Reconfigurable Control Design with Neural Network Augmentation for a Modified F-15 Aircraft

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Reconfiguration

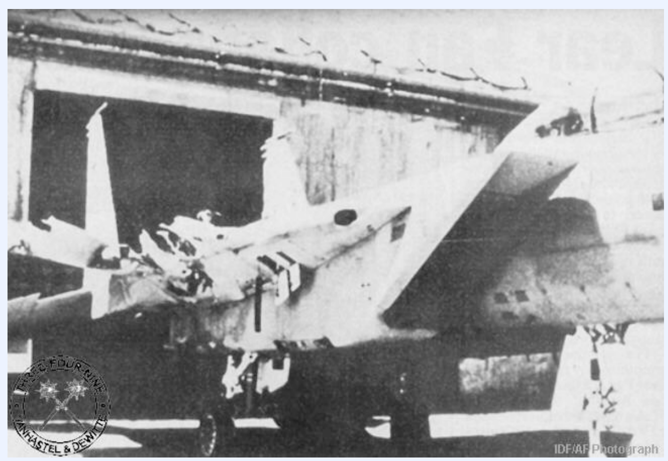
Presentation Outline

- 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

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.



Control Reconfiguration

General Background / Concepts

- **Why Adaptive Control.**
  - **Handles uncertainties and unpredicted parameter deviations.**

- **Why Robust Control (Such as Robust LQR servo design)**
  - **Handles unmodeled dynamics.**
  - **Has good flight experience.**

- **Solution to Adaptive & Robust control issues.**
  - **Merge adaptive augmentation into a robust baseline controller.**

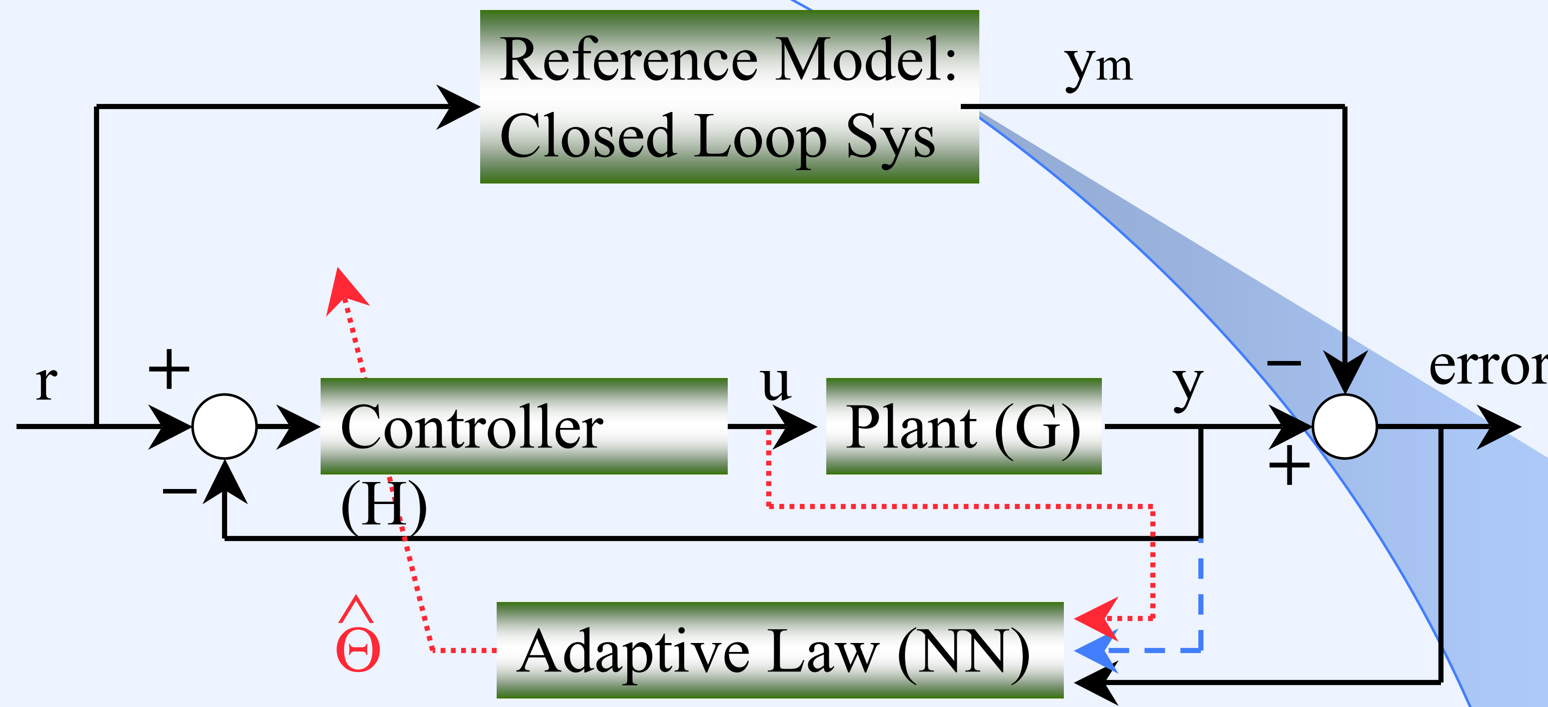
General Statements on Adaptive Controller

- **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

$\dot{X} = Ax + Bu + Ew \quad$ 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

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

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 :

- ℵ LQR Servo = LQR PI
- ℵ Jammed or failed surface is treated as a disturbance to the system.
- ℑ 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.

$$J = \int_0^T (x' Qx + u' Ru)dt$$

- The algebraic Riccati equation

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

- And the optimal control is given by:

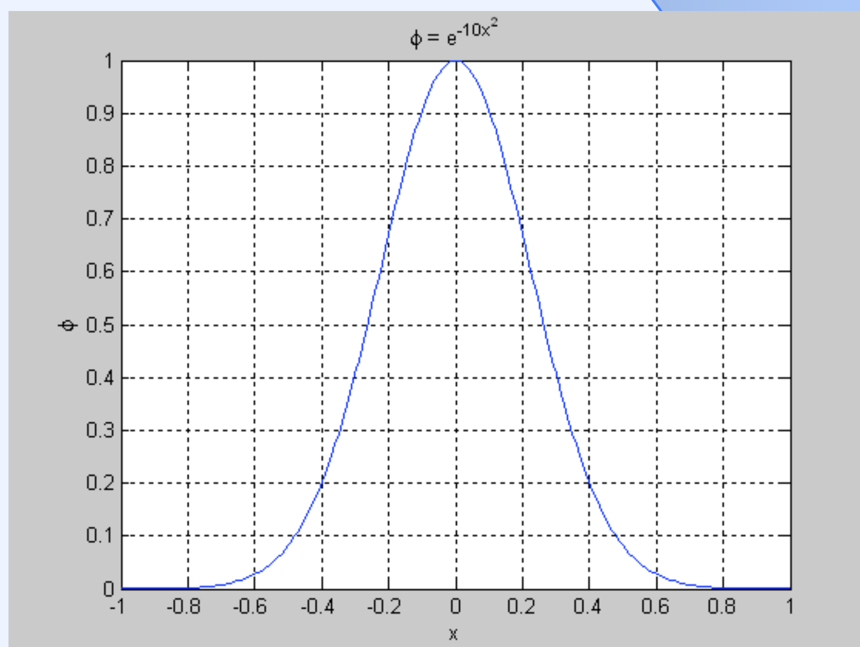
$$u(t) = -R^{-1} B' Px(t) = Kx(t)$$

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

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



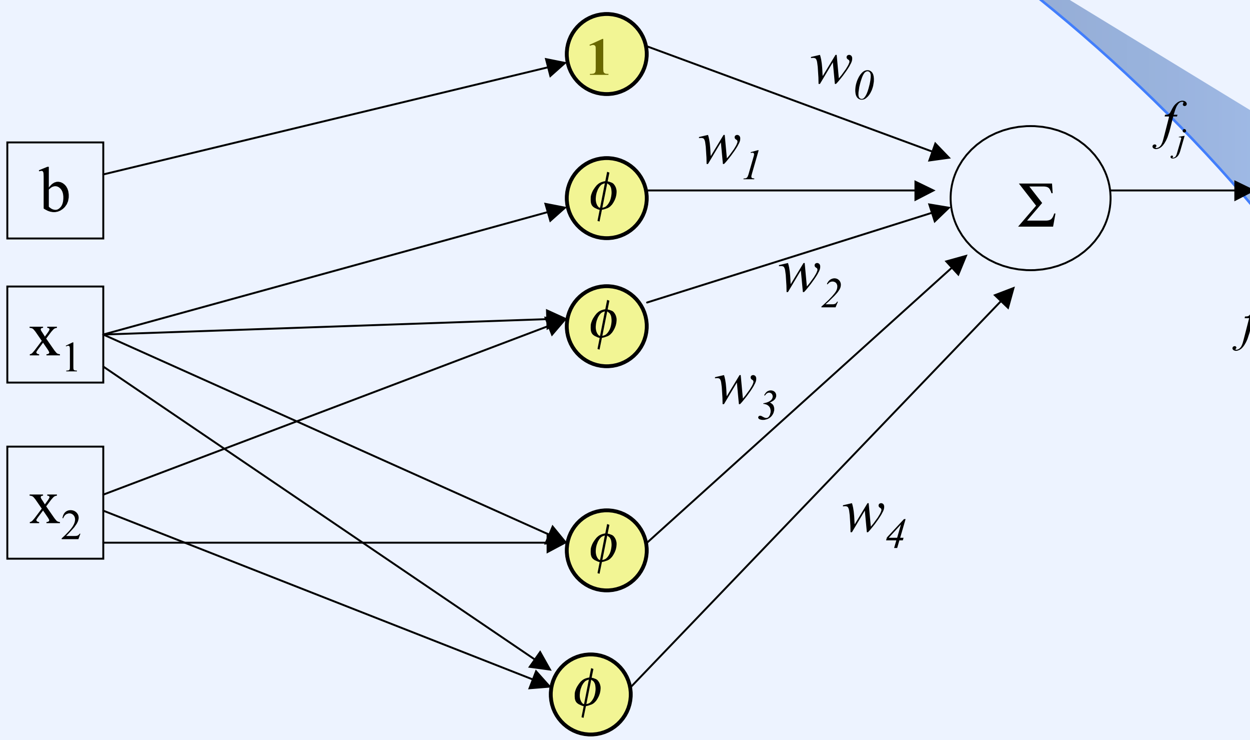
RBF Network Outputs

- 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



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

ϕ means activation function

Failures Investigated

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

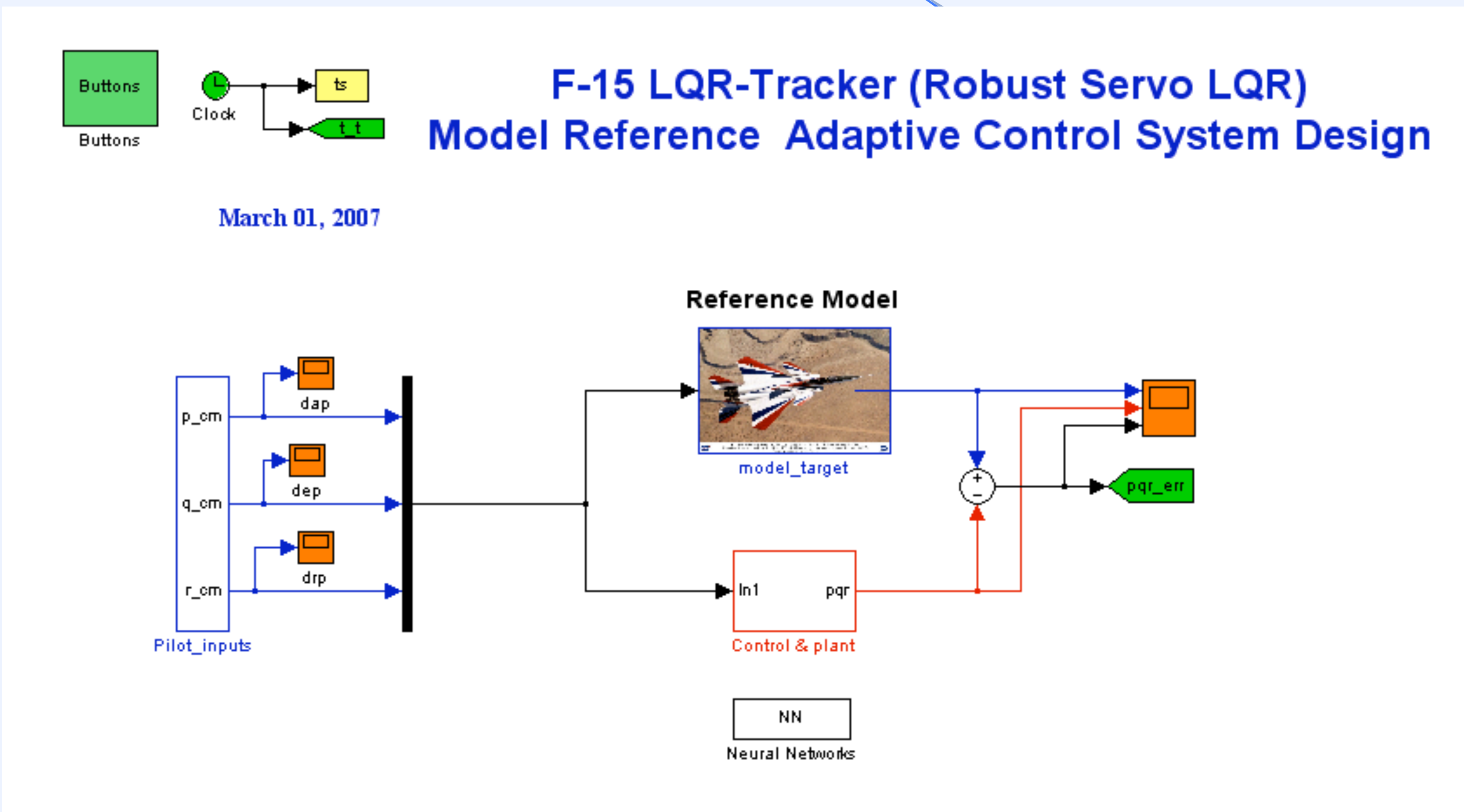
- Aerodynamic Failures or uncertainties (A Matrix problems / lost aero surfaces, bent wings)
  - Or Not well known aero terms due to modelling errors.

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

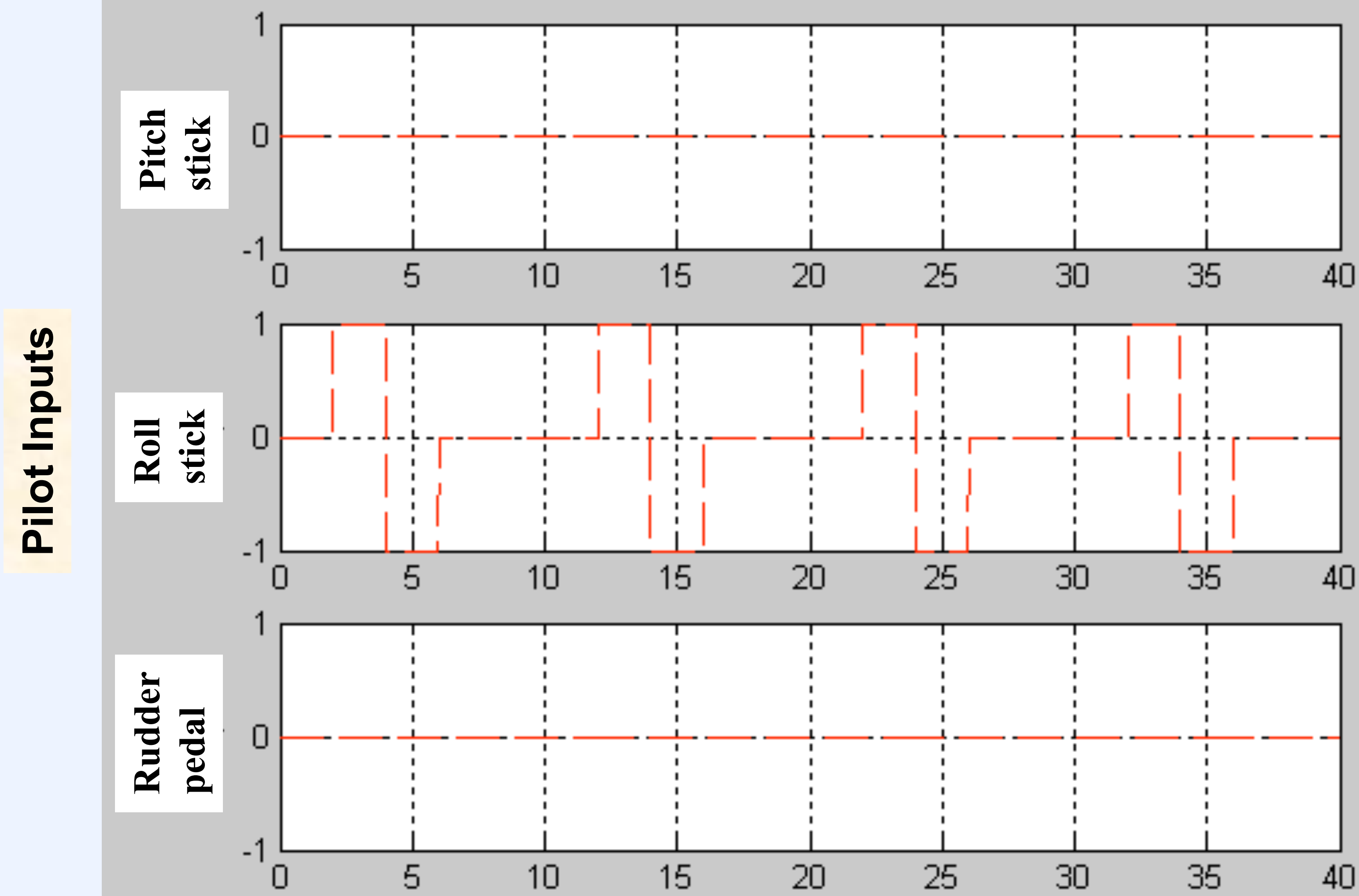
Control Reconfiguration Results

- **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



Long Axis Data

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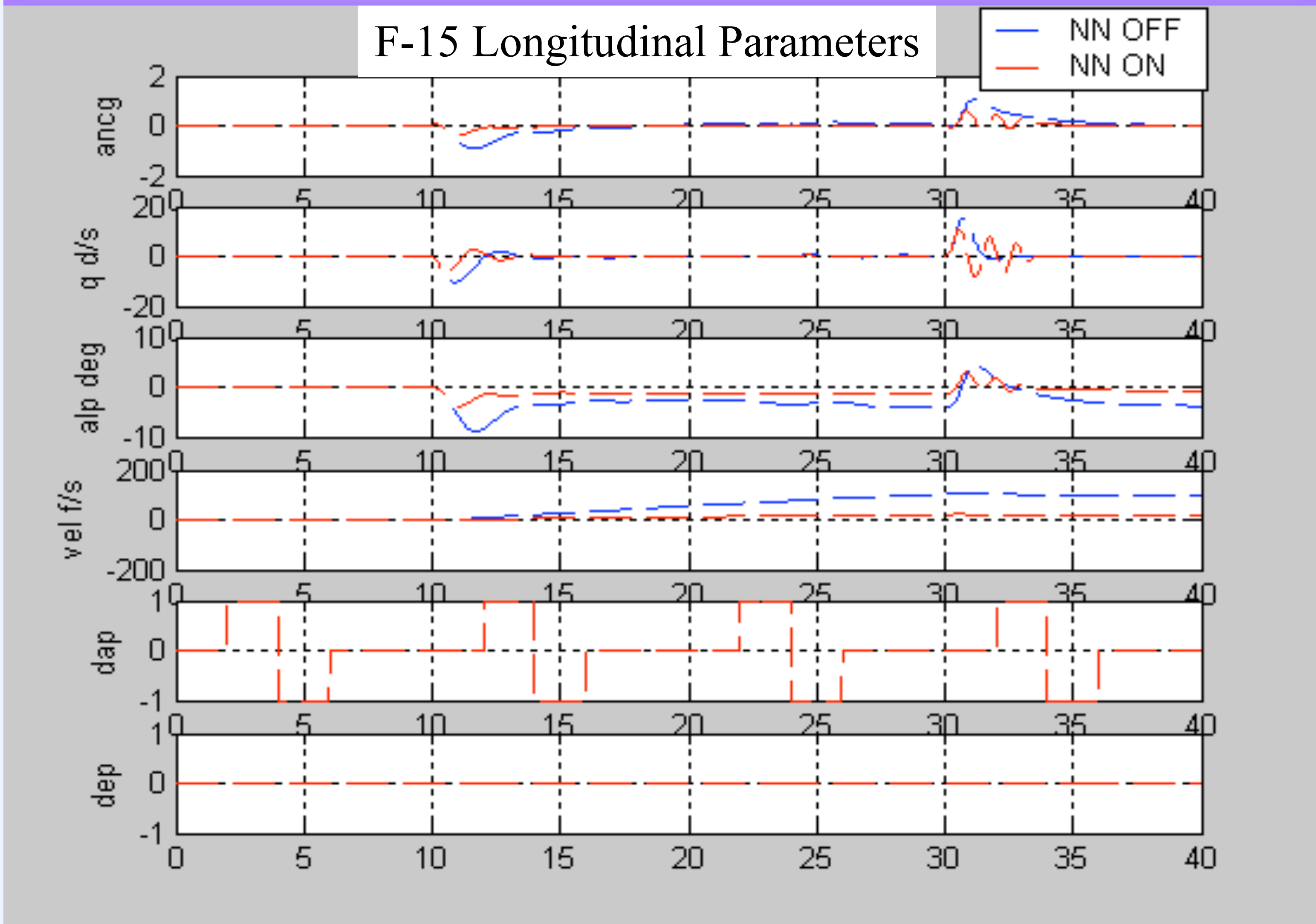
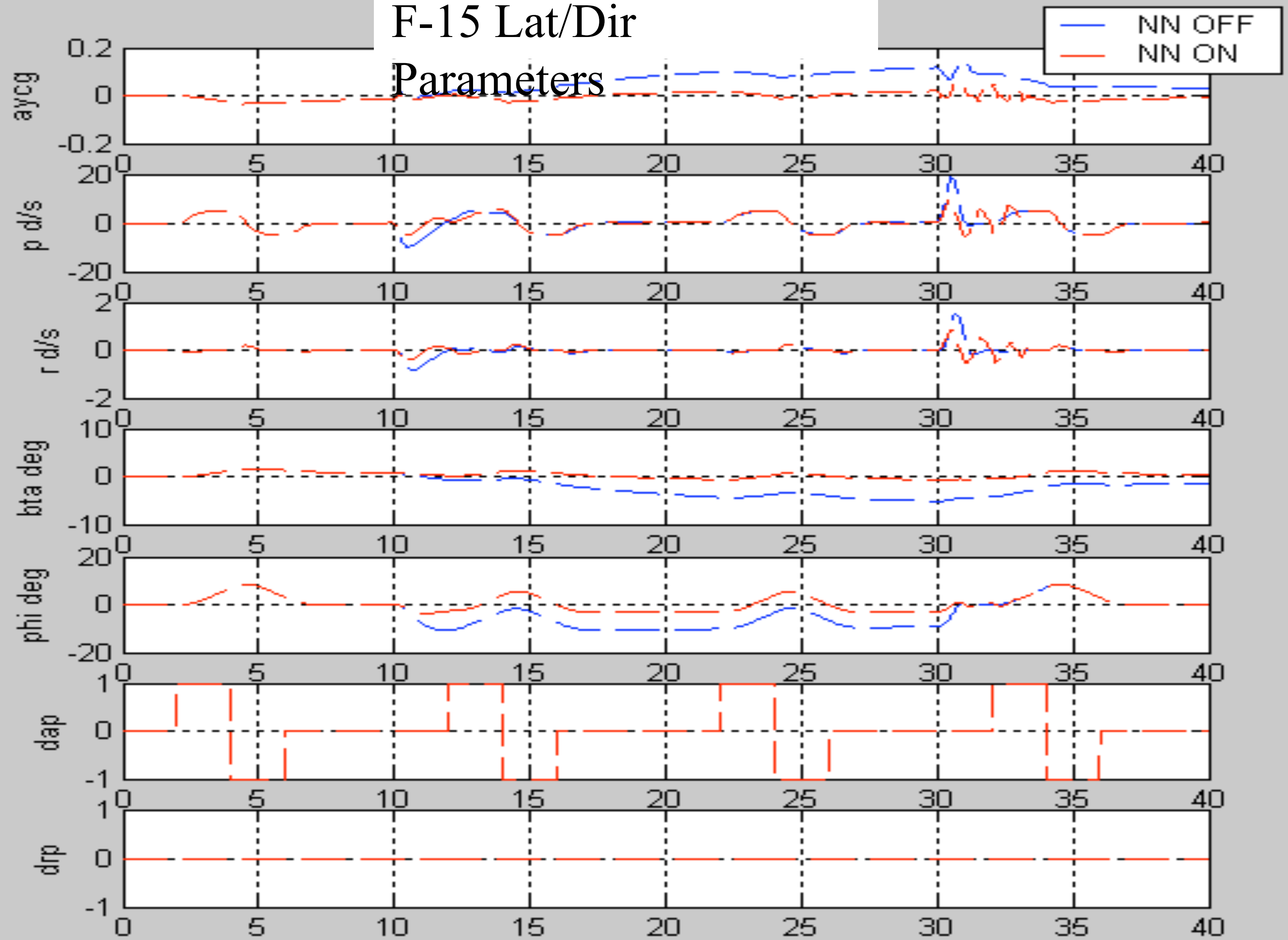


Lat/Dir Axis Data

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

F-15 Lat/Dir Parameters



Neural Network Signals

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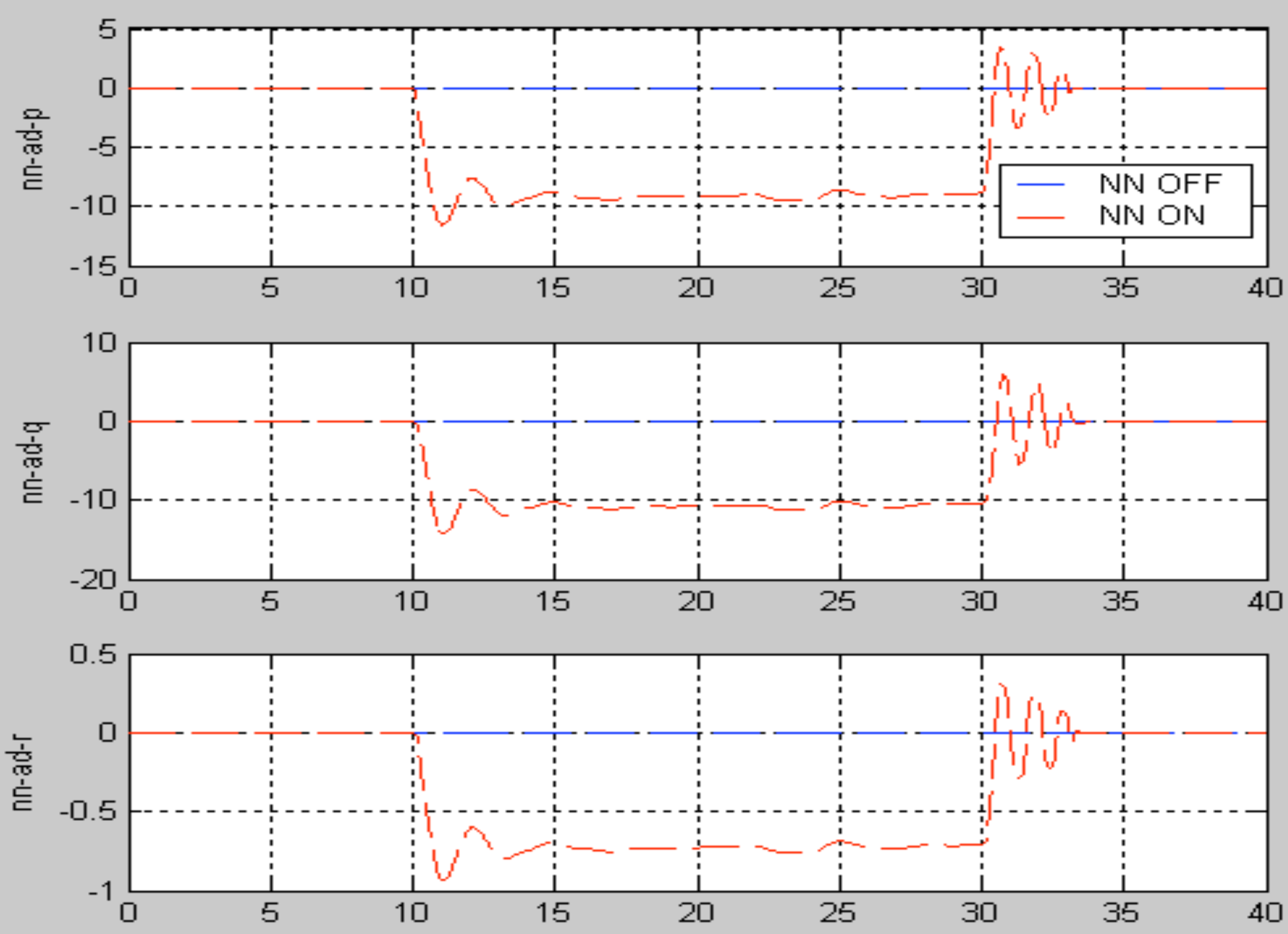

Surface Positions

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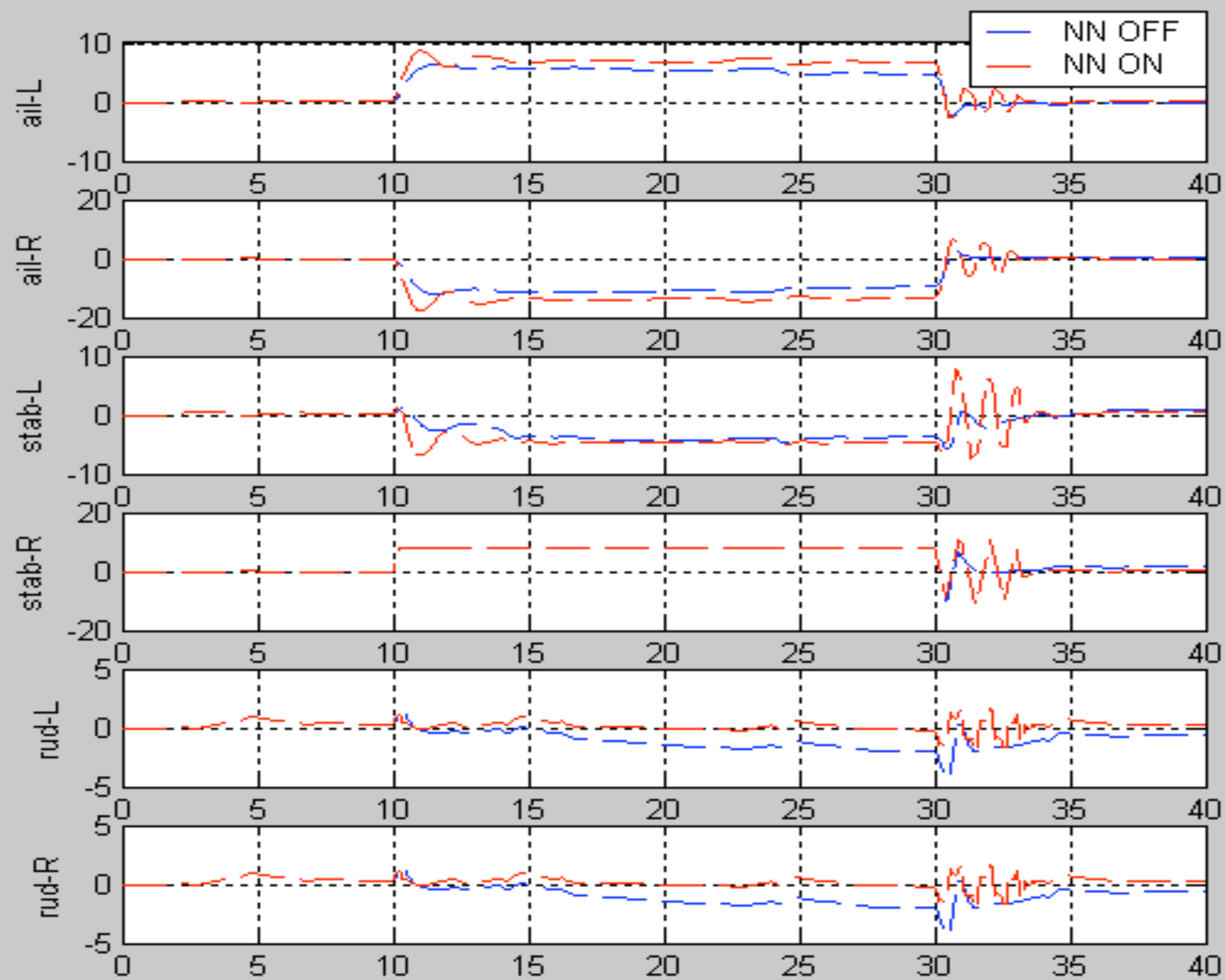
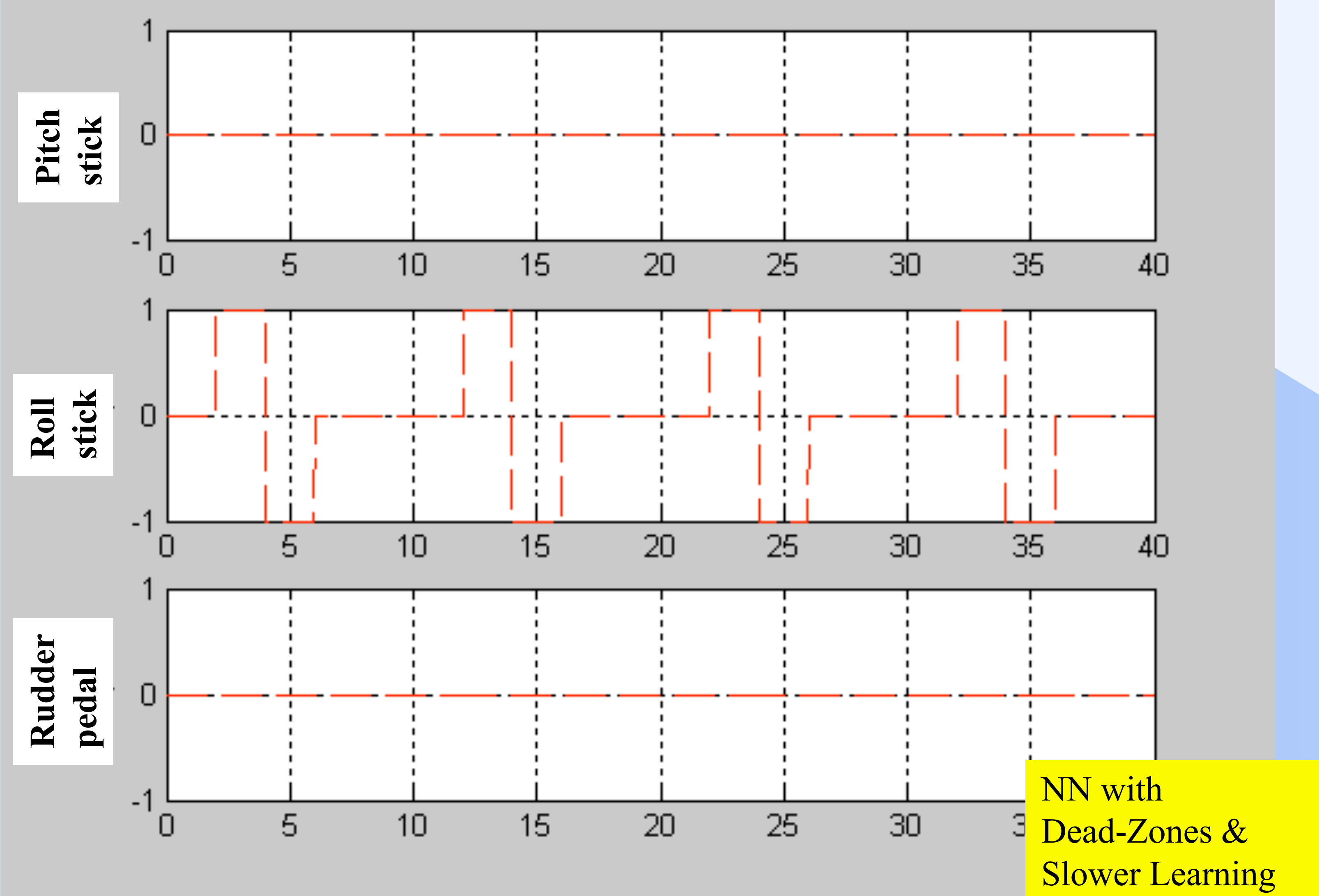


Control Reconfiguration Results

- **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
Failure goes away at 30 seconds / Pilot Input is Roll doublets

Pilot Inputs



Long Axis Data

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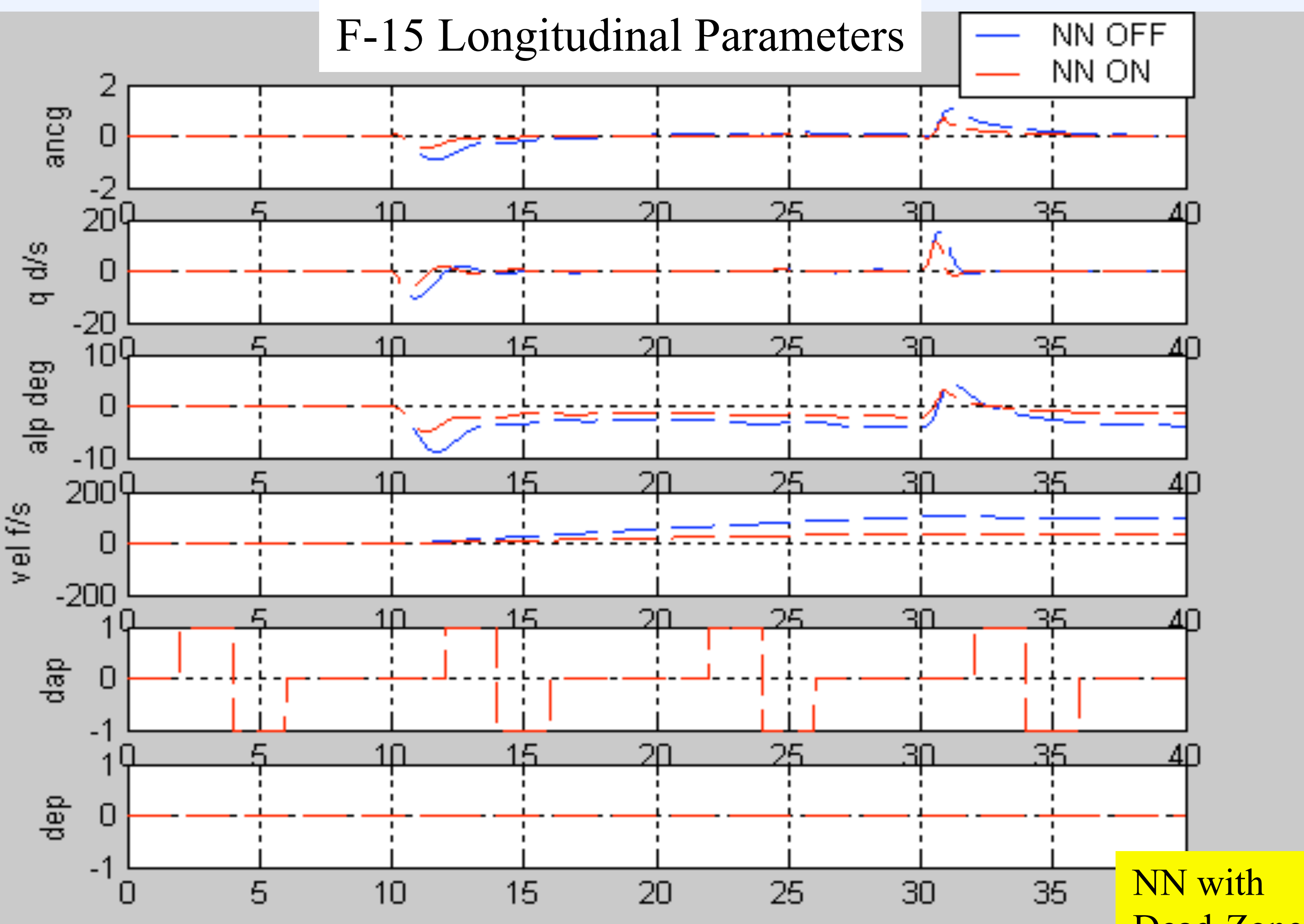
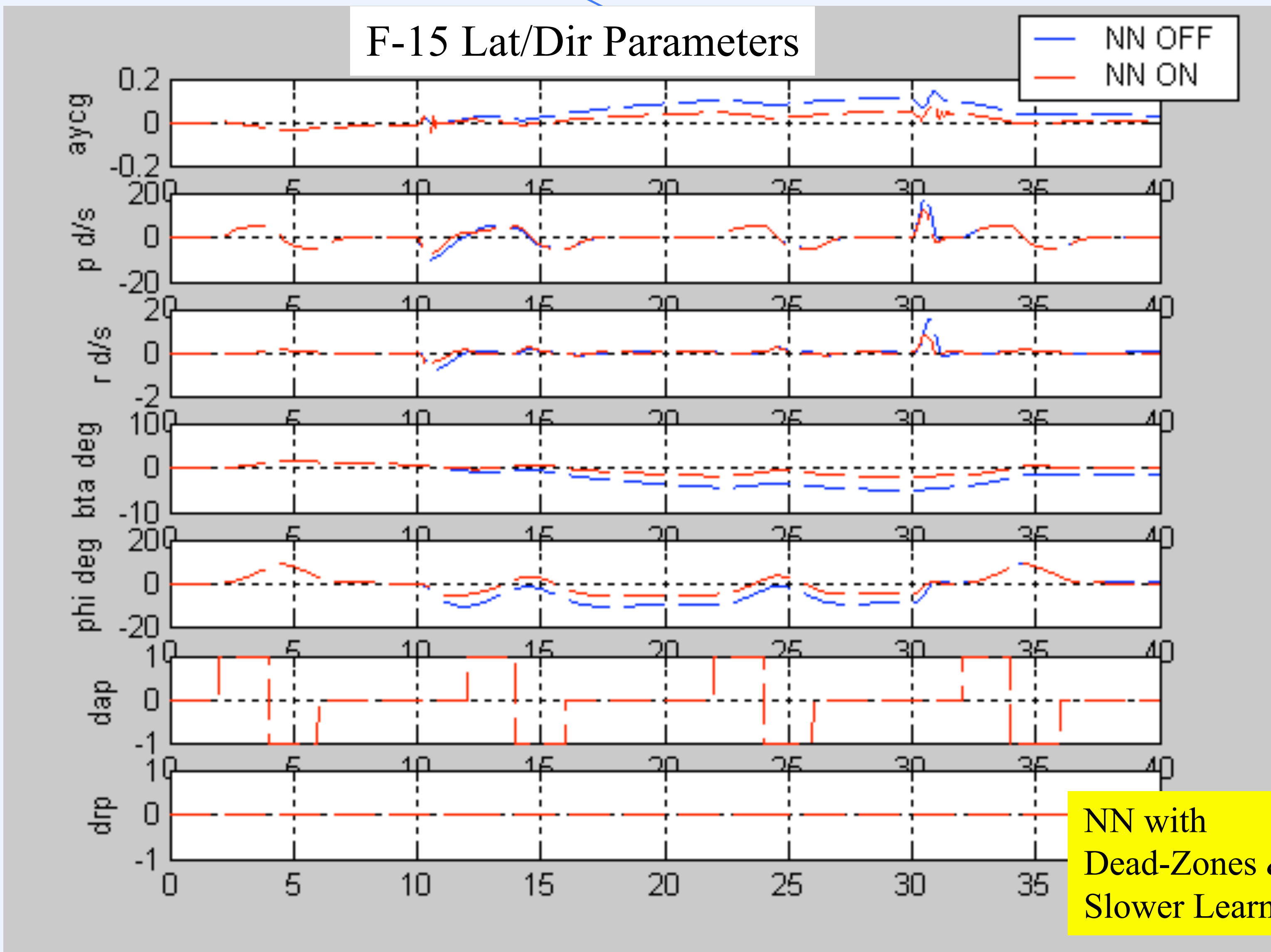


NN with
Dead-Zones &
Slower Learning

Lat/Dir Axis Data

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



NN with
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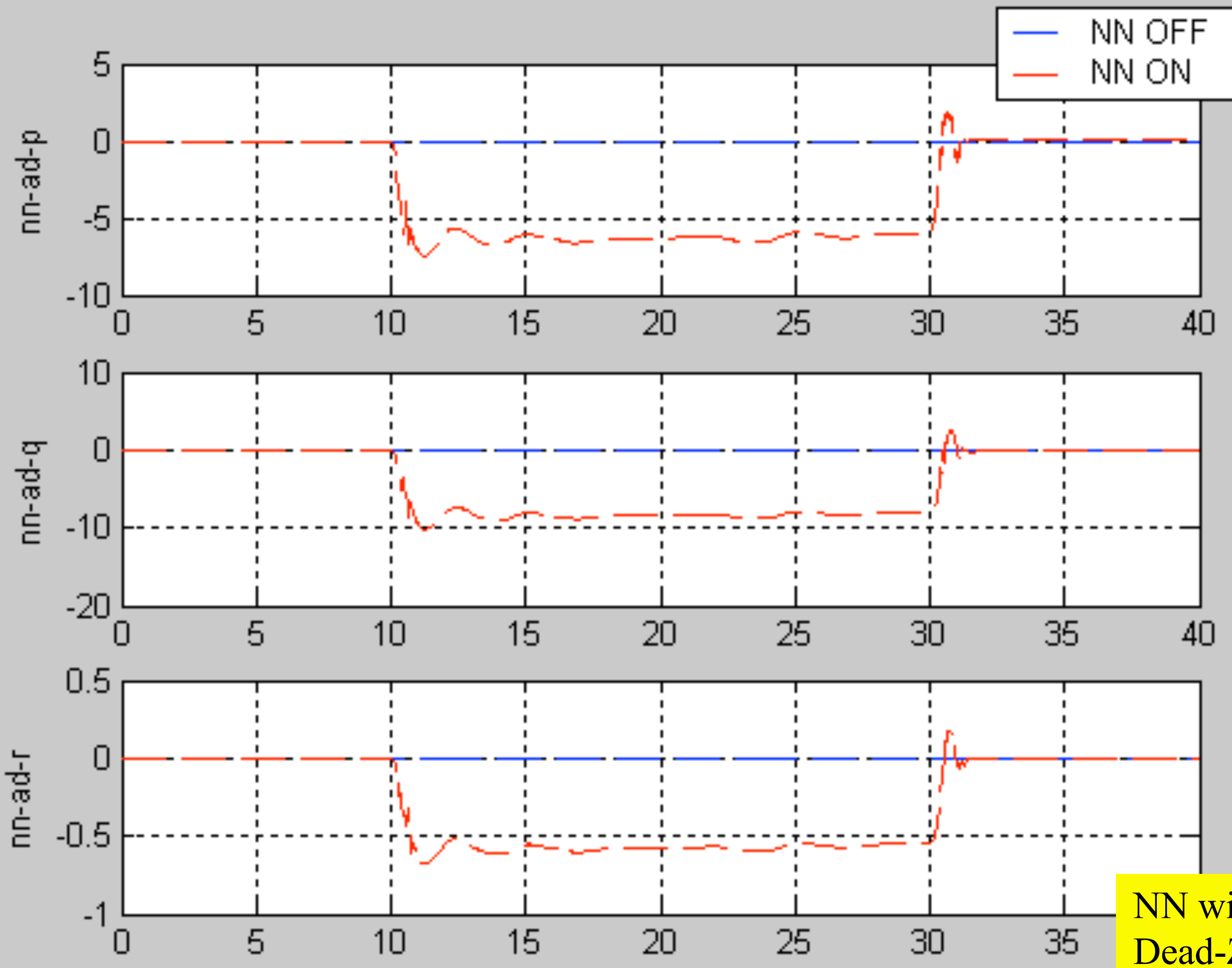

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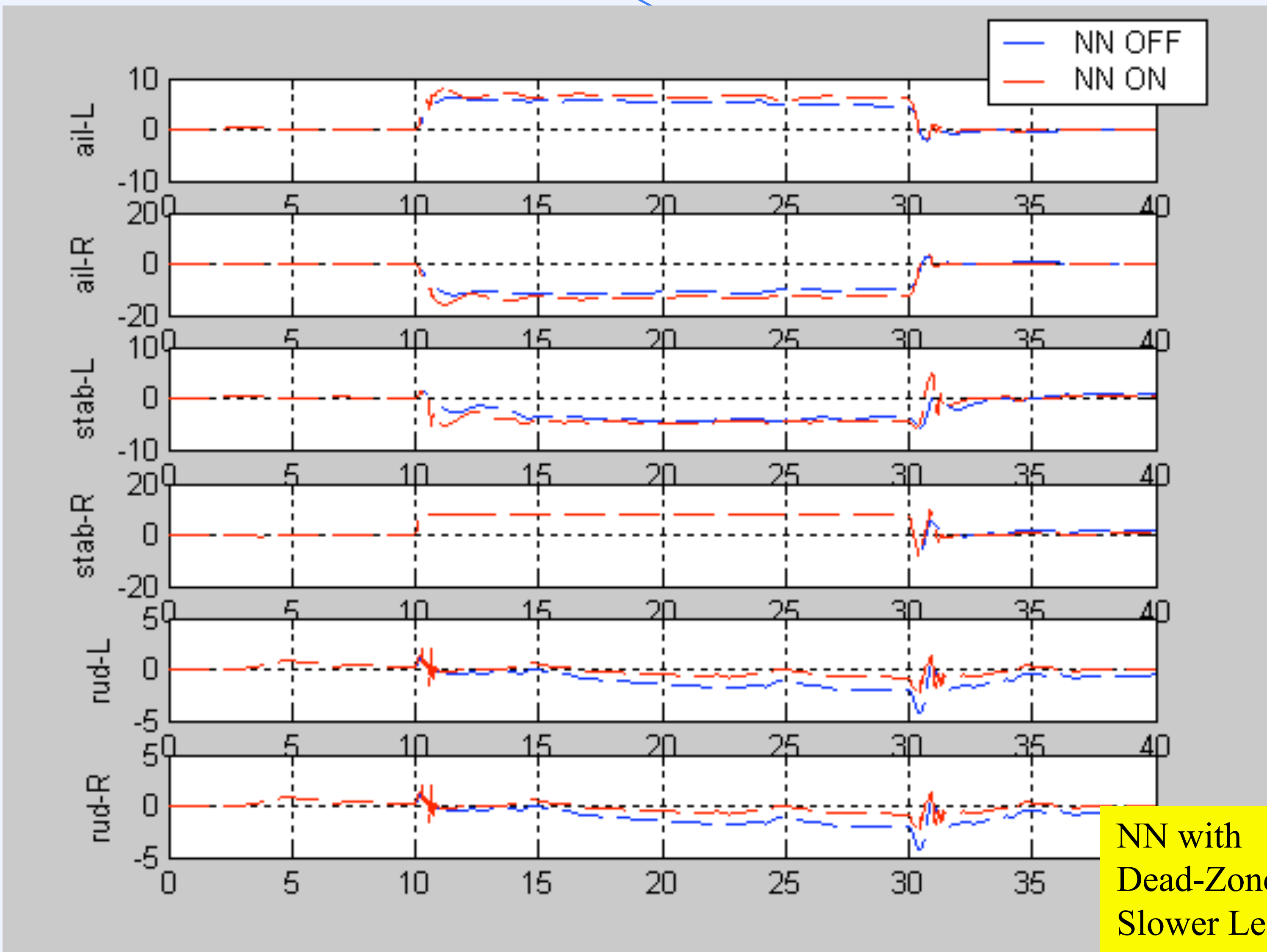

NN with
Dead-Zones &
Slower Learning

Control Reconfiguration Conclusions

- **Conclusions & Remarks**

- **Method presented:**
  - **Robust LQR Servomechanism design with Model Reference Adaptive Control**
    - **Reference Model was a “healthy” 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.**