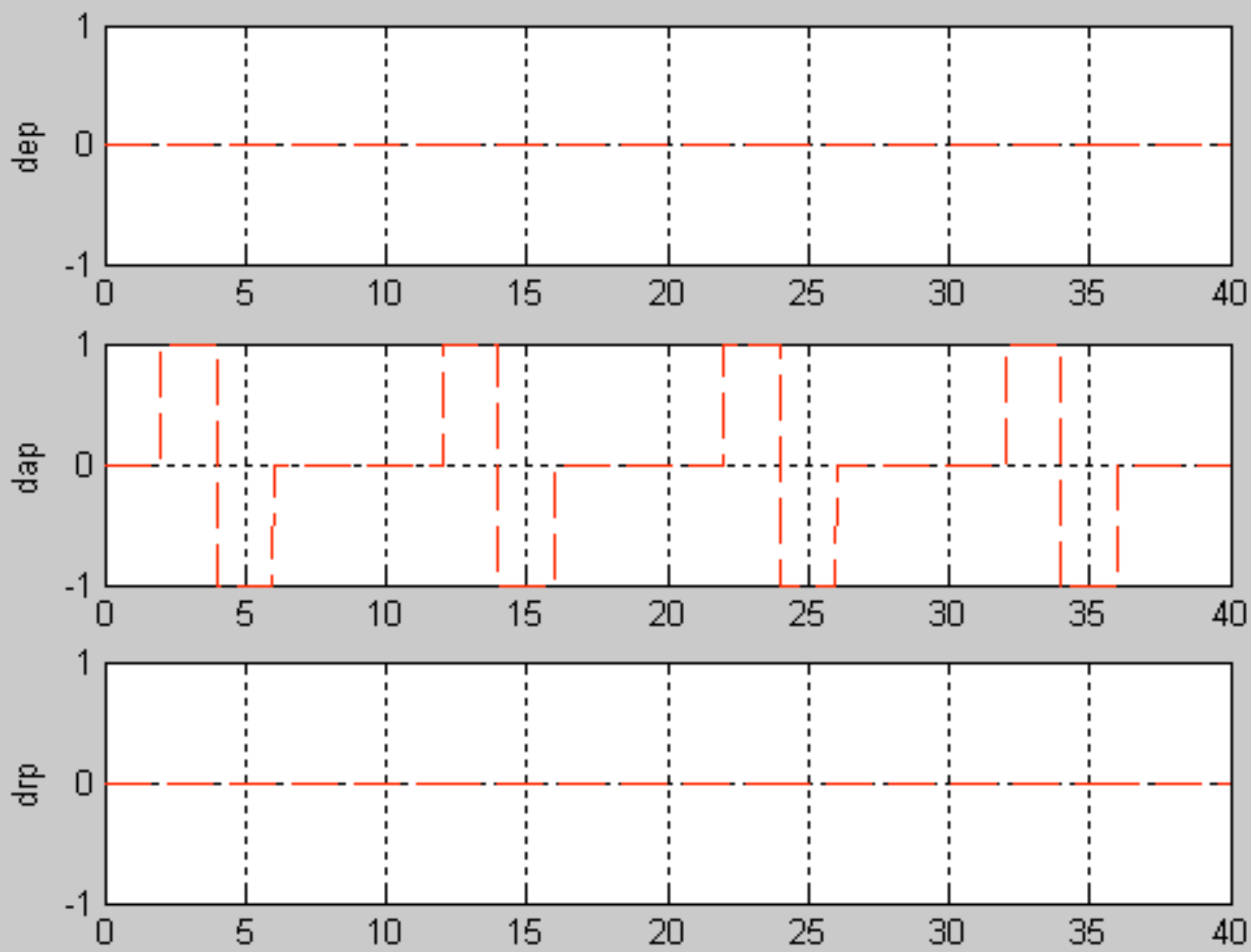
- **Time History of Surface Failure (B matrix)**
- **Failure = Right Stabilator Jammed.**
  - **At time = 10 seconds / 8 deg from trim.**
  - **At time = 30 seconds Failure goes away (crew fixed the failure).**
- **Neural Networks**
  - **Neural Networks turned off for the first run.**
  - **Neural Networks turned on for second run.**
  - **Without Dead Zones.**

Robust Model Reference Adaptive Control Design



Failure = Right Stab 8. deg at 10 seconds with & without NN
Failure goes away at 30 seconds / Pilot Input is Roll doublets

Pilot Inputs



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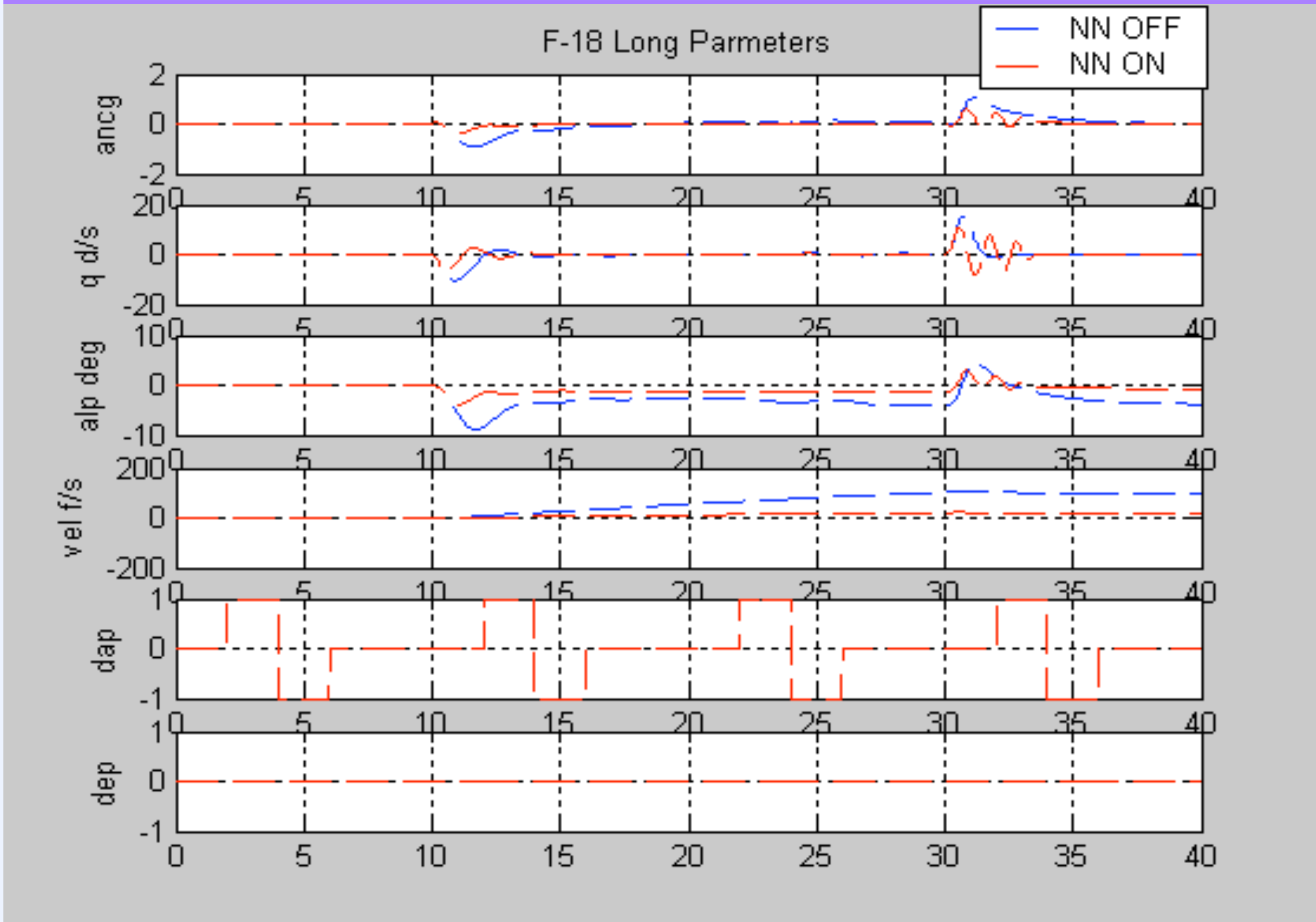
Long Axis Data



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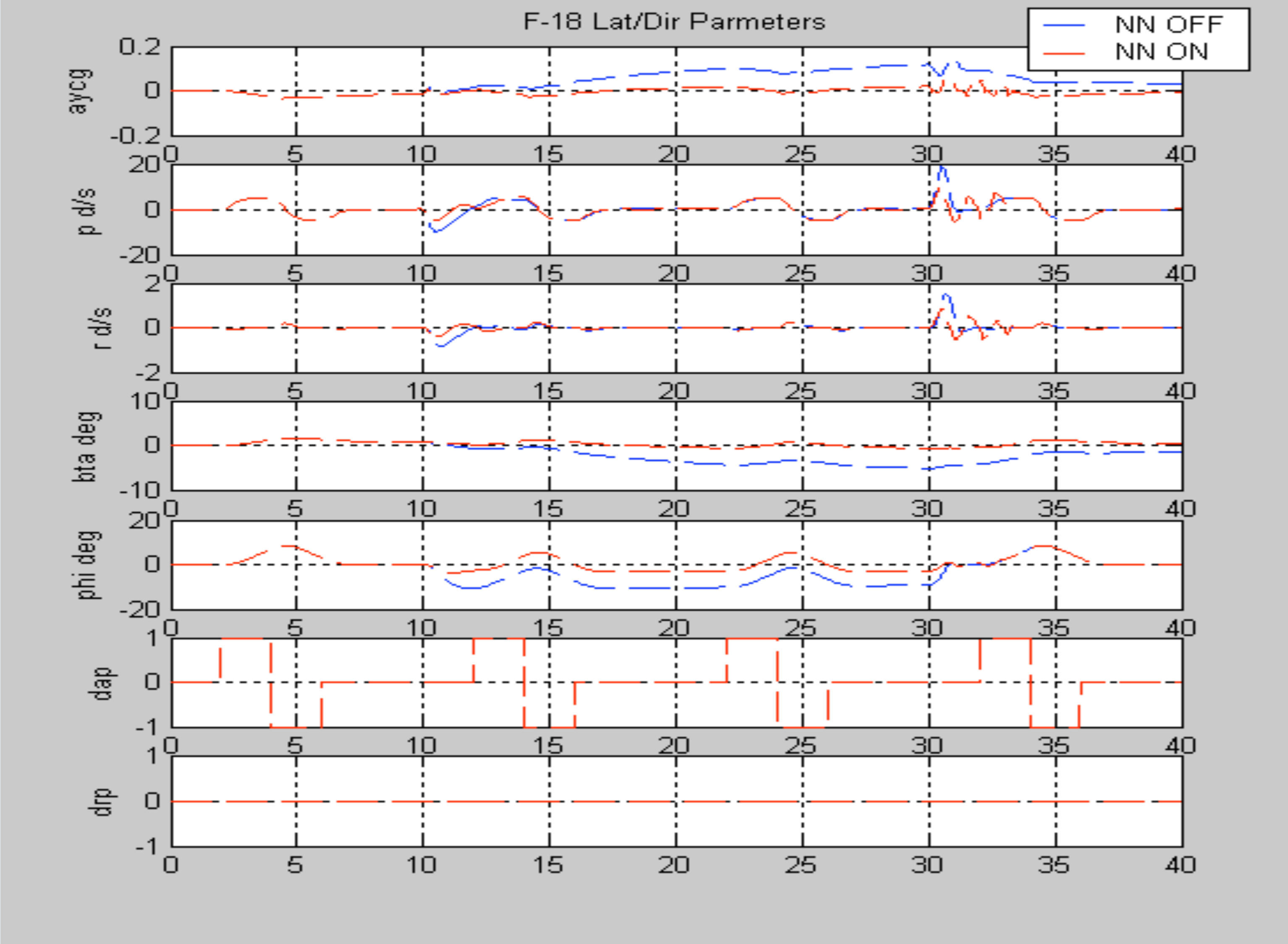
Lat/Dir Axis Data



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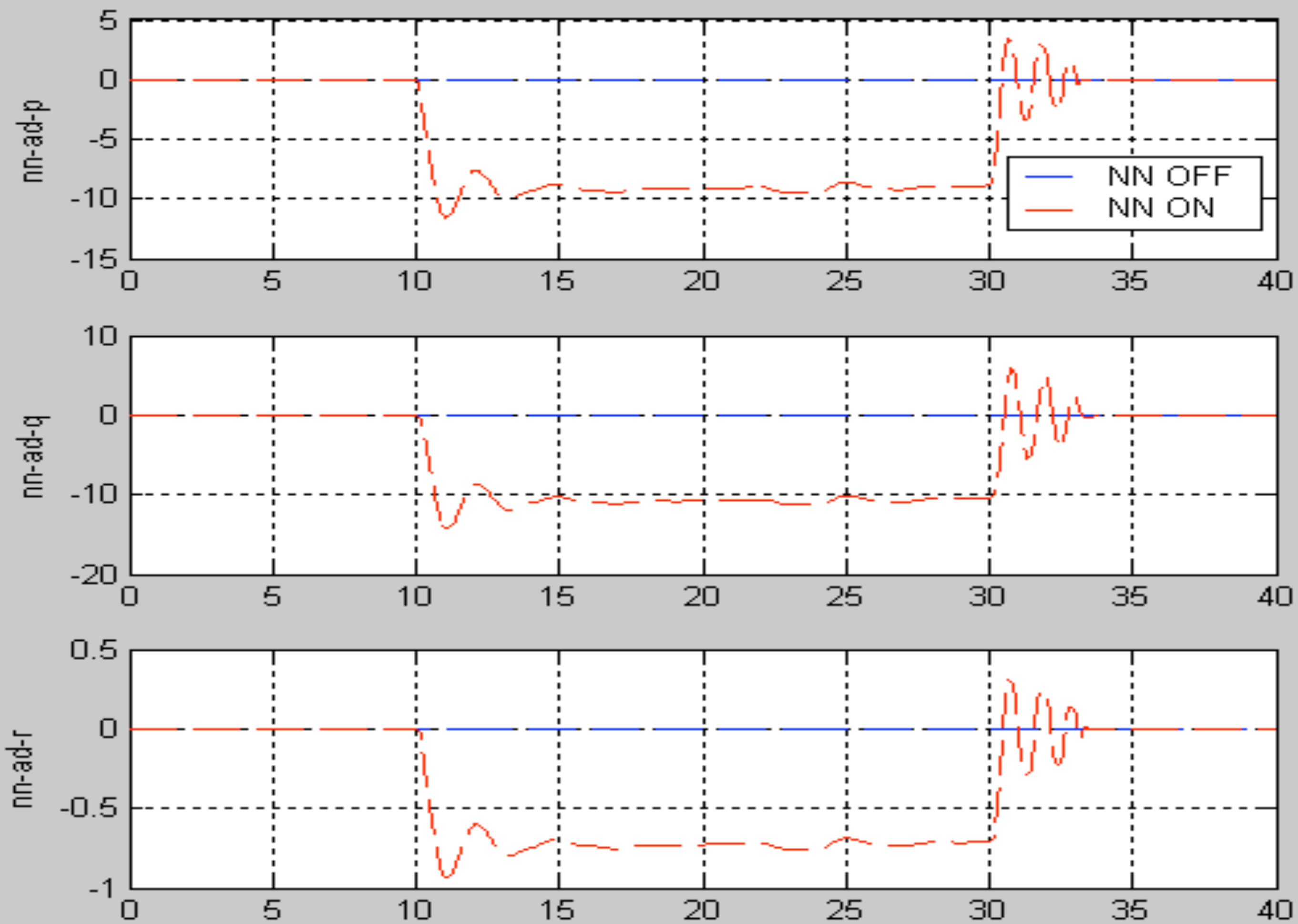
Neural Network Signals



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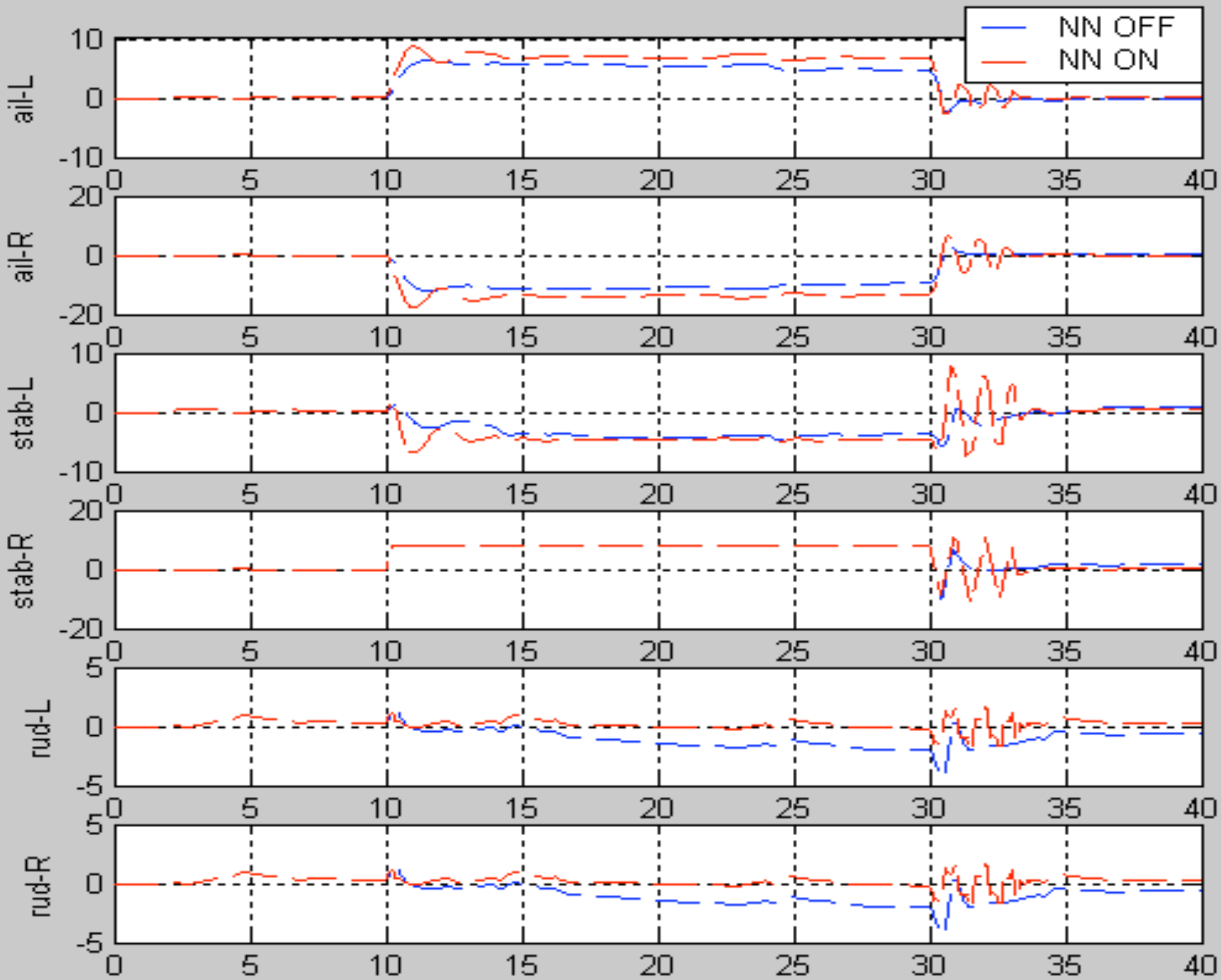
Surface Positions



Control Reconfiguration Results

- **Time History of Surface Failure (B matrix)**
- **Failure = Right Stabilator Jammed.**
  - **At time = 10 seconds / 8 deg from trim.**
  - **At time = 30 seconds Failure goes away (crew fixed the failure).**
- **Neural Networks**
  - **Neural Networks turned off for the first run.**
  - **Neural Networks turned on for second run.**
  - **With Dead Zones & 20% decrease in learning rates.**

Failure = Right Stab 8. deg at 10 seconds with & without NN
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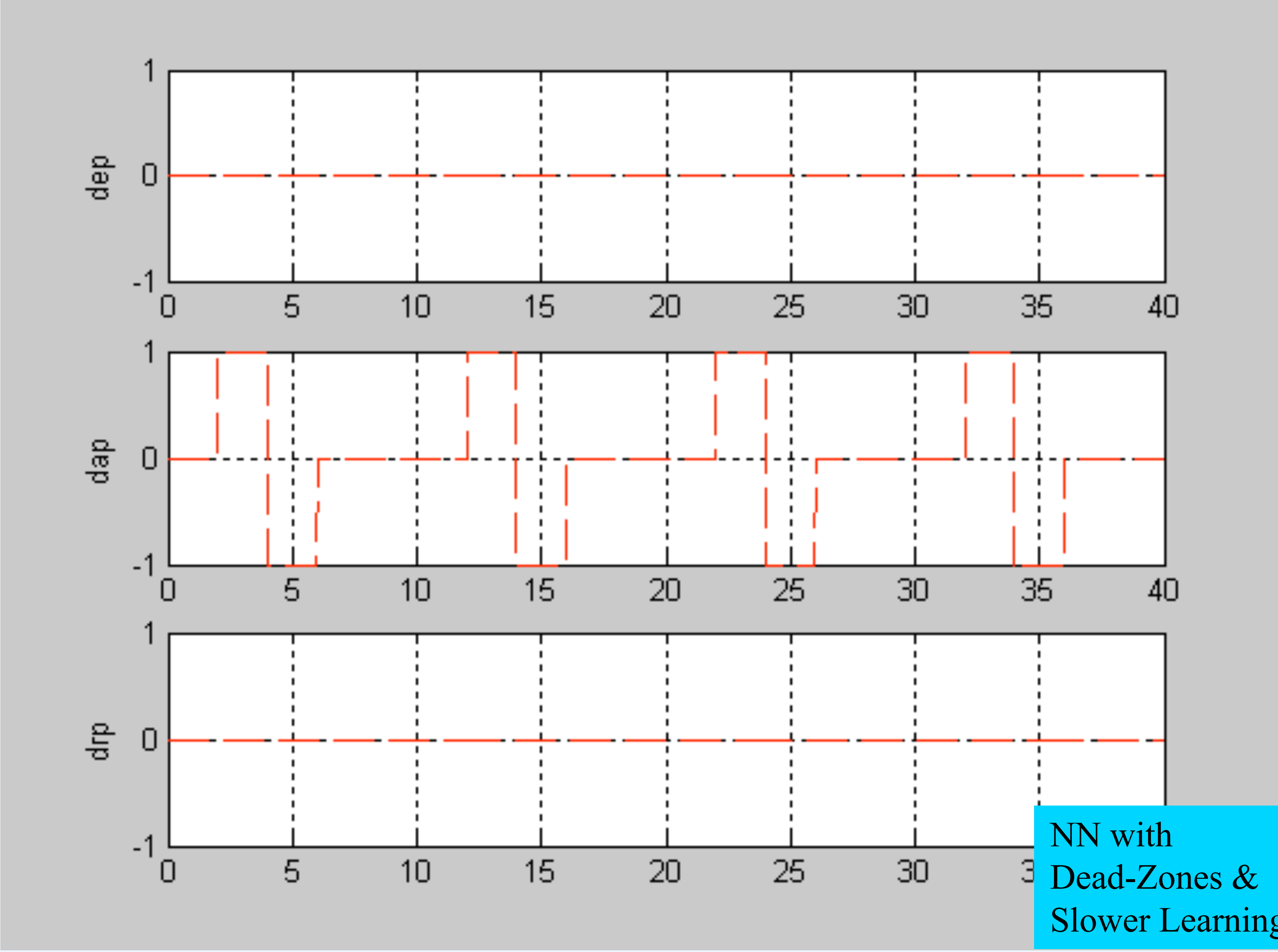
Pilot Inputs



NN with Dead-Zones & Slower Learning

Failure = Right Stab 8. deg at 10 seconds with & without NN
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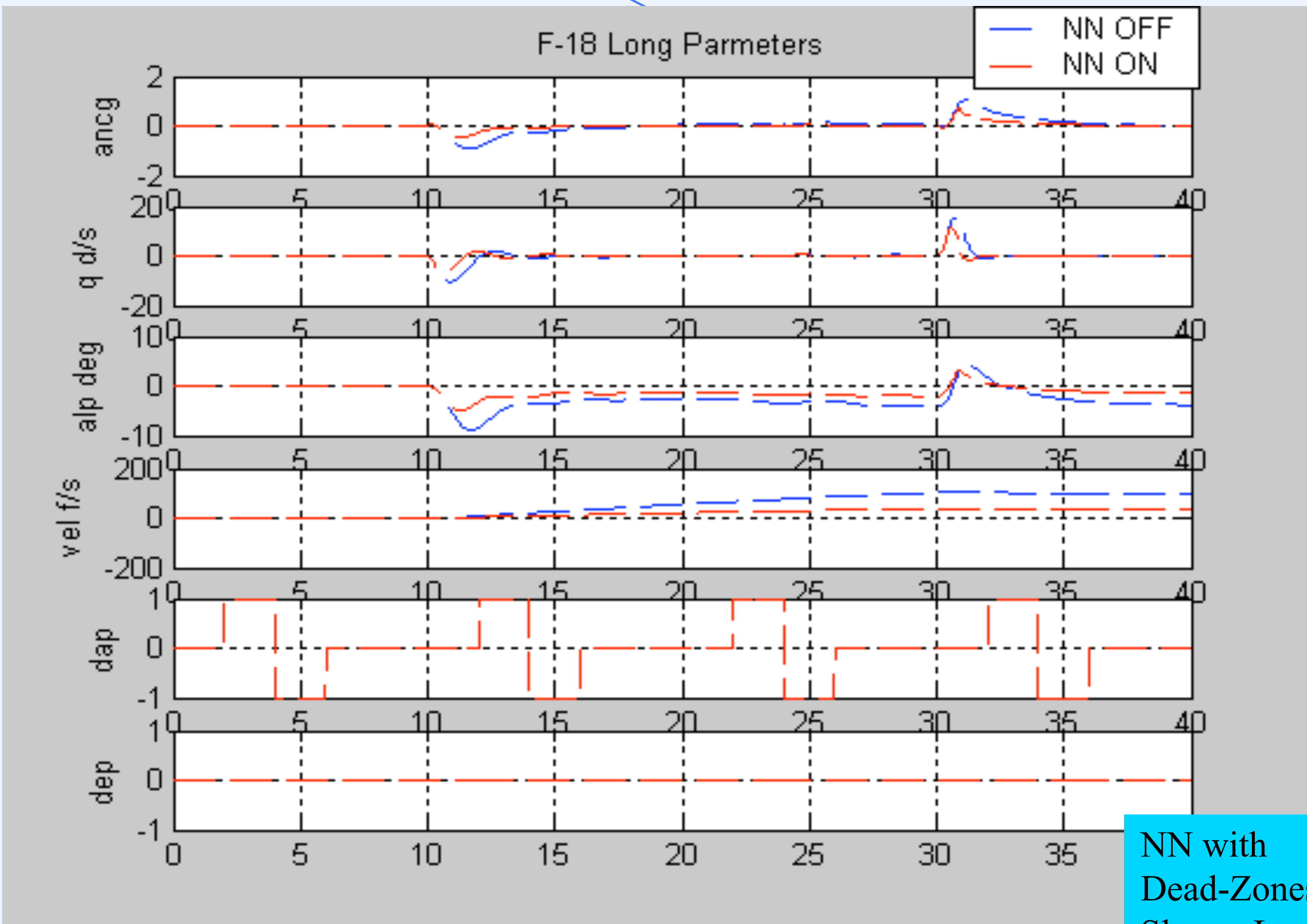
Long Axis Data



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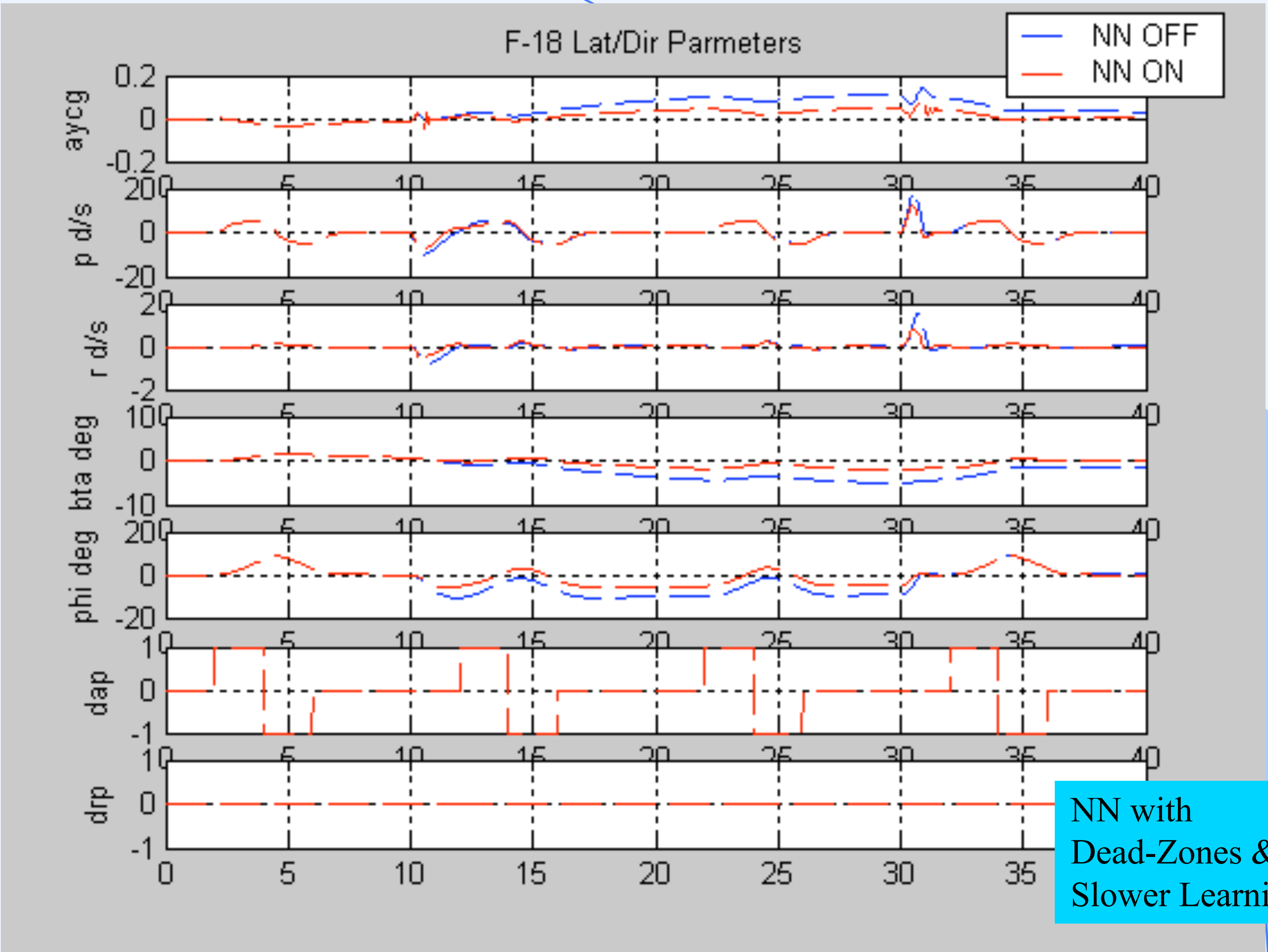

NN with
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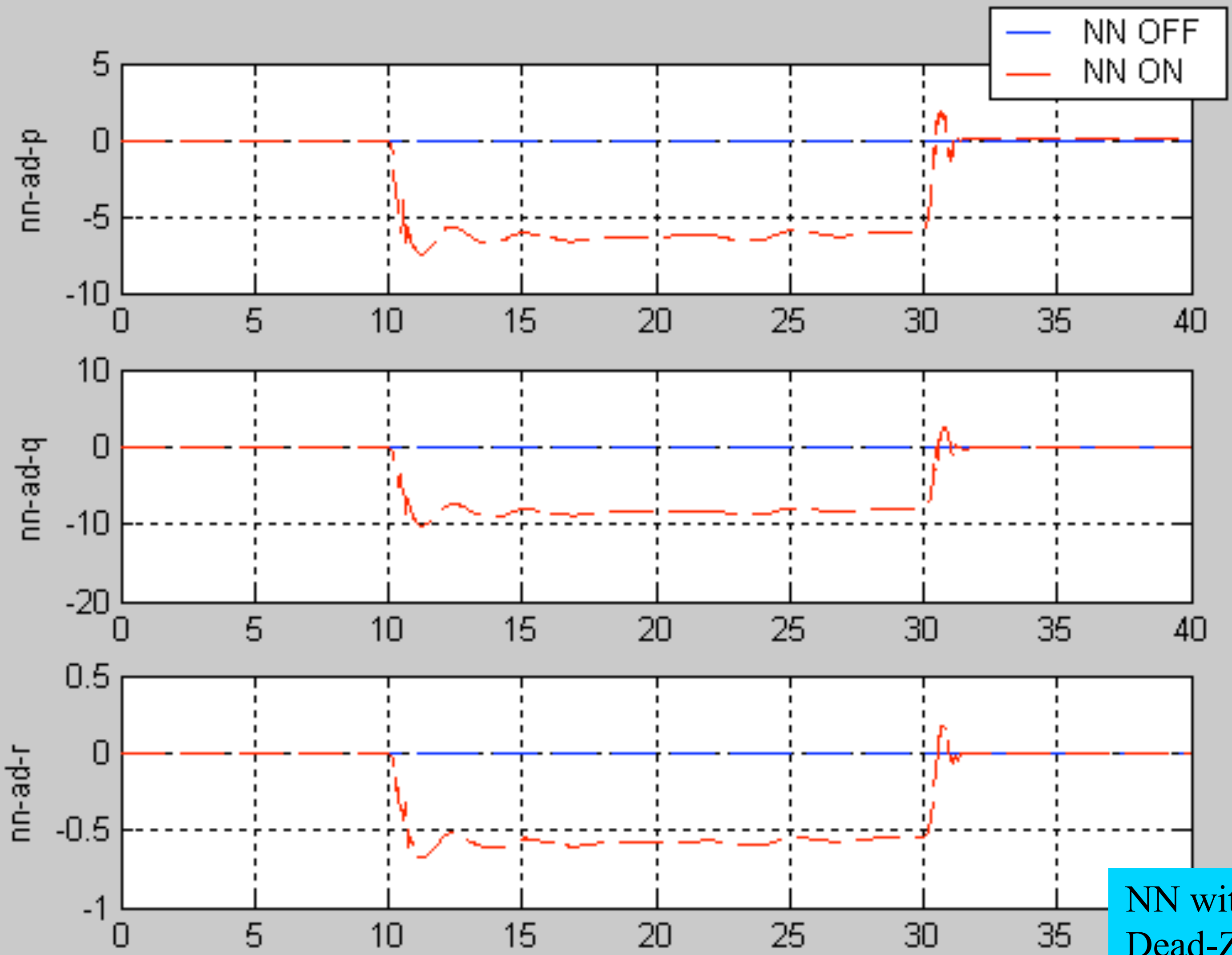

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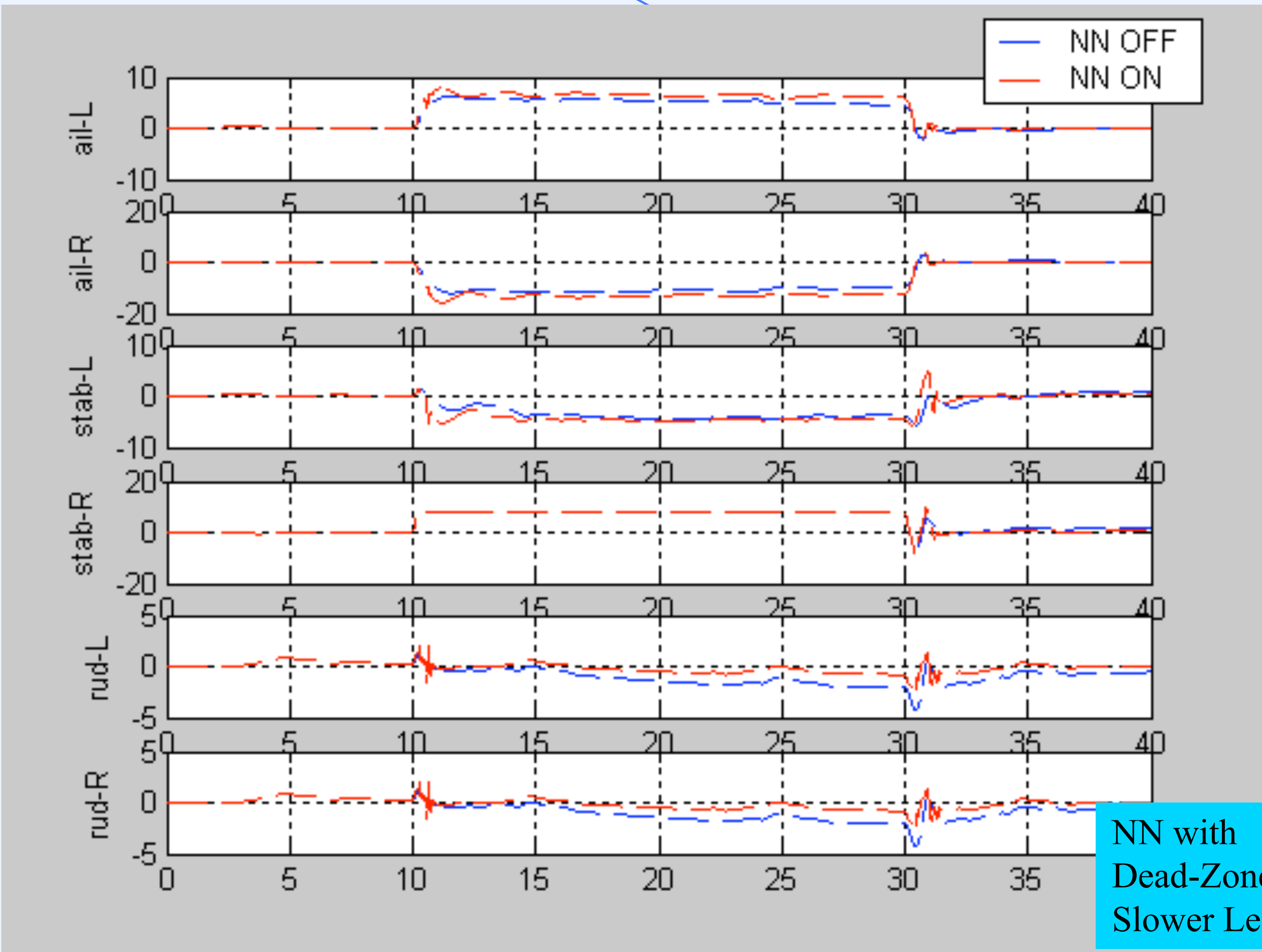

NN with
Dead-Zones &
Slower Learning

Control Reconfiguration Conclusions

- **Conclusions & Remarks**

- **Method presented:**
  - **Robust LQR Servomechanism design with Model Reference Adaptive Control**
    - **Reference Model was a “health” aircraft.**
  - **Used Radial Basis Function Neural Networks**

- **Results:**
  - **LQR Servomechanism behaved well with a failure.**
  - **Using the Neural Networks improved the tracking compared to not using the neural networks.**

- **Lesson learned:**
  - **Test the removal of the failure with Neural Networks active to ensure good performance.**
    - **The crew could fix the problems and you don’t want the adaptive system to go unstable.**

Appreciations / Thanks

- Eugene Lavretsky, Ph.D Boeing
- Ping Lu, Iowa State University