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Technical University of Munich

How to AI?
Timeseries Prediction using Neural Networks

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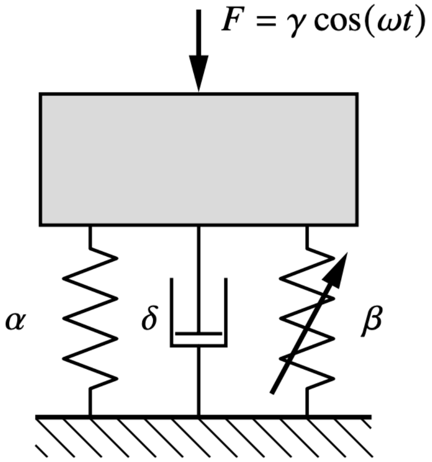
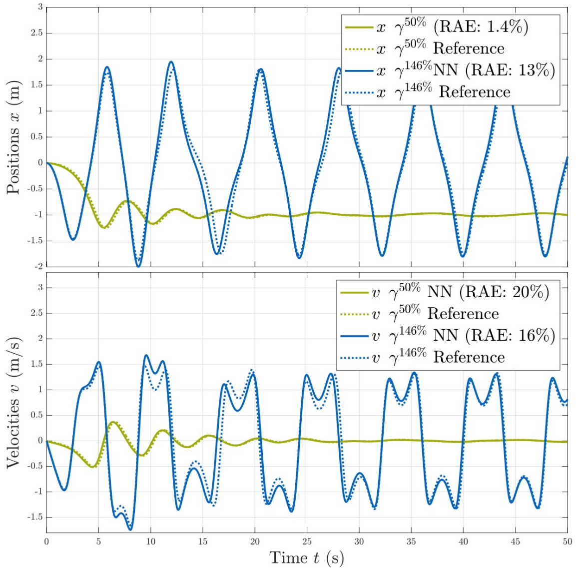
Workshop Goal





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Outline

- Motivation

- Generating Training Data
- Creating Network
- Evaluating Network Performance

Learning Outcomes

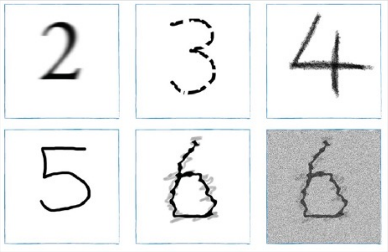
- Understanding NN Basics
- Gaining some matlab experience
- Maybe some ideas how you can use NNs

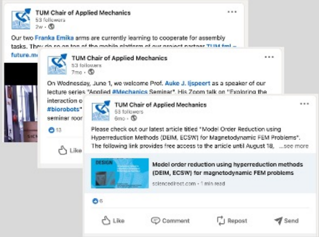
Motivation - Types of Neural Networks (Classification)

Input Data x
Boundary conditions,
Seed state, Goal

Efficient non-linear information processing pipelines

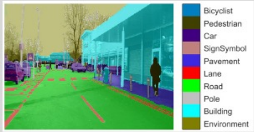
Output Data y





Feedforward Neural Networks (Convolution) Gradient Descent Optimization

Labels + Confidence Values: 1: 4%, 2: 0%, 3: 96%...



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Motivation - Types of Neural Networks (Generative Adversaries)

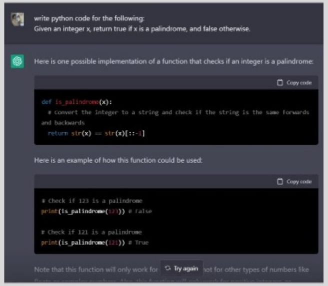
Input Data x
Boundary conditions,
Seed state, Goal

Text describing the desired outcome or image prompts

Efficient non-linear
information processing
pipelines

Generator + Discriminator Network Competing to Fool Each Other

Output Data y



Chat GPT

Motivation - Types of Neural Networks (Recurrent)

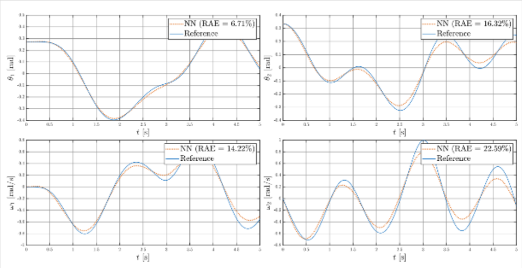
Input Data x
Boundary conditions, Seed state, Goal

Efficient non-linear information processing pipelines

Output Data y

Time Data | Initial Conditions

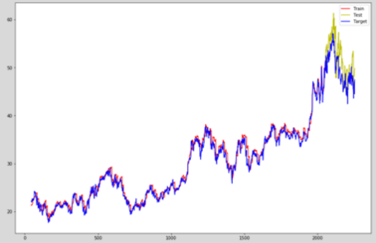
Recursively Applied Feedforward Network | Feedback of Output + Internal States



"had a general"
"council to consider what measures they could take to outwit their common enemy , the cat"

"Hello my name is Bob"
"Hallo ich heise Bob"

Image/video captioning

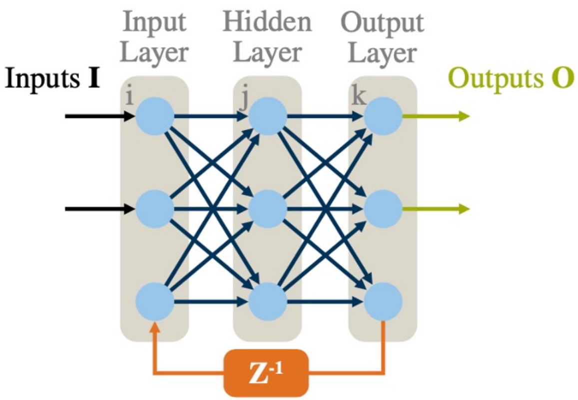


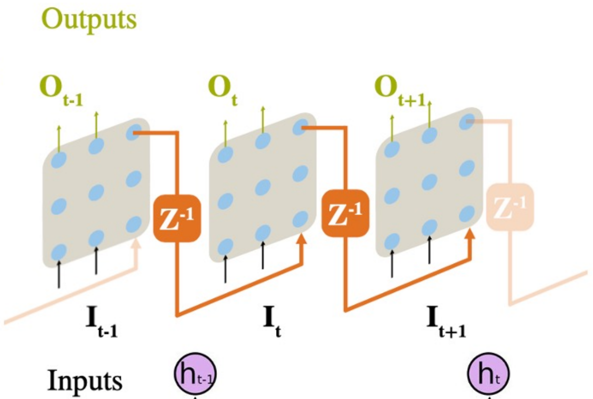
Motivation - Types of Neural Networks (Recurrent)

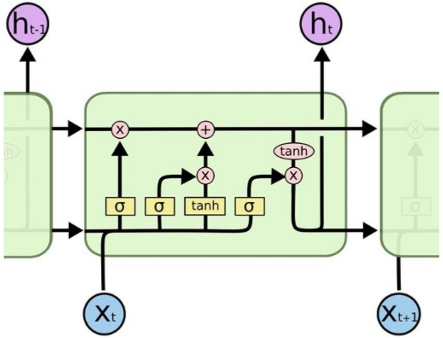
Input Data x
Boundary conditions,
Seed state, Goal

Efficient non-linear information processing pipelines

Output Data y







LSTM:
- Training optimized
- Recollection of long-term trends

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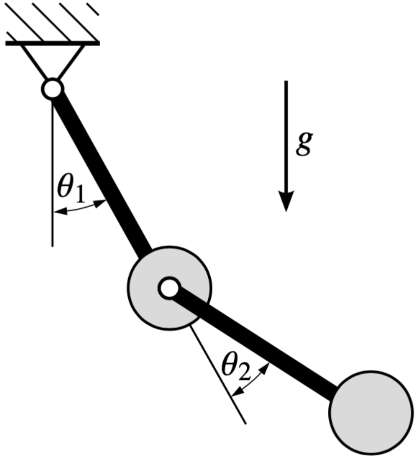
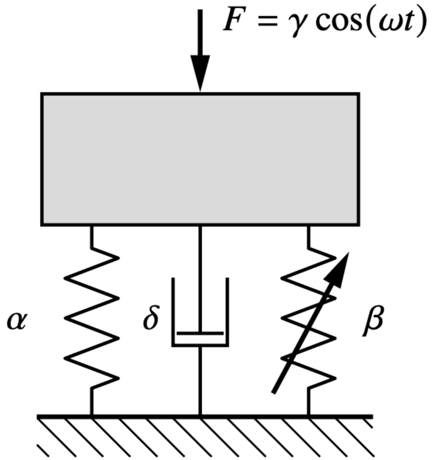
Case Study

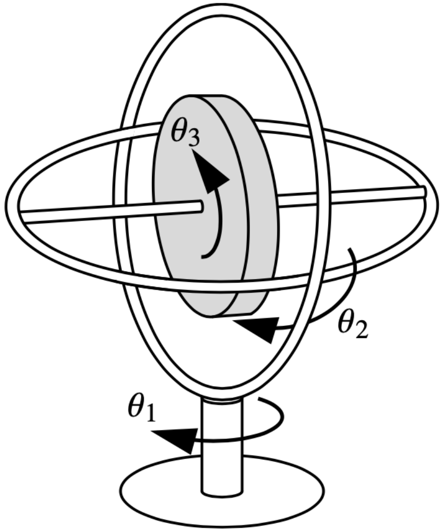
Reduction + Characterization of unkown dynamics



Double pendulum



Duffing oscillator



3D Gyroscope

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Case Study

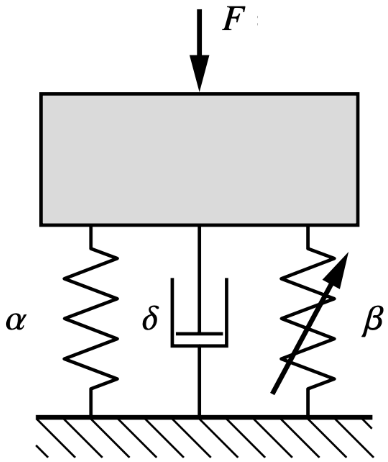
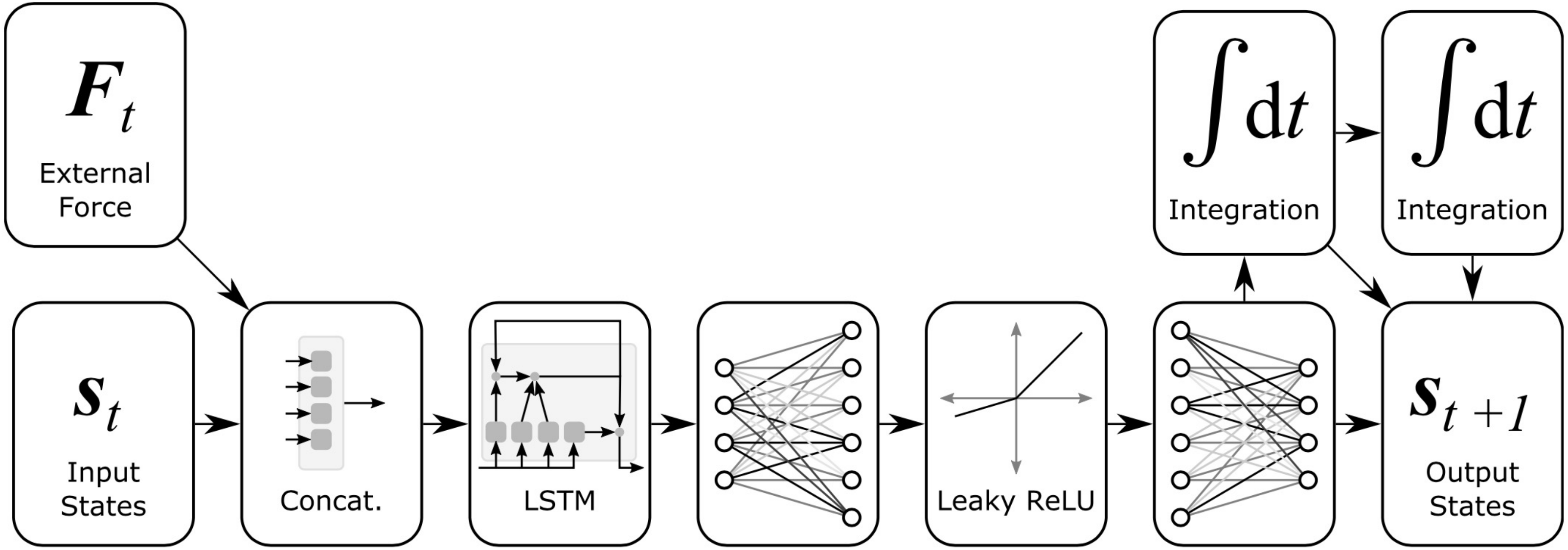


Table 1.1: Duffing Oscillator Parameters

	variable name	symbol	Default Value	Unit
mass	*mass*	m	1	kg
damping	*delta*	δ	0.3	Ns/m
non-linear damping	*epsilon*	ϵ	0	Ns^3/m^3
stiffness	*alpha*	α	-1	N/m
non-linear stiffness	*beta*	β	1	N/m^3
excitation amplitude	*gamma*	γ	0.65	N
excitation frequency	*omega*	ω	1.2	rad/s

$$m\ddot{x} + \delta\dot{x} + \epsilon\dot{x}^3 + \alpha x + \beta x^3 = F(t)$$

Case Study


F_t
External Force
s_t
Input States
Concat.
LSTM
Leaky ReLU
$\int dt$
Integration
$\int dt$
Integration
s_{t+1}
Output States

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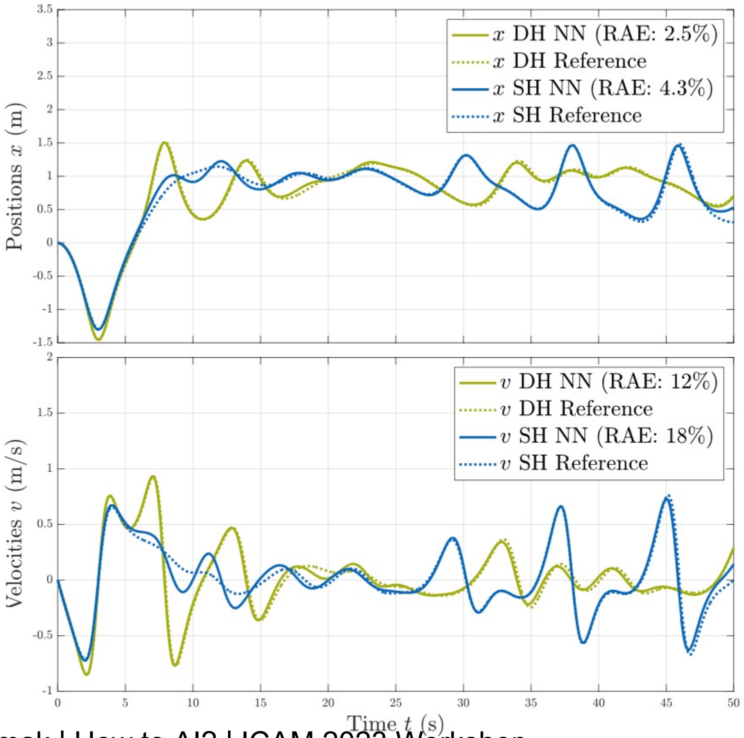
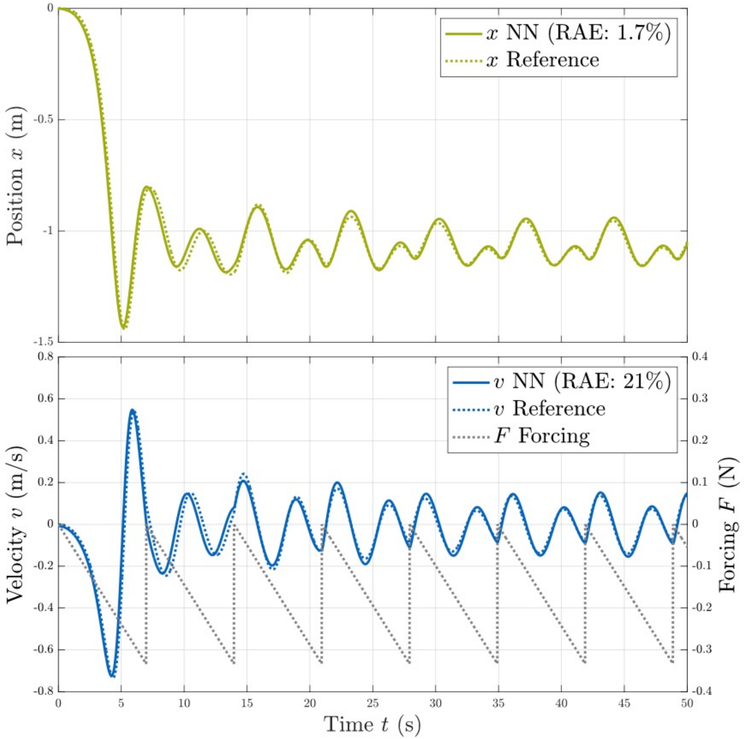
Results





How did we get here?

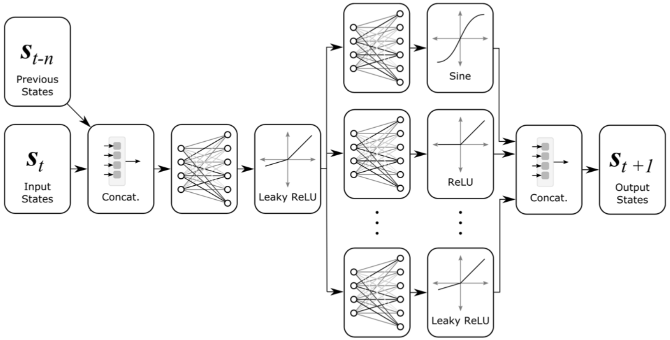
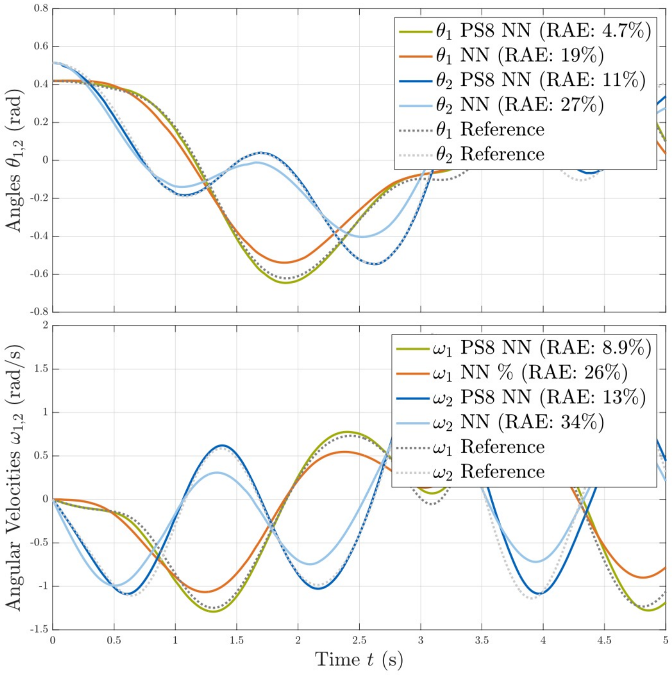
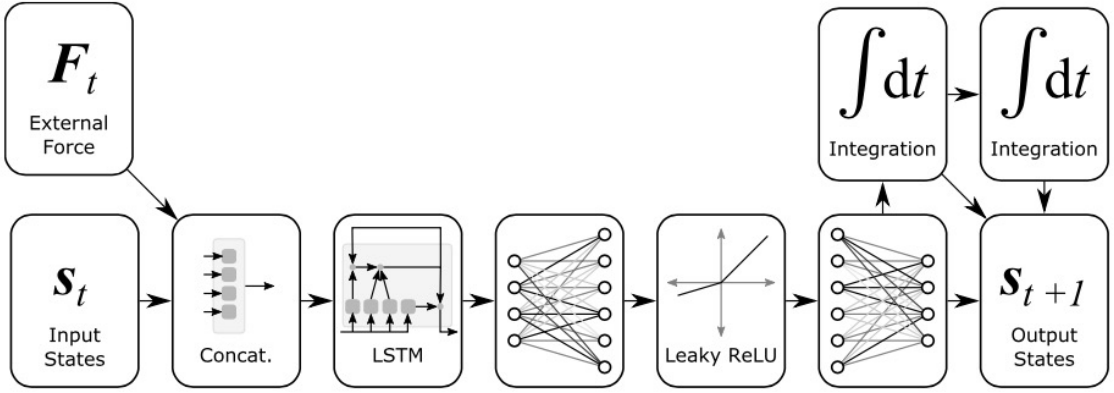


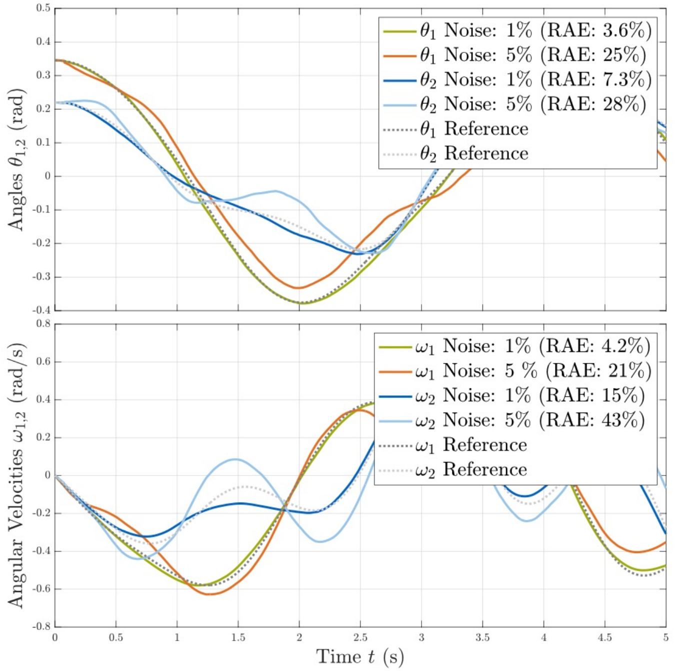
TABLE 3: DUFFING OSCILLATOR WITH PREVIOUS STEPS

Previous Steps	RMSE (m)	RMSE (m/s)
reference	0.5046	0.2654
6	0.4096	0.2376
7	0.2462	0.1531
8	0.2422	0.1347
9	0.3469	0.1874
10	0.4219	0.2108



Research direction





RMSE

Trained with closed loop	θ_1 (rad)	θ_2 (rad)	ω_1 (rad/s)	ω_2 (rad/s)
no	0.0253	0.0327	0.0693	0.1125
yes	0.0101	0.0169	0.0311	0.0579

Frequency (Hz)	RMSE (m)	RMSE (m/s)
50	0.4679	0.2576
100	0.2422	0.1347
200	0.5141	0.3004

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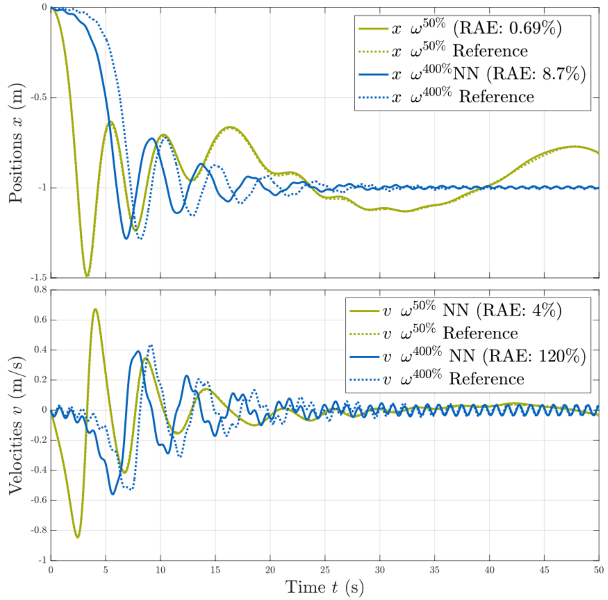
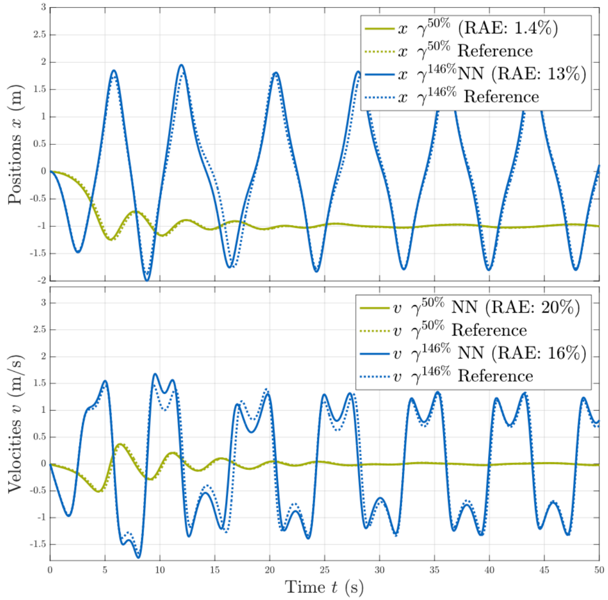
Research direction: Extrapolation



(a) Extrapolation of excitation frequency



(b) Extrapolation of excitation amplitude

FIGURE 10: DUFFING OSCILLATOR TRAINED ON 20 s OF DATA, EXTRAPOLATING WITH UNSEEN EXCITATION FORCE TO 50 s

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Research direction

- Adding more physics to cost function
- Real measurements

Automatic Hyper-parameter Optimization

- Monte Carlo
- Evolutionary
- Gradient Based

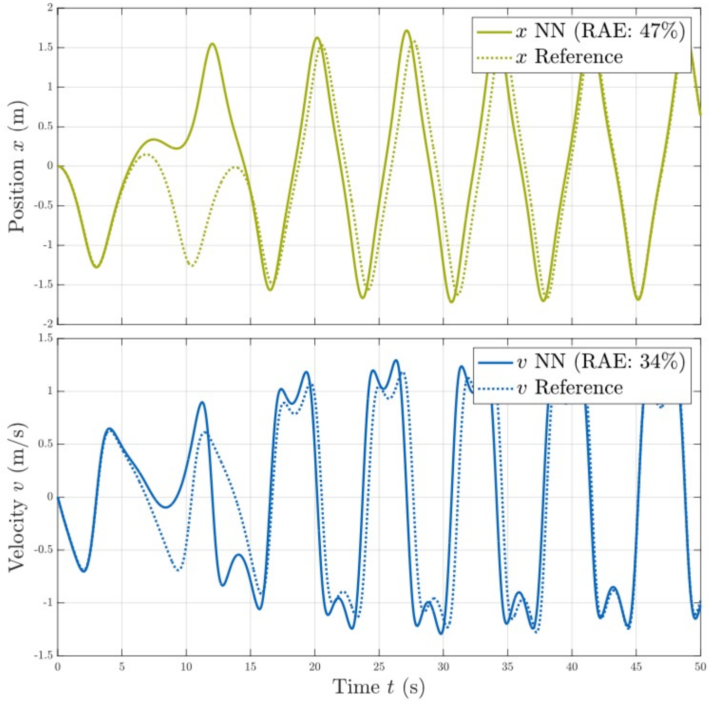
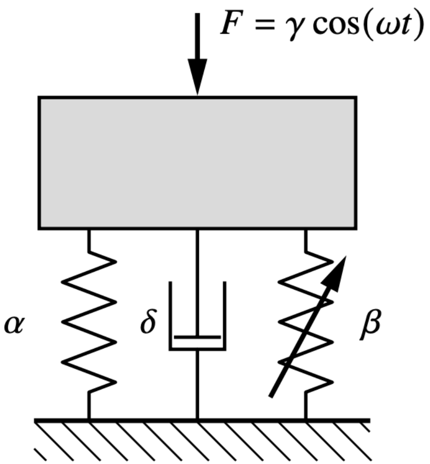


FIGURE 9: EXAMPLE OF NN HAVING DIFFICULTY PREDICTING THE TRANSITION BETWEEN THE TRANSIENT- AND STEADY-STATE-PHASE

Reference Simulation



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```
% Example of matlab struct syntax
structure_name.first_variable_name  = 0; % kg
structure_name.second_variable_name = 0; % Ns/m
```

$$m\ddot{x} + \delta\dot{x} + \epsilon\dot{x}^3 + \alpha x + \beta x^3 = F(t)$$

$$F(t) = \gamma\cos(\omega t)$$

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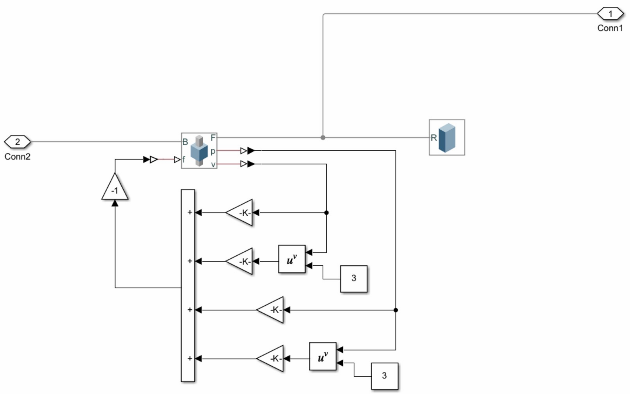
Reference Simulation



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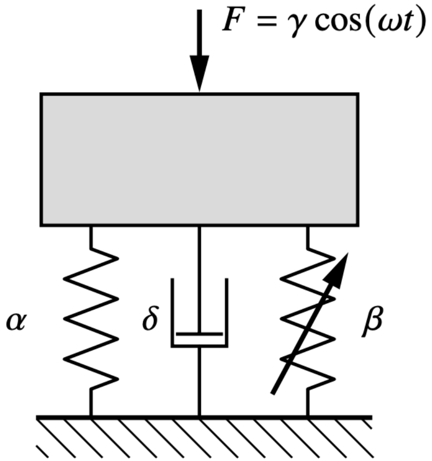
$$F(t) = \gamma\cos(\omega t)$$

Generate Dataset

1. Vary force frequency and amplitude
2. Run simulation
3. Store data
4. Repeat

Network evaluation

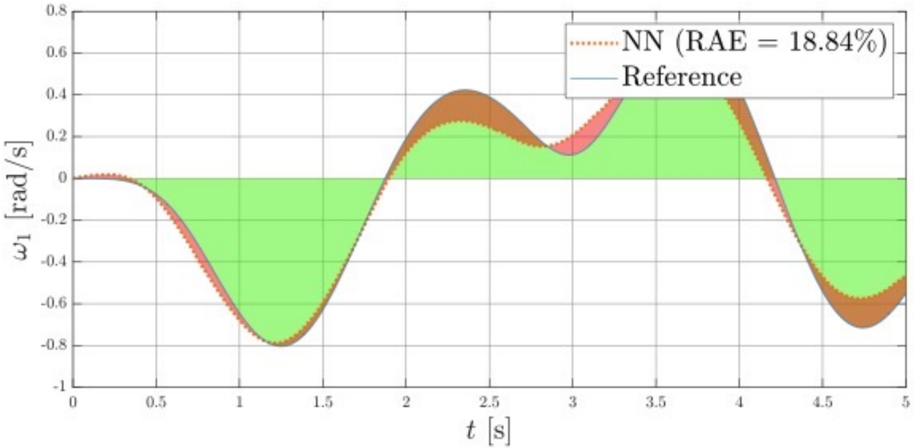


Explicit calculation of velocity
Implicit calculation of position

$$v_{t+1} = v_t + \Delta t a_t \quad \text{and} \quad x_{t+1} = x_t + \Delta t v_{t+1}$$

Relative Area Error

$$\mathrm{RAE} \equiv \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|}{\sum_{i=1}^{N} |y_i|}$$



Add Noise?

Roughly 5% of signal amplitude