UAV Trajectory Modeling Using Neural Networks

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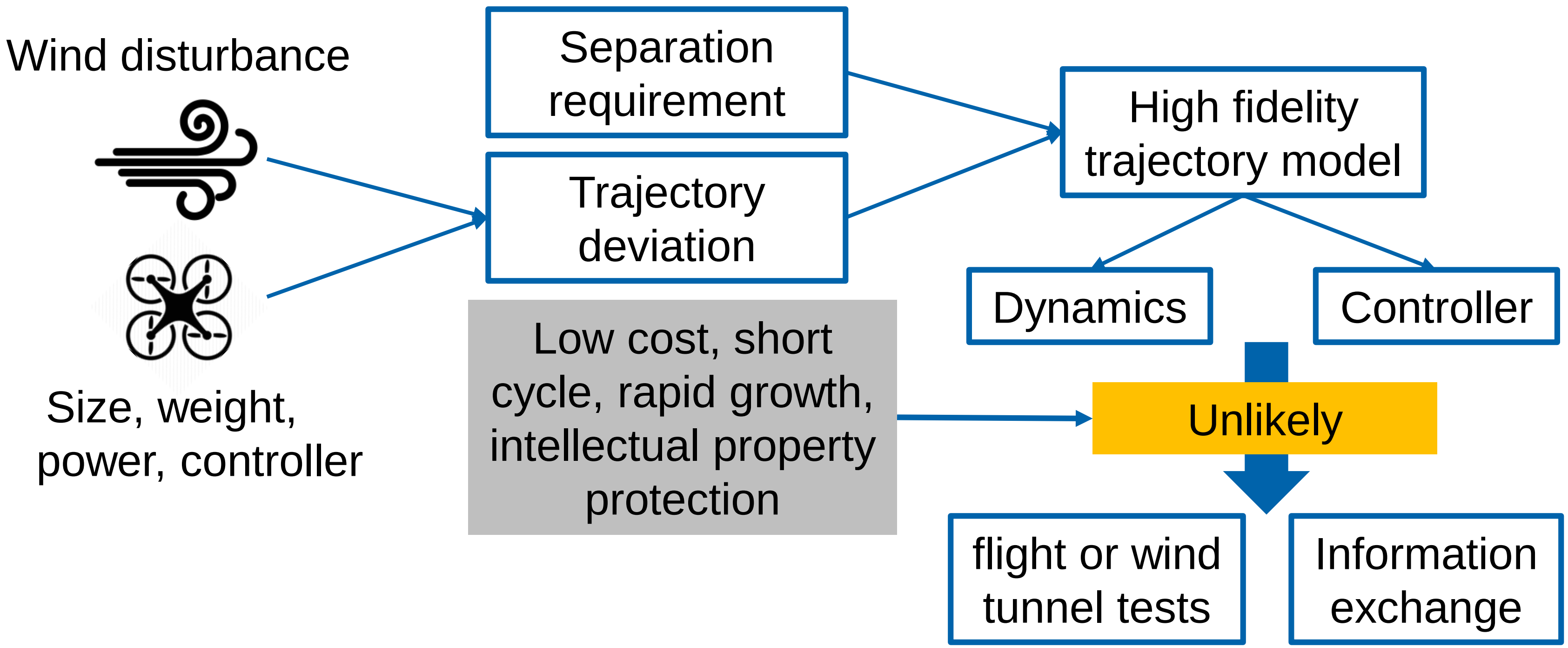
Motivation

Trajectory models are required for traffic management study



Objective: Study the feasibility of modeling trajectory using Neural Networks

Outline

- Approach
  - General trajectory model
  - Neural Network method
- Experiment
- Summary

Conventional Trajectory Model

Dynamics

Moment

$$\begin{bmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} \frac{J_y - J_z}{J_x} qr \\ \frac{J_z - J_x}{J_y} pr \\ \frac{J_x - J_y}{J_z} pq \end{bmatrix} + \begin{bmatrix} \frac{1}{J_x} M_\phi \\ \frac{1}{J_y} M_\theta \\ \frac{1}{J_z} M_\psi \end{bmatrix}$$

Controller

Kinematic

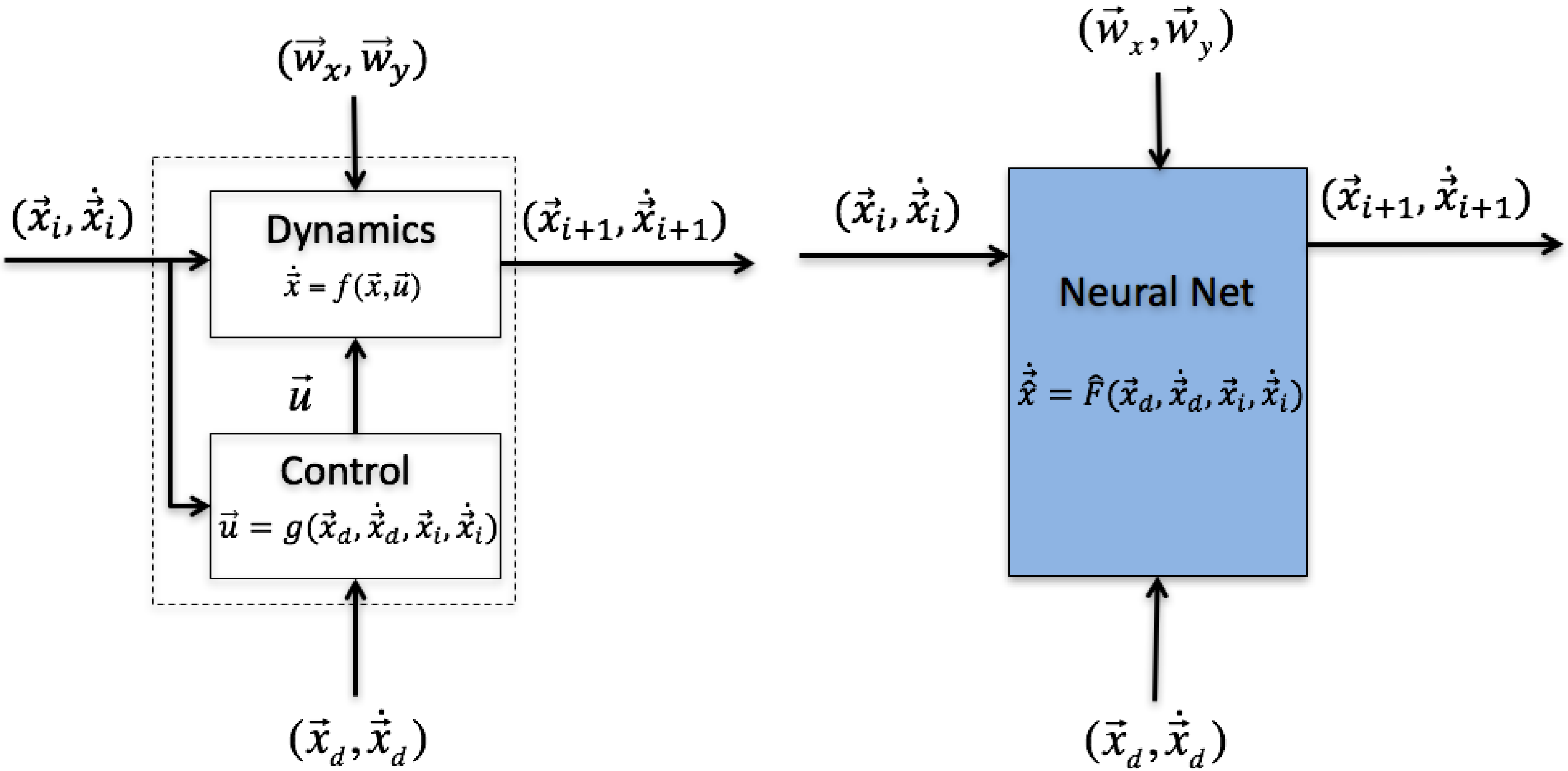
$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \frac{\sin\phi}{\cos\theta} & \frac{\cos\phi}{\cos\theta} \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix}$$

Force

$$\begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} rv - qw \\ pw - ru \\ qu - pv \end{bmatrix} + \begin{bmatrix} -g\sin\theta \\ g\cos\theta\sin\phi \\ g\cos\theta\cos\phi \end{bmatrix} + \frac{1}{m} \begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix}$$

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{bmatrix} = \begin{bmatrix} c\theta c\psi & s\phi s\theta c\psi - c\phi s\psi & c\phi s\theta c\psi + s\phi s\psi \\ c\theta s\psi & s\phi s\theta s\psi + c\phi c\psi & c\phi s\theta s\psi - s\phi c\psi \\ s\theta & -s\phi c\theta & -c\phi c\theta \end{bmatrix} \begin{bmatrix} u \\ v \\ w \end{bmatrix}$$

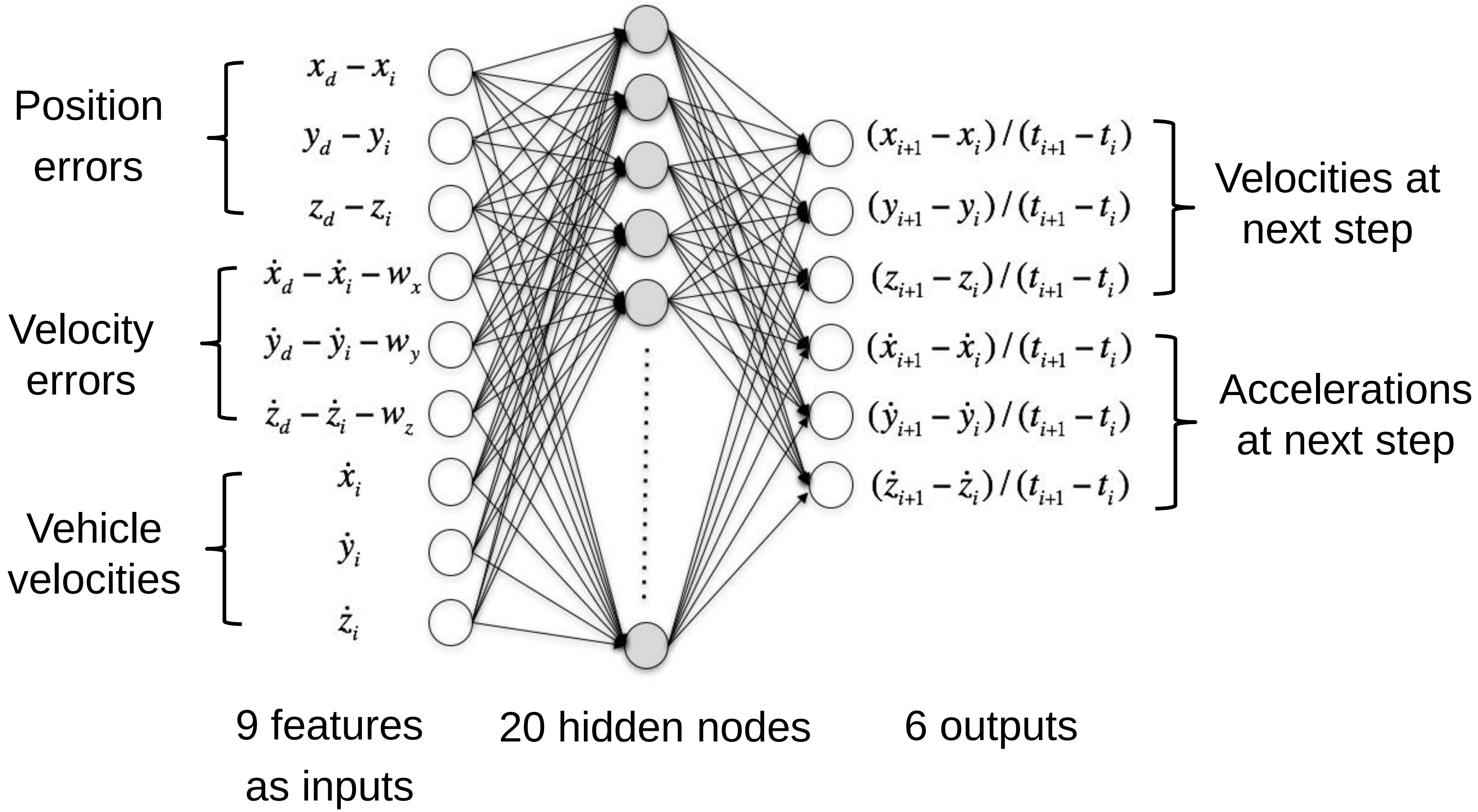
Neural Network Trajectory Model



NN captures both dynamics and controller

Neural Network Structure

Multiple Layer Perceptron (MLP) Neural Network



Outline

- Approach
- Experiment
  - Data generation
  - Training
  - Trajectory prediction
- Summary

Data generation – Quadrotor trajectory model

Dynamics:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{y} \\ \ddot{y} \\ \ddot{z} \\ \ddot{\phi} \\ \ddot{\theta} \\ \ddot{\psi} \end{bmatrix} = \begin{bmatrix} \dot{x} + \omega_e \\ -(\cos\phi \sin\theta \cos\psi + \sin\phi \sin\psi) F_z/m \\ \dot{y} + \omega_n \\ (-\cos\phi \sin\theta \sin\psi + \sin\phi \cos\psi) F_z/m \\ -g + \cos\phi \cos\theta \, F_z/m \\ M_\phi / J_x \\ M_\theta / J_y \\ M_\psi / J_z \end{bmatrix}$$

Controller: [proportional-derivative (PD)]

$$\begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} k_p(x_d - x) + k_d(\dot{x}_d - \dot{x}) \\ k_p(y_d - y) + k_d(\dot{y}_d - \dot{y}) \end{bmatrix}$$

$$\begin{bmatrix} \phi_d \\ \theta_d \end{bmatrix} = \frac{m}{F_z} \begin{bmatrix} -\sin\psi & -\cos\psi \\ \cos\psi & -\sin\psi \end{bmatrix}^{-1} \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix}$$

$$\begin{bmatrix} M_\phi \\ M_\theta \end{bmatrix} = \begin{bmatrix} k_{p,\phi}(\phi_d - \phi) + k_{d,\phi}(\dot{\phi}_d - \dot{\phi}) \\ k_{p,\theta}(\theta_d - \theta) + k_{d,\theta}(\dot{\theta}_d - \dot{\theta}) \end{bmatrix} l$$

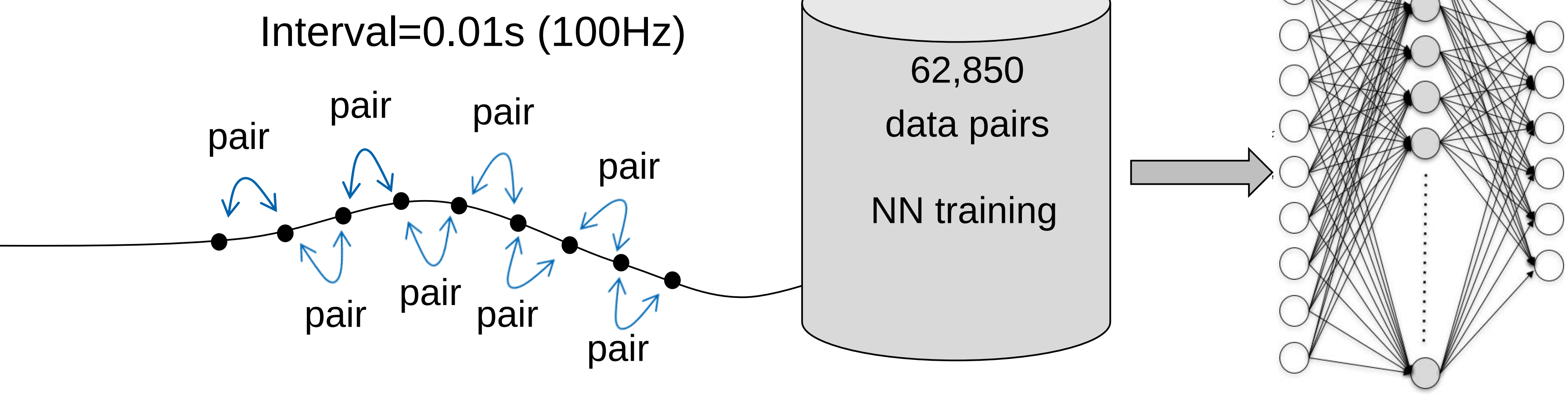
$$k_{p,\phi} = 4.5, k_{d,\phi} = 0.5, k_{p,\theta} = 4.5, k_{d,\theta} = 0.5, k_p = 7.5, k_d = 4.2$$

Training Setup

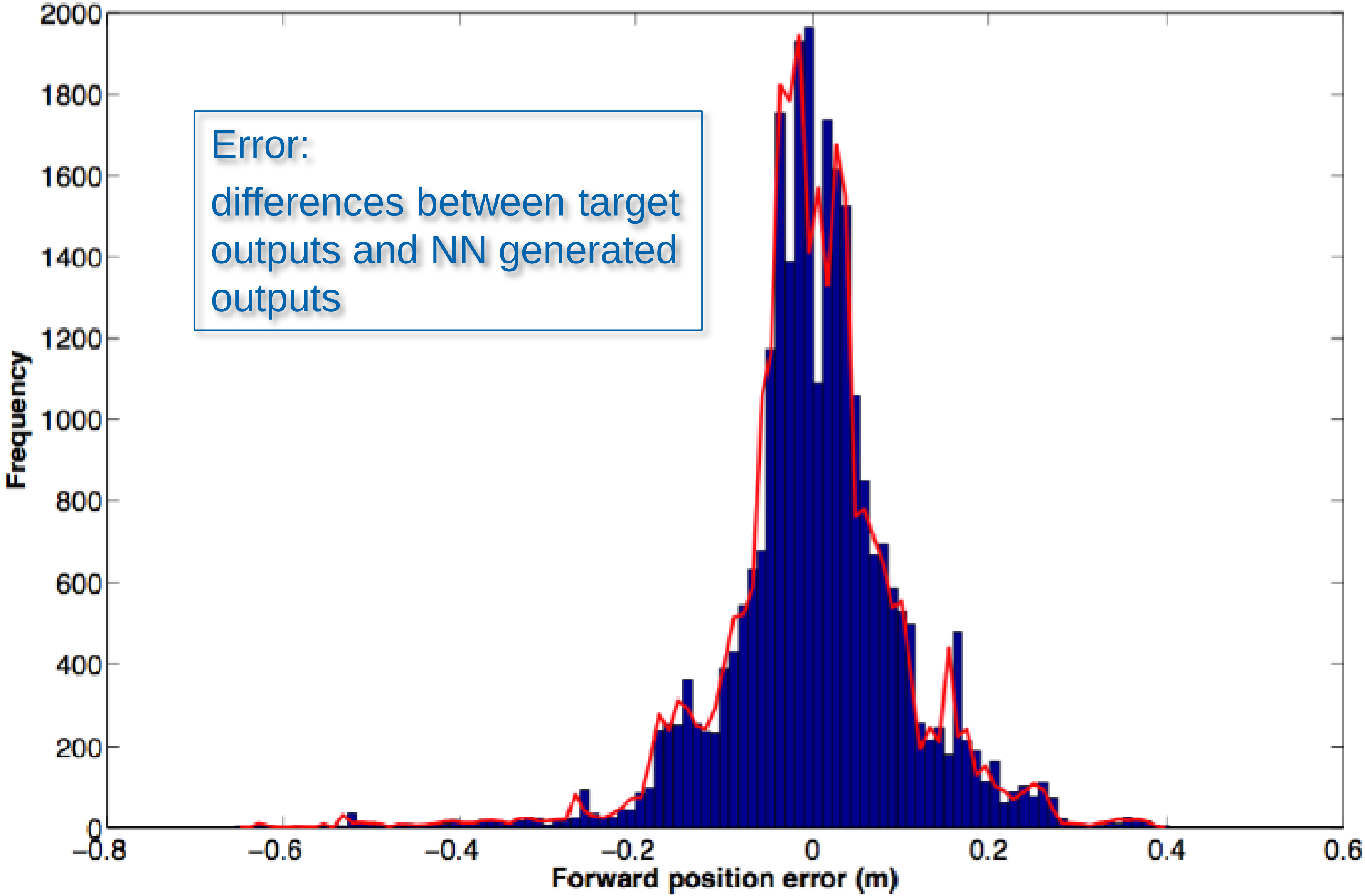
Total 35 trajectories in horizontal plane:

Parameters	Values	Units
Desired ground speed	2,5,8,11,12,13,14,15	m/s
Cross wind speed	3-5 selected values in [1.0, 9.5]	m/s

Trajectory #i (~20 s):



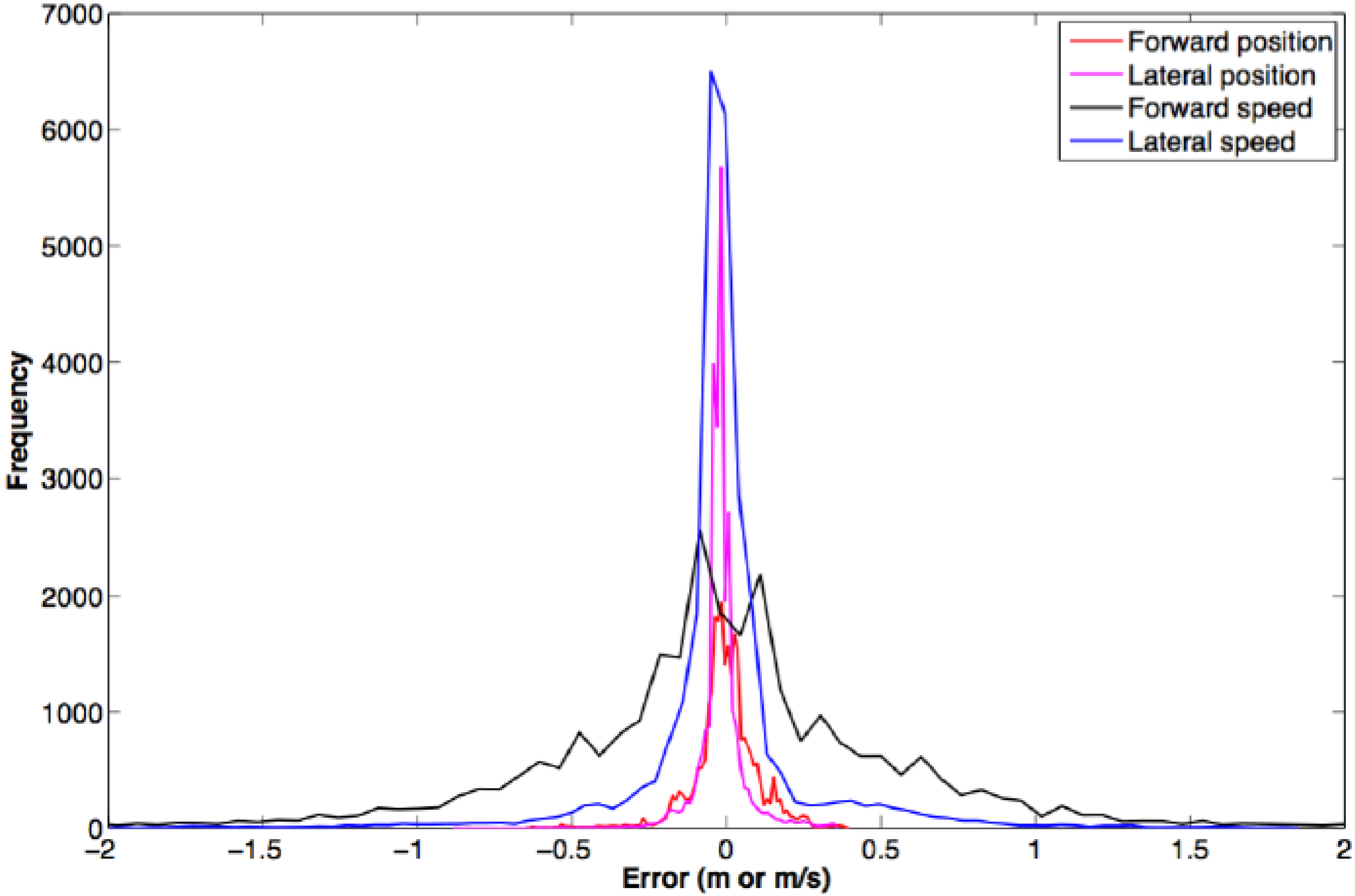
Training Performance: Forward-position Errors



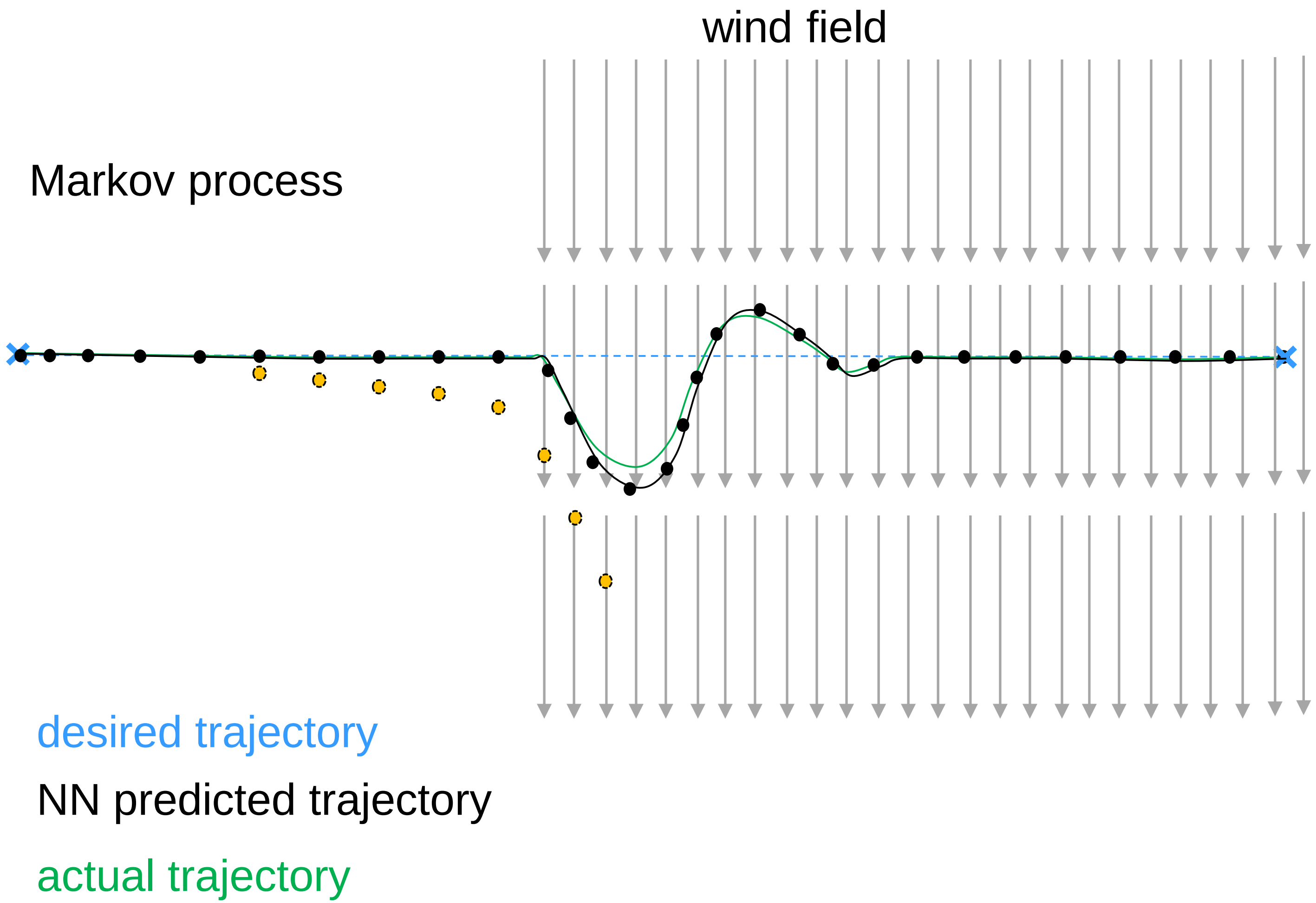
Error:

differences between target outputs and NN generated outputs

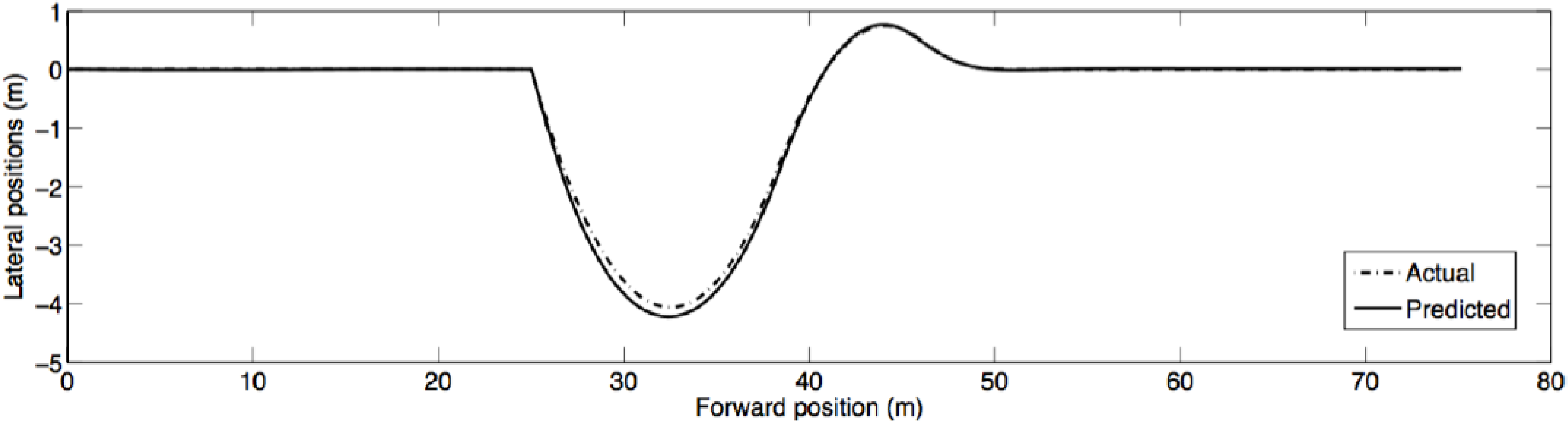
Training Performance: All Output Errors

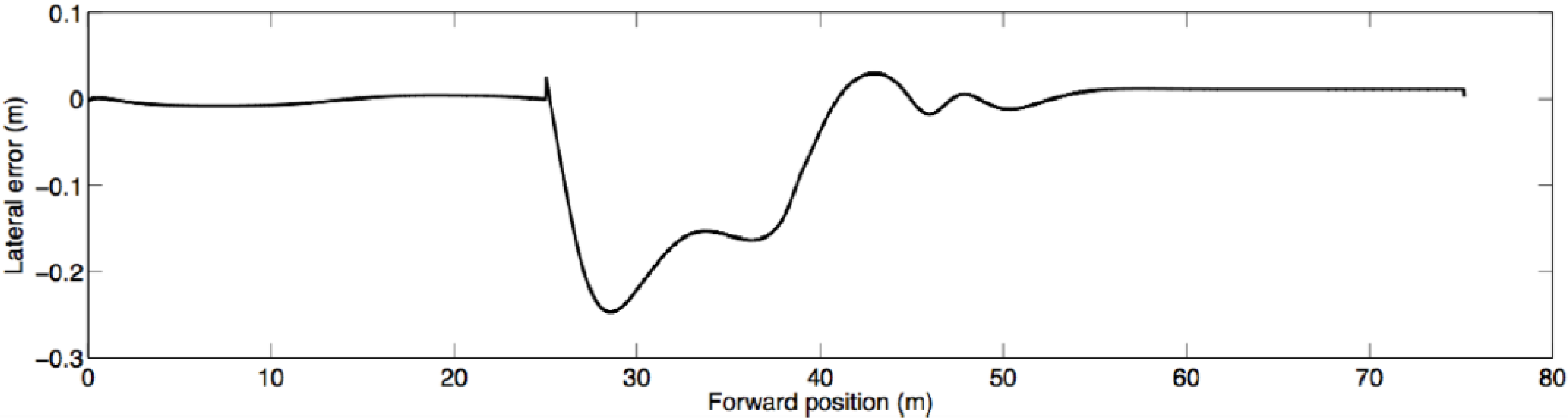


Trajectory Prediction Approach

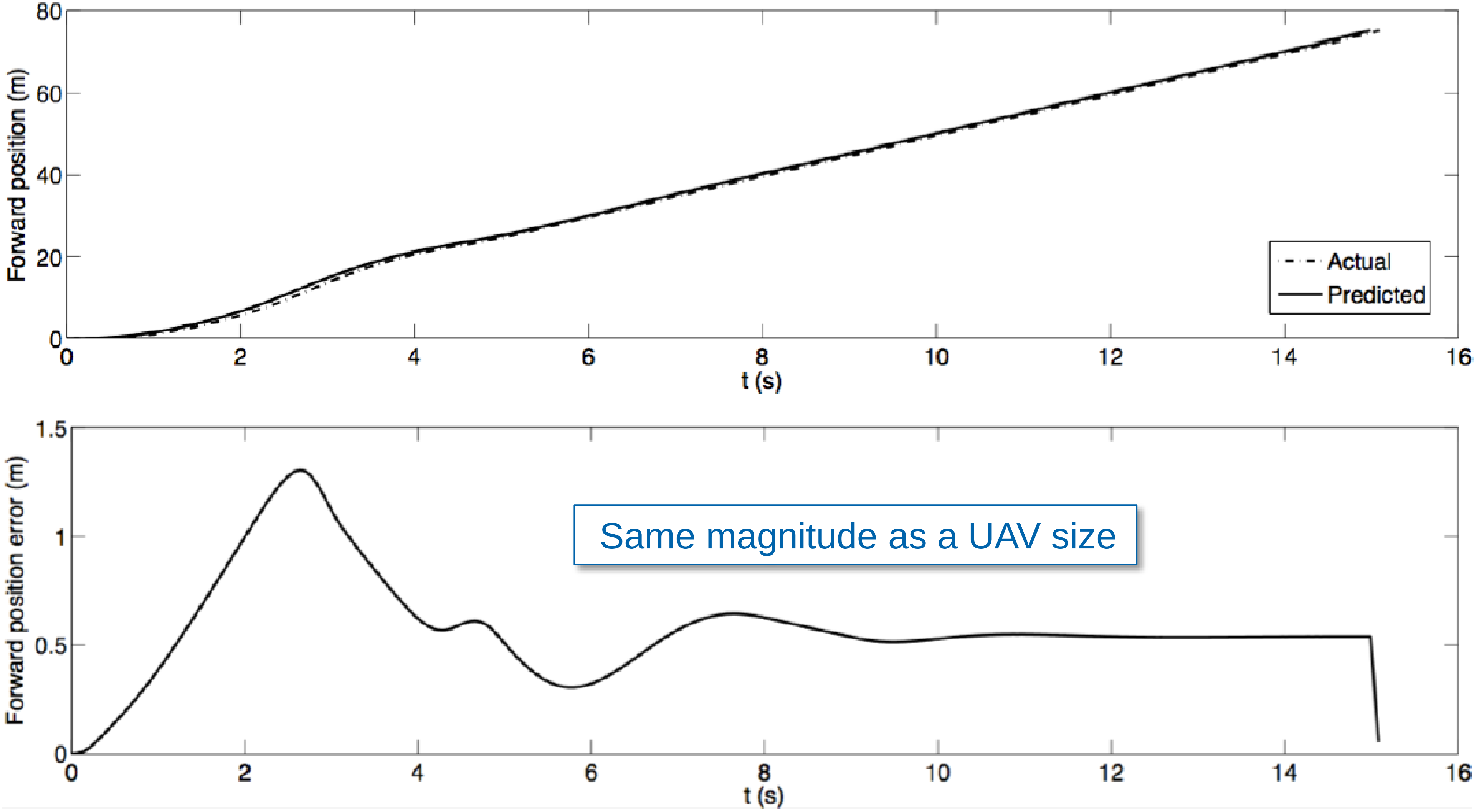


Position Error in Spatial Dimension

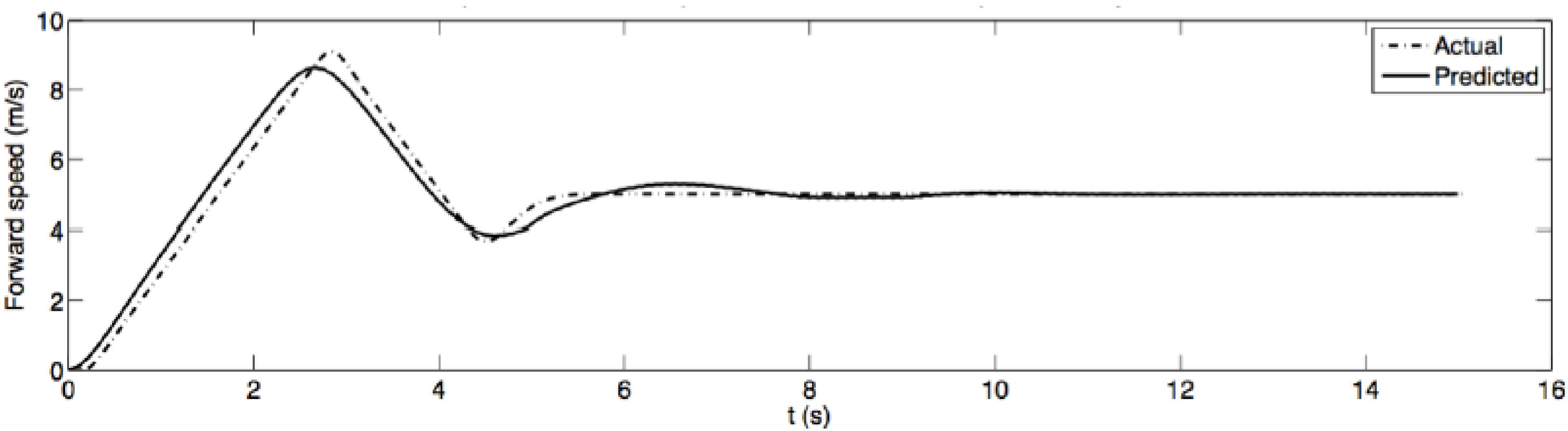


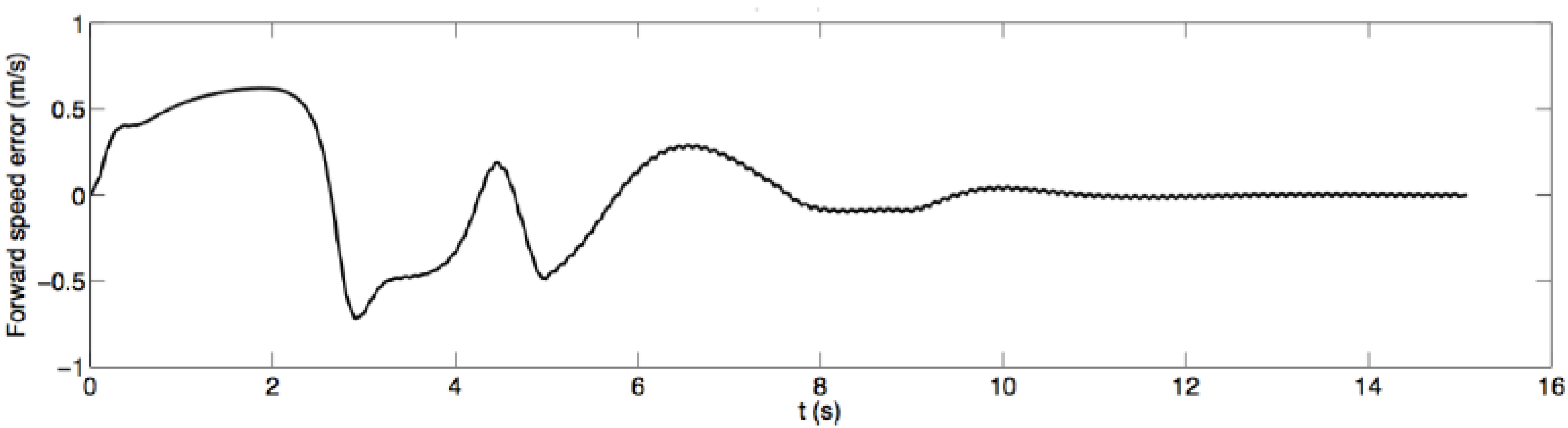


Position Error in Temporal Dimension



Forward Speed Error





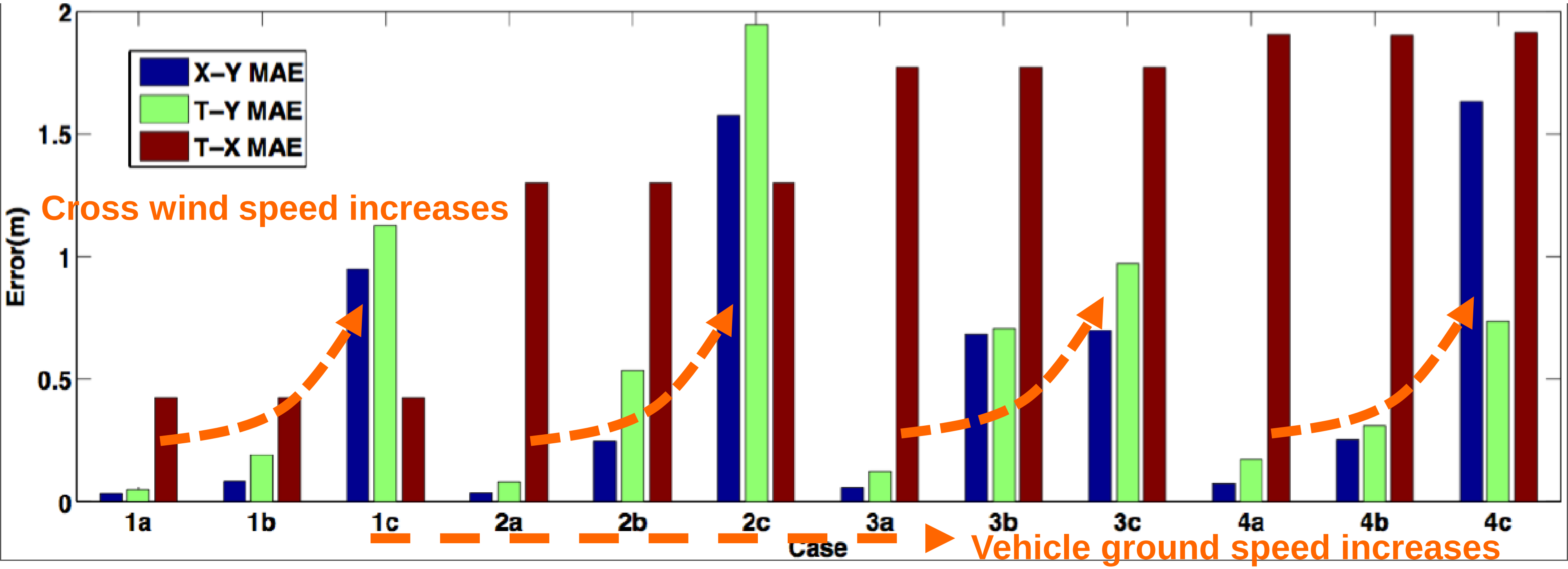
Prediction Verification Cases

12 prediction cases:

Case	1a	1b	1c	2a	2b	2c	3a	3b	3c	4a	4b	4c
Vehicle ground speed (m/s)	2.0	2.0	2.0	5.0	5.0	5.0	8.0	8.0	8.0	11.0	11.0	11.0
Cross wind speed (m/s)	0.7	2.4	7.5	0.9	5.0	8.6	1.4	6.7	9.5	1.9	4.0	9.2

Prediction Verification

MAE – Maximum Absolute Error



- Forward speed error increases with the vehicle speed
- Lateral speed error increases with the cross wind speed
- All errors are smaller than 2 m
- Spatial errors are smaller than temporal errors

Summary

- Proposed a Neural Network based approach for UAV trajectory prediction
- Conducted experiments using a sample vehicle trajectory model
- The concept is promising with the trajectory prediction accuracy of two meters

Future Work

- Perform experiments using data collected from flight tests
- Extend the application to vertical direction
- Explore different machine learning methods and setups

Questions?

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