

# Plant Modeling for an Autonomous Vehicle

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## Objective and Contributions

### Objective

- Provide accurate plant models of each autonomous vehicle subsystem to be used for designing controllers

### Contribution

- Determine if System Identification or Neural Network modeling produces better models
- Non-linearity modeling

### Applications

- Use in testing to help develop more accurate vehicle controllers
- Create a guide for modeling future vehicle subsystems

## Problem Setup

- Conducted a literature review to look for existing solutions
- System Architecture

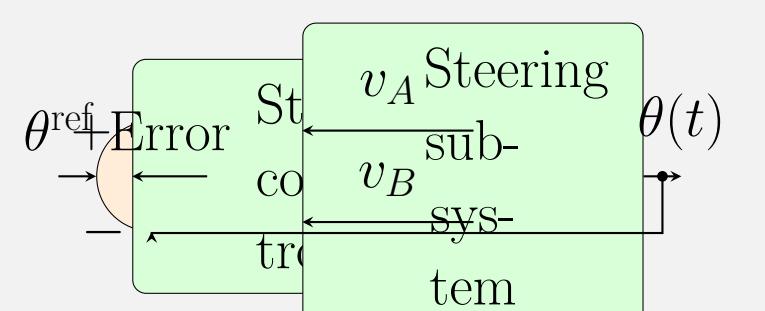


Figure 1:Steering subsystem block diagram.

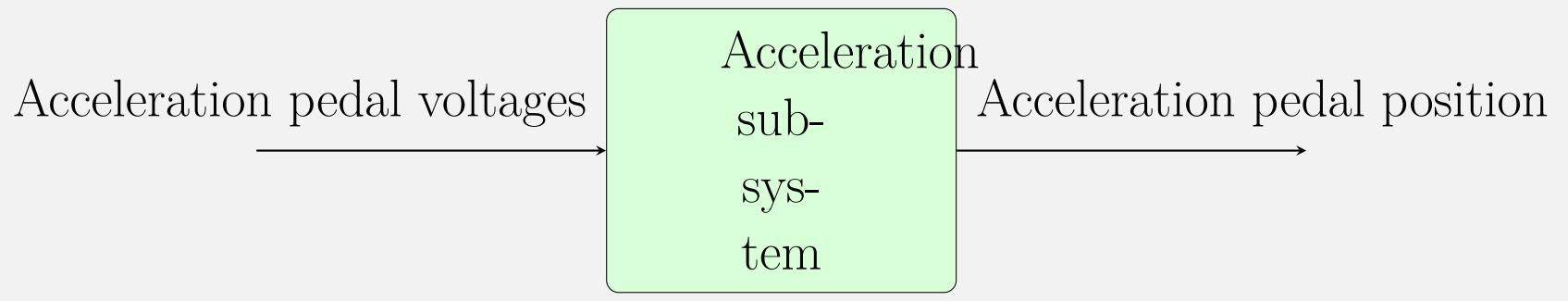


Figure 2:Acceleration subsystem block diagram

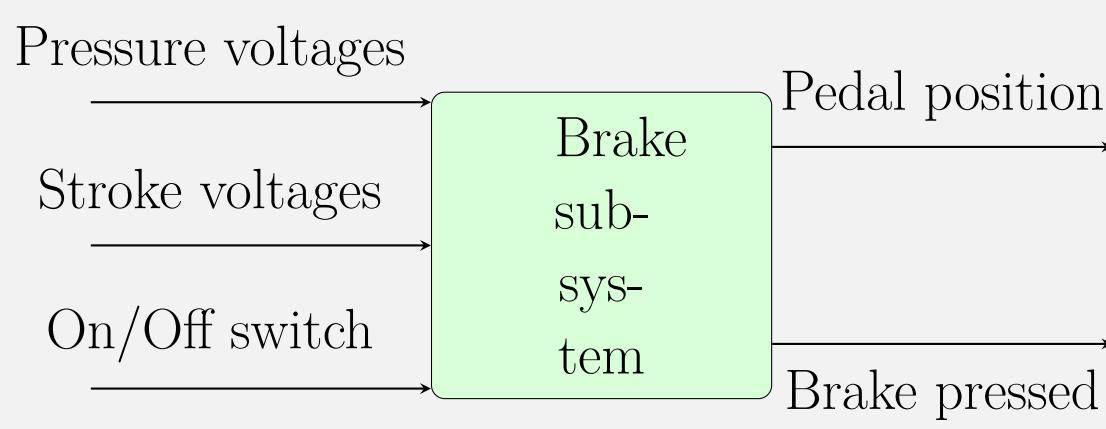


Figure 3:Brake subsystem block diagram

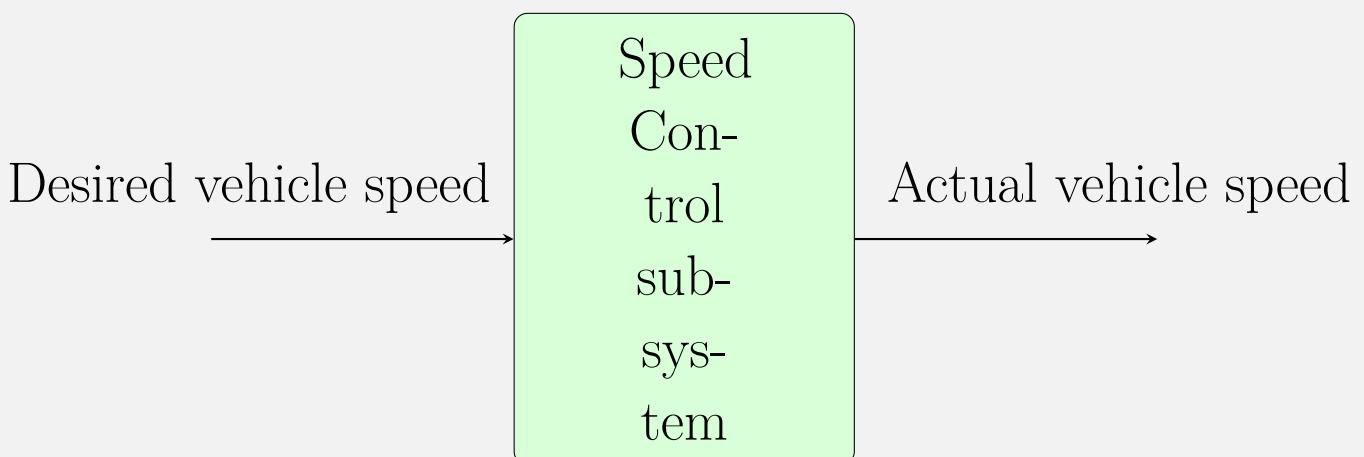


Figure 4:Speed Control subsystem block diagram

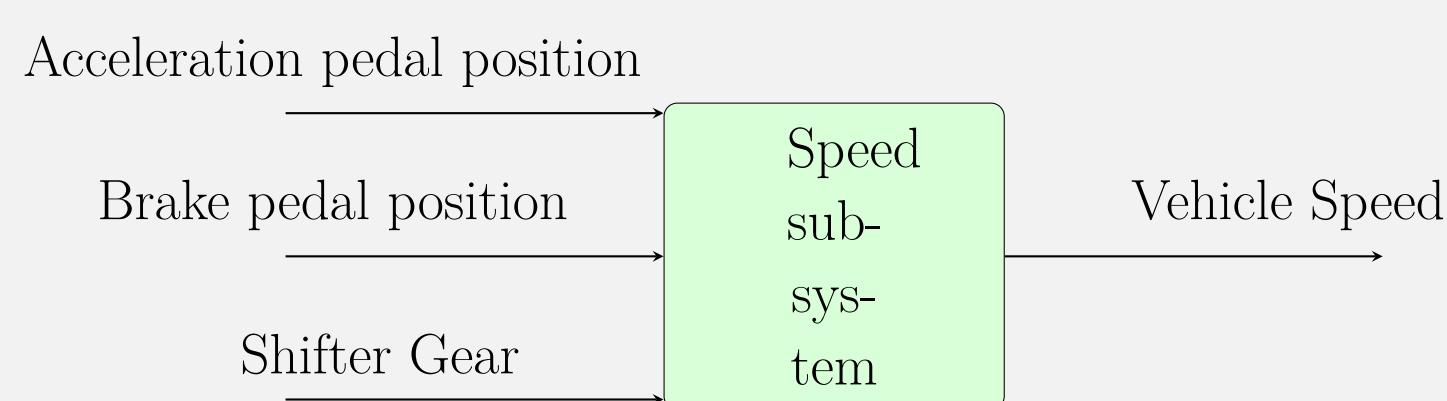


Figure 5:Speed subsystem block diagram

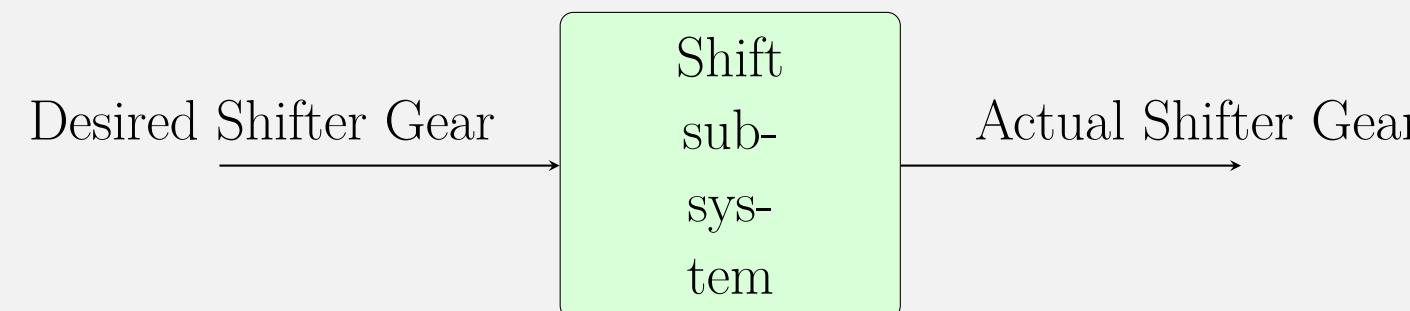


Figure 6:Shift subsystem block diagram

- Collected data using a Lexus RX450H vehicle platform

## Transfer Function Modeling

- MATLAB's System Identification Toolbox used to create models
- Models needed to meet best fit and error requirements

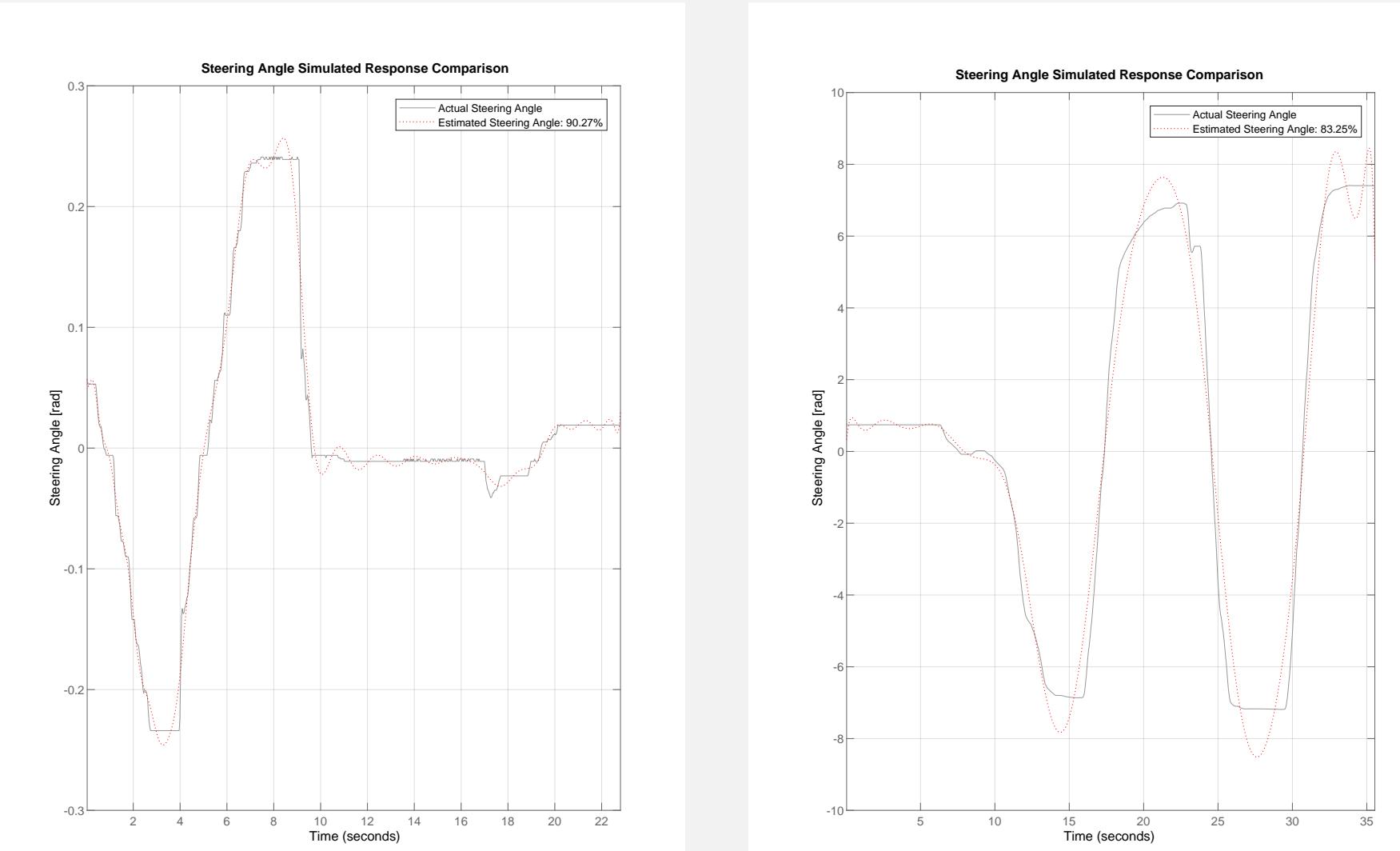


Figure 7:Steering System Estimated Steering Angle Comparison

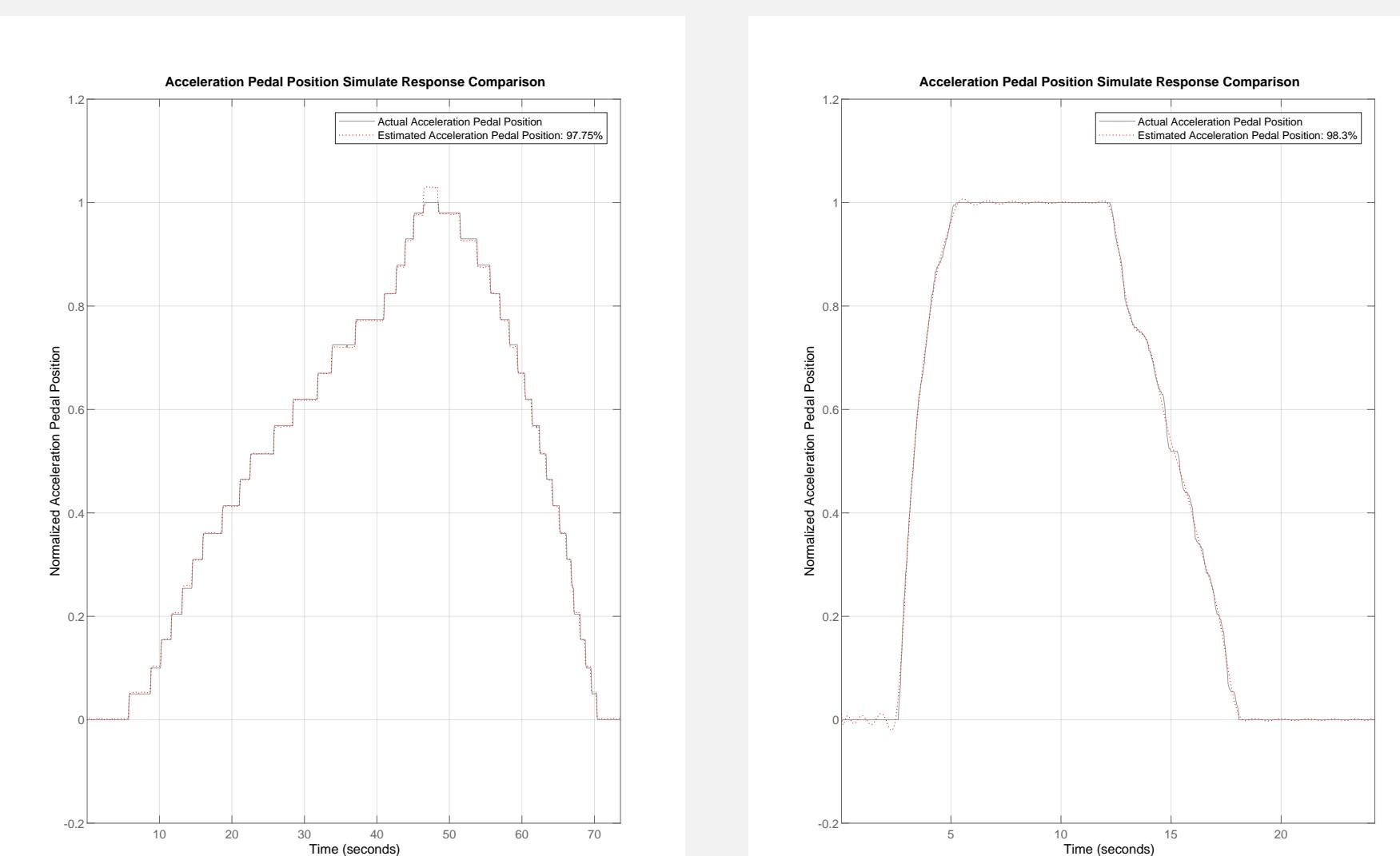


Figure 8:Acceleration System Estimated Pedal Position Comparison

## Neural Network Modeling

- Used MATLAB's Neural Network Time Series App
- Generated models using the Bayesian Regularization Algorithm
- Models trained using collected log data

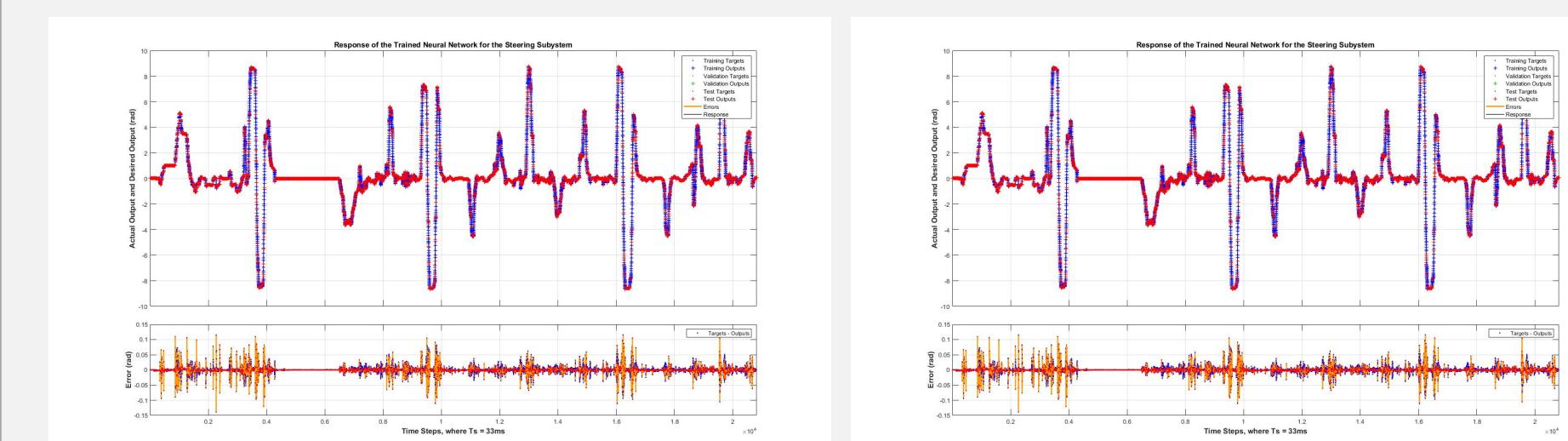


Figure 9:Steering System Training Plots

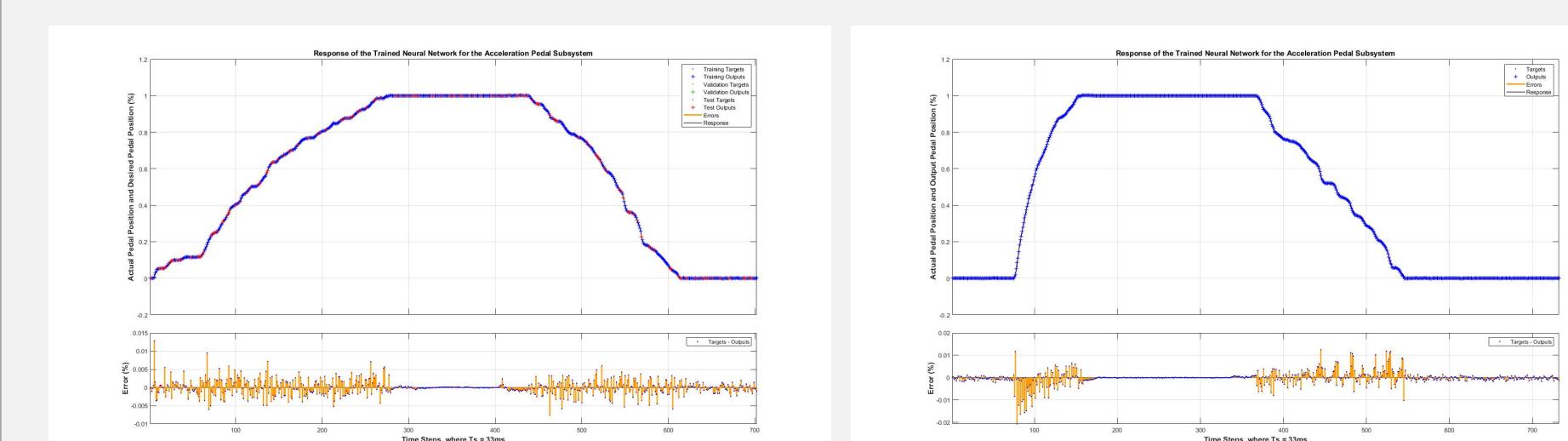


Figure 10:Acceleration System Training Plots

## Neural Network Algorithm

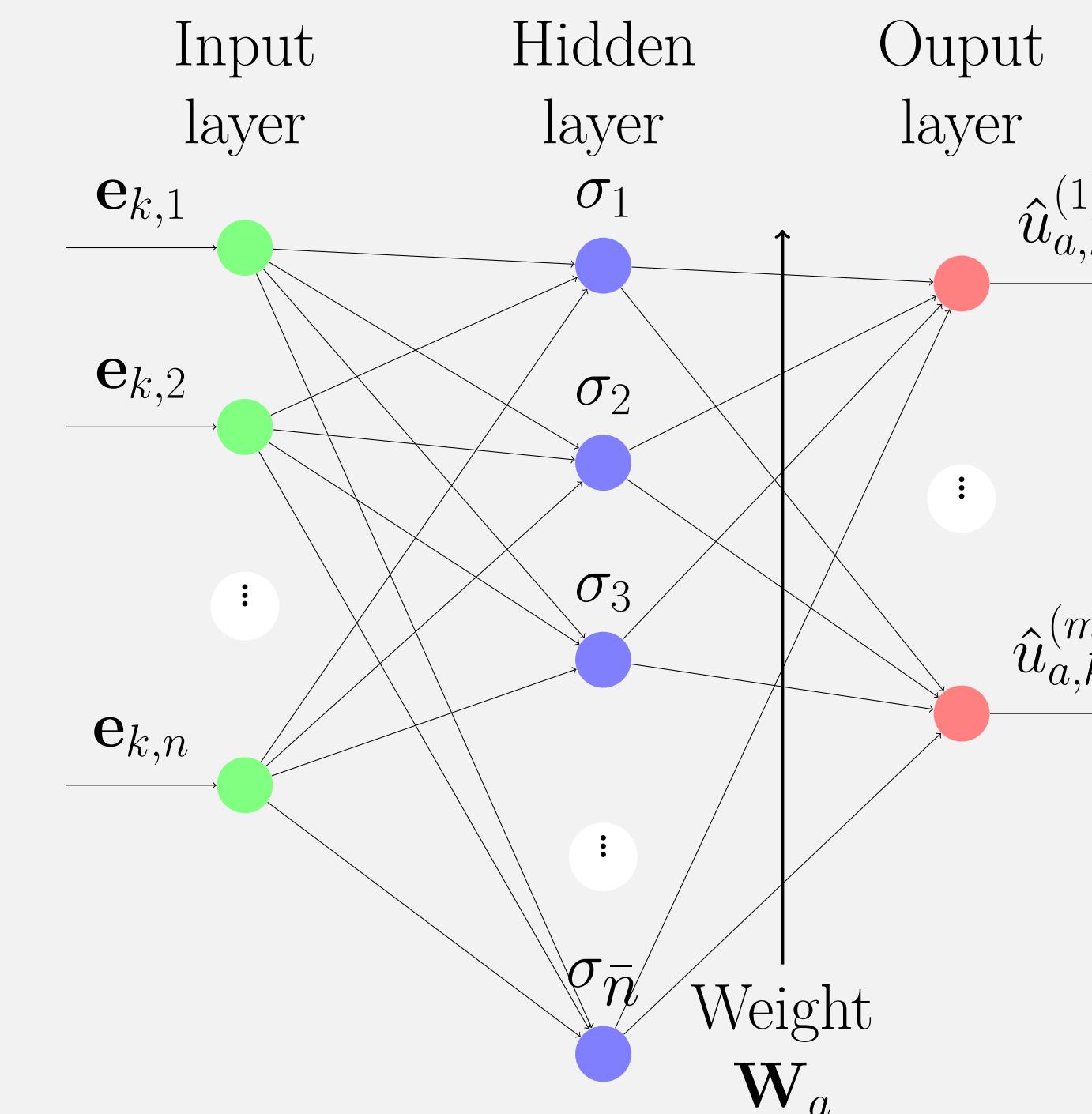


Figure 12:Actor neural network structure for approximating control input.

- Approximate neural network signal

$$\hat{\mathbf{u}}_{a,k} = \mathbf{W}_a^T \boldsymbol{\sigma}(\mathbf{e}_k),$$

- Define the weight matrix

$$\mathbf{W}_a = \begin{bmatrix} w_a^{1,1} & w_a^{1,2} & \dots & w_a^{1,m} \\ w_a^{2,1} & w_a^{2,2} & \dots & w_a^{2,m} \\ \vdots & \ddots & \dots & \vdots \\ w_a^{\bar{n},1} & w_a^{\bar{n},2} & \dots & w_a^{\bar{n},m} \end{bmatrix}.$$

- Compute the sum-of-squared error

$$\Sigma \mathbf{W}_a \approx \mathbf{U}^{[d]}, \quad \text{with}$$

$$\Sigma \mathbf{W}_a \equiv \hat{\mathbf{U}}$$

$$\delta_a = \frac{1}{2} \|\mathbf{U}^{[d]} - \hat{\mathbf{U}}\|^2$$

- Find the actor weight by minimizing the sum-of-square error

$$\delta_a = \frac{1}{2} \text{Tr} [(\mathbf{U}^{[d]} - \Sigma \mathbf{W}_a)^T (\mathbf{U}^{[d]} - \Sigma \mathbf{W}_a)].$$

- Take the derivative of  $\delta_a$  with respect to  $\mathbf{W}_a$  and set  $\frac{\partial \delta_a}{\partial \mathbf{W}_a}$  to zero

$$\frac{\partial \delta_a}{\partial \mathbf{W}_a} = -\Sigma^T \mathbf{U}^{[d]} + \Sigma^T \Sigma \mathbf{W}_a$$

$$\mathbf{W}_a = (\Sigma^T \Sigma)^T \Sigma^T \mathbf{U}^{[d]}.$$

- Use the gradient descent approach to minimize the least square order alter weights when training the neural network

$$\begin{aligned} \mathbf{W}_a^{(r+1)} &= \mathbf{w}_a^{(r)} - \ell_a \frac{\partial \delta_a}{\partial \mathbf{W}_a} \\ &= \mathbf{w}_a^{(r)} - \ell_a (-\Sigma^T \mathbf{U}^{[d]} + \Sigma^T \Sigma \mathbf{W}_a^{(r)}) \\ &= \mathbf{w}_a^{(r)} - \ell_a \Sigma^T (\Sigma \mathbf{W}_a^{(r)} - \mathbf{U}^{[d]}) \end{aligned}$$

## Experimental Results

- Preliminary model testing conducted before sending models to AutonomousStuff
- Official testing conducted using dSPACE software and HIL Bench



Figure 13:Experimental Setup

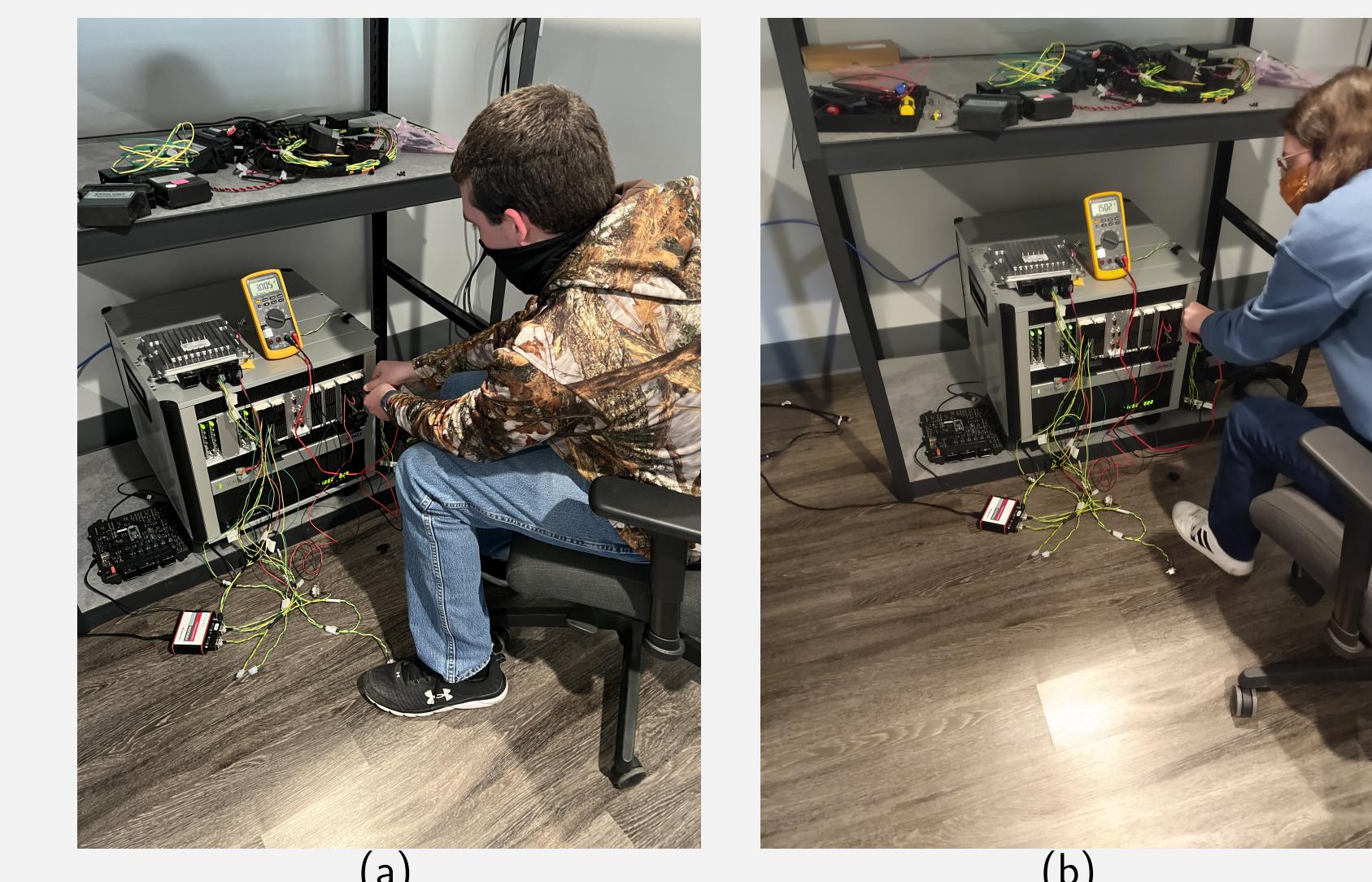


Figure 14:Verifying voltage measurements on the HIL Bench

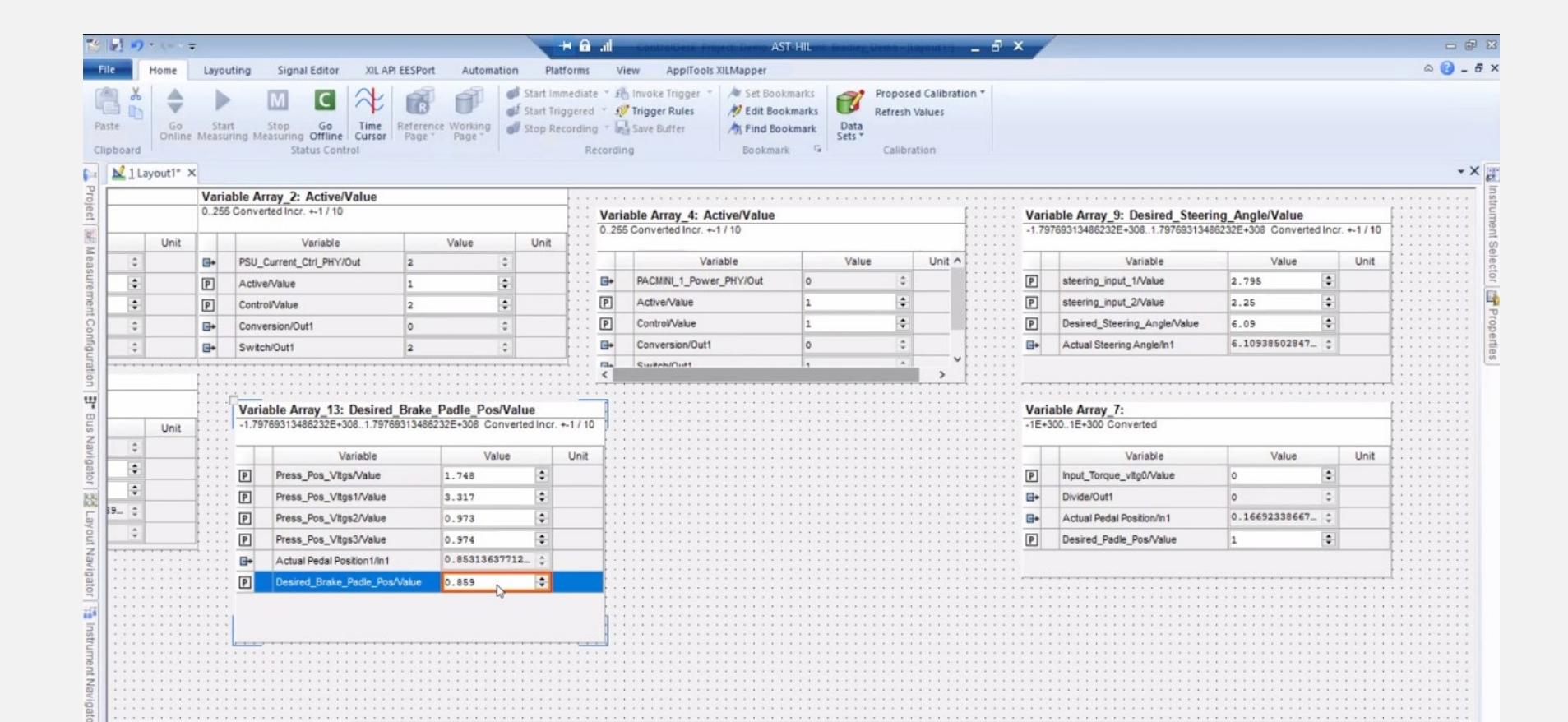


Figure 15:Model validation setup

## Conclusion and Future Work

- Using Neural Networks produced more accurate models than System Identification
- Test models using Hardware-in-the-Loop
- Create new vehicle controllers