

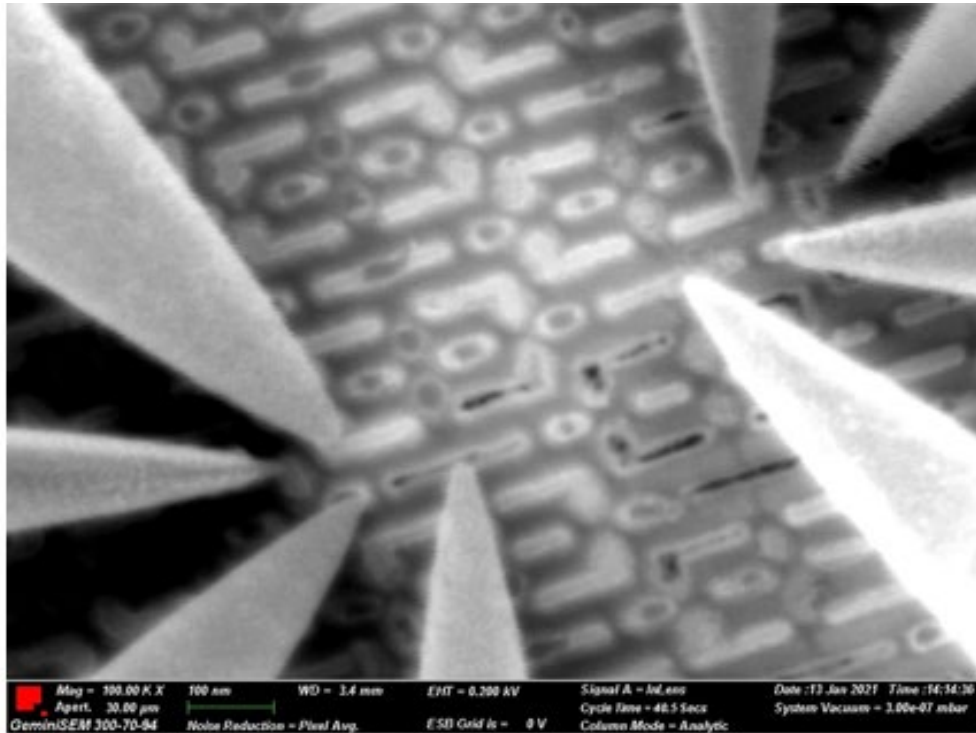
Evaluating ML Models for Modelling Piezo Dynamics

29.7.24

David Kleindiek

Introduction

- Nanoprobng
- Semiconductors Failure Analysis



- Driven by piezo motors
- Sub-nanometre accuracy

Devices

MM3E

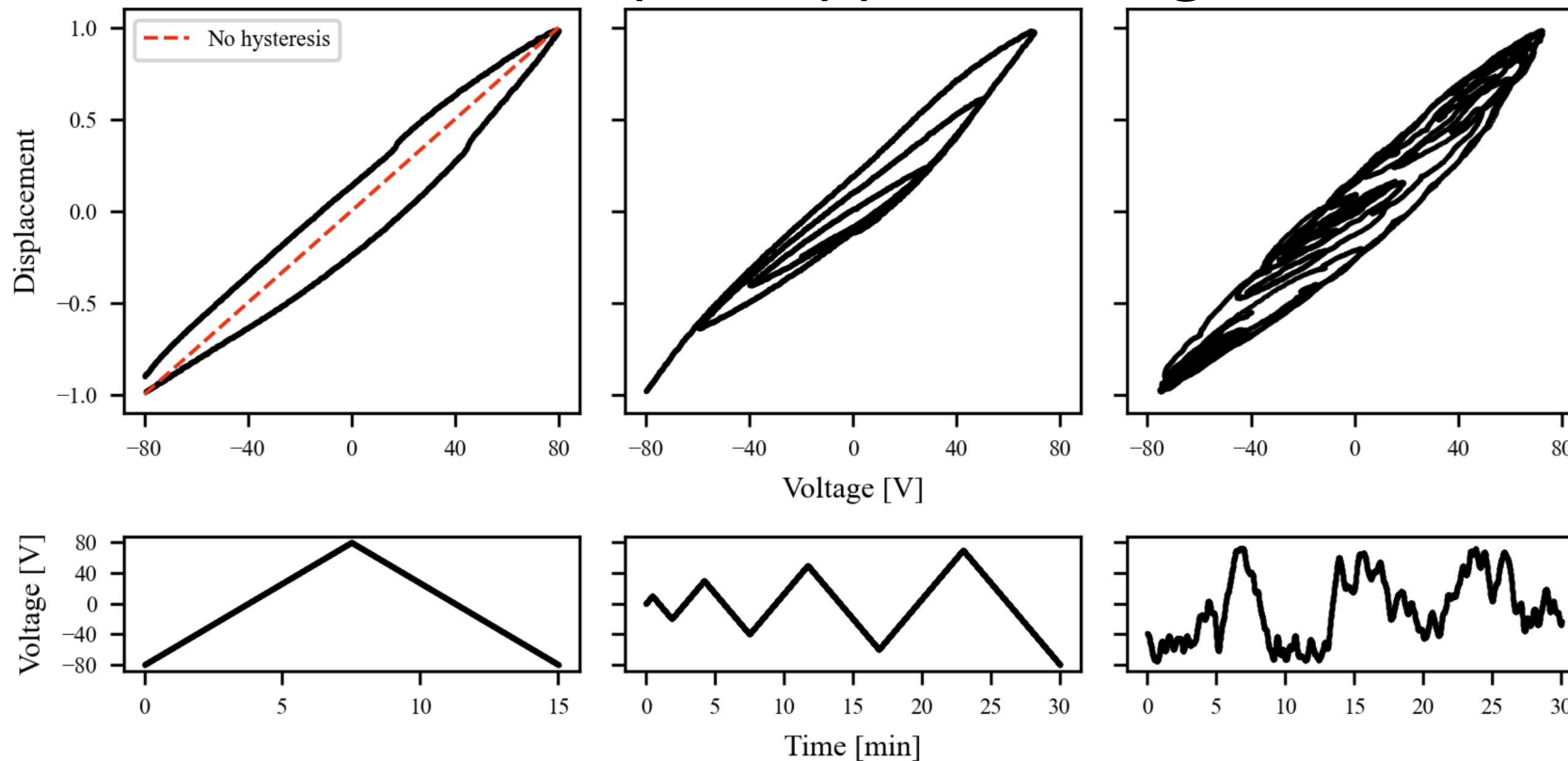
- Three axis
- Input voltage: -80V to 80V
- Max displacement: a, b=20 μ m, c=3 μ m
- Encoder resolution: a, b=250nm c=20nm

➡ C Axis used to capture data



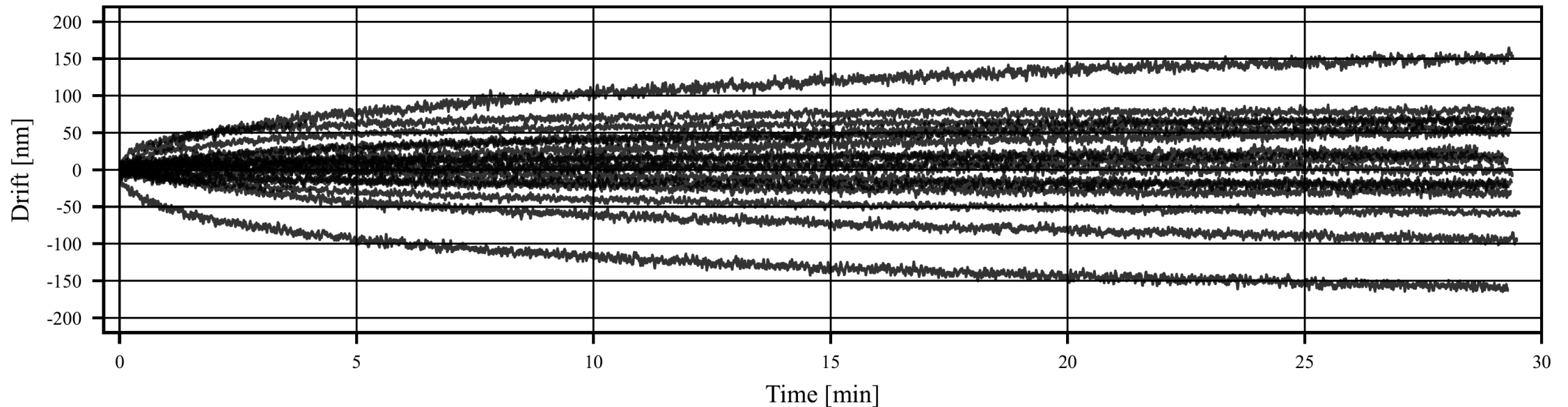
Challenges: Hysteresis

- Non-linear relation between input voltage and displacement
- Dependent on current and past applied voltages



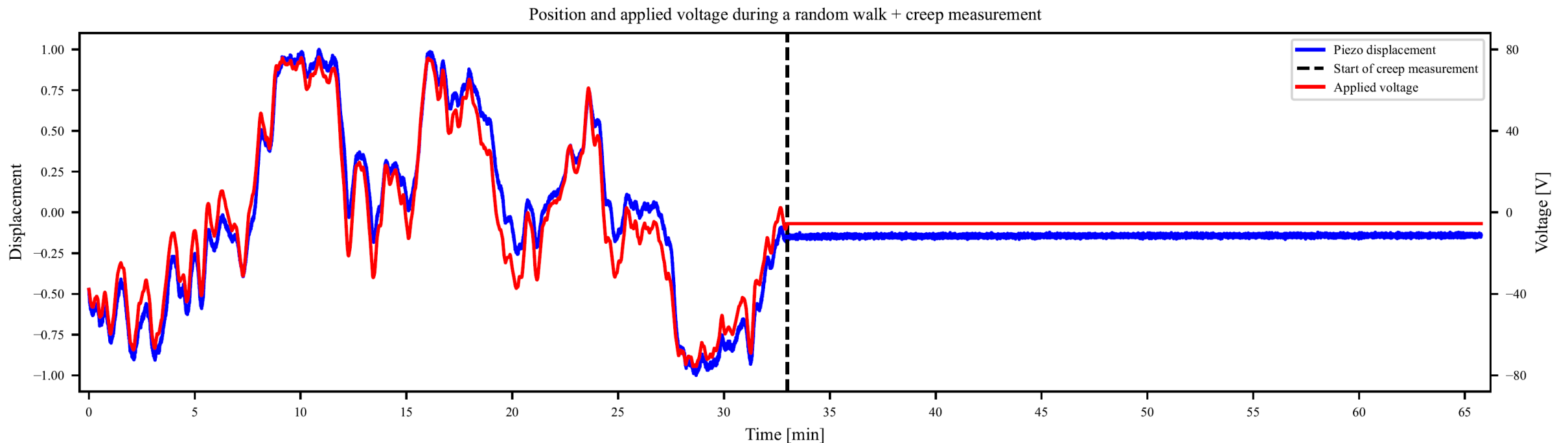
Challenges: Creep

- Slow drift of displacement after voltage step
- Up to 15% deviation from desired position
- Time dependent on previous applied voltages



Data collection

- Modified random walk
- >32 hours of movement data
- >7 hours of creep recording



Feature engineering

- Dependency on past applied voltages
- Step size
- ➔ Rolling exponential sums
- ➔ Lagged position
- ➔ Voltage differentiating
- Lasso regression for feature selection

Models

- Linear Regression
- Vanilla Neural Network
- Long short-term memory
- Kolmogorov-Arnold Networks

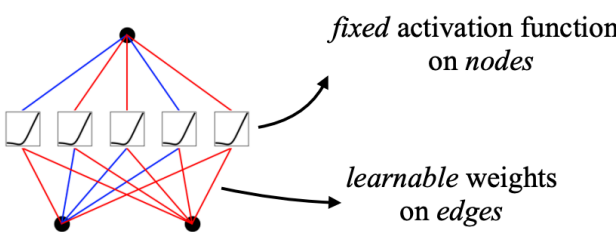
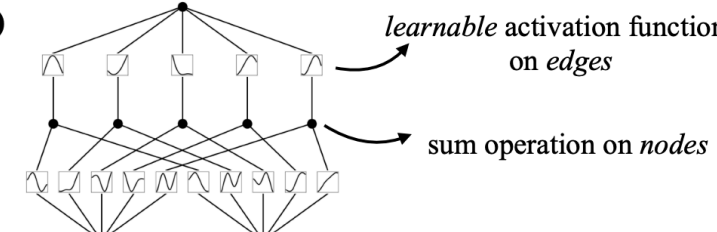
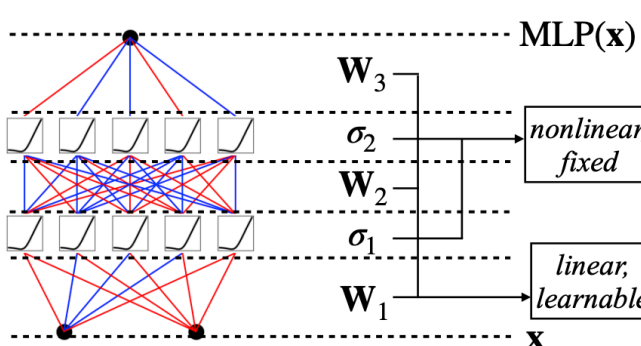
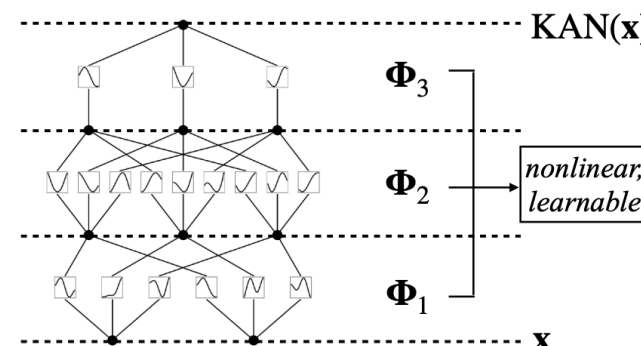
Hyperparameter Optimization Framework:



OPTUNA

<https://github.com/optuna/optuna>

KAN: Kolmogorov-Arnold Networks

Model	Multi-Layer Perceptron (MLP)	Kolmogorov-Arnold Network (KAN)
Theorem	Universal Approximation Theorem	Kolmogorov-Arnold Representation Theorem
Formula (Shallow)	$f(\mathbf{x}) \approx \sum_{i=1}^{N(\epsilon)} a_i \sigma(\mathbf{w}_i \cdot \mathbf{x} + b_i)$	$f(\mathbf{x}) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^n \phi_{q,p}(x_p) \right)$
Model (Shallow)	<p>(a)</p>  <p>fixed activation functions on nodes</p> <p>learnable weights on edges</p>	<p>(b)</p>  <p>learnable activation functions on edges</p> <p>sum operation on nodes</p>
Formula (Deep)	$\text{MLP}(\mathbf{x}) = (\mathbf{W}_3 \circ \sigma_2 \circ \mathbf{W}_2 \circ \sigma_1 \circ \mathbf{W}_1)(\mathbf{x})$	$\text{KAN}(\mathbf{x}) = (\Phi_3 \circ \Phi_2 \circ \Phi_1)(\mathbf{x})$
Model (Deep)	<p>(c)</p>  <p>\mathbf{W}_3</p> <p>σ_2</p> <p>\mathbf{W}_2</p> <p>σ_1</p> <p>\mathbf{W}_1</p> <p>\mathbf{x}</p> <p>nonlinear, fixed</p> <p>linear, learnable</p>	<p>(d)</p>  <p>Φ_3</p> <p>Φ_2</p> <p>Φ_1</p> <p>\mathbf{x}</p> <p>nonlinear, learnable</p>

- Faster scaling
- Interpretability

KAN: Training

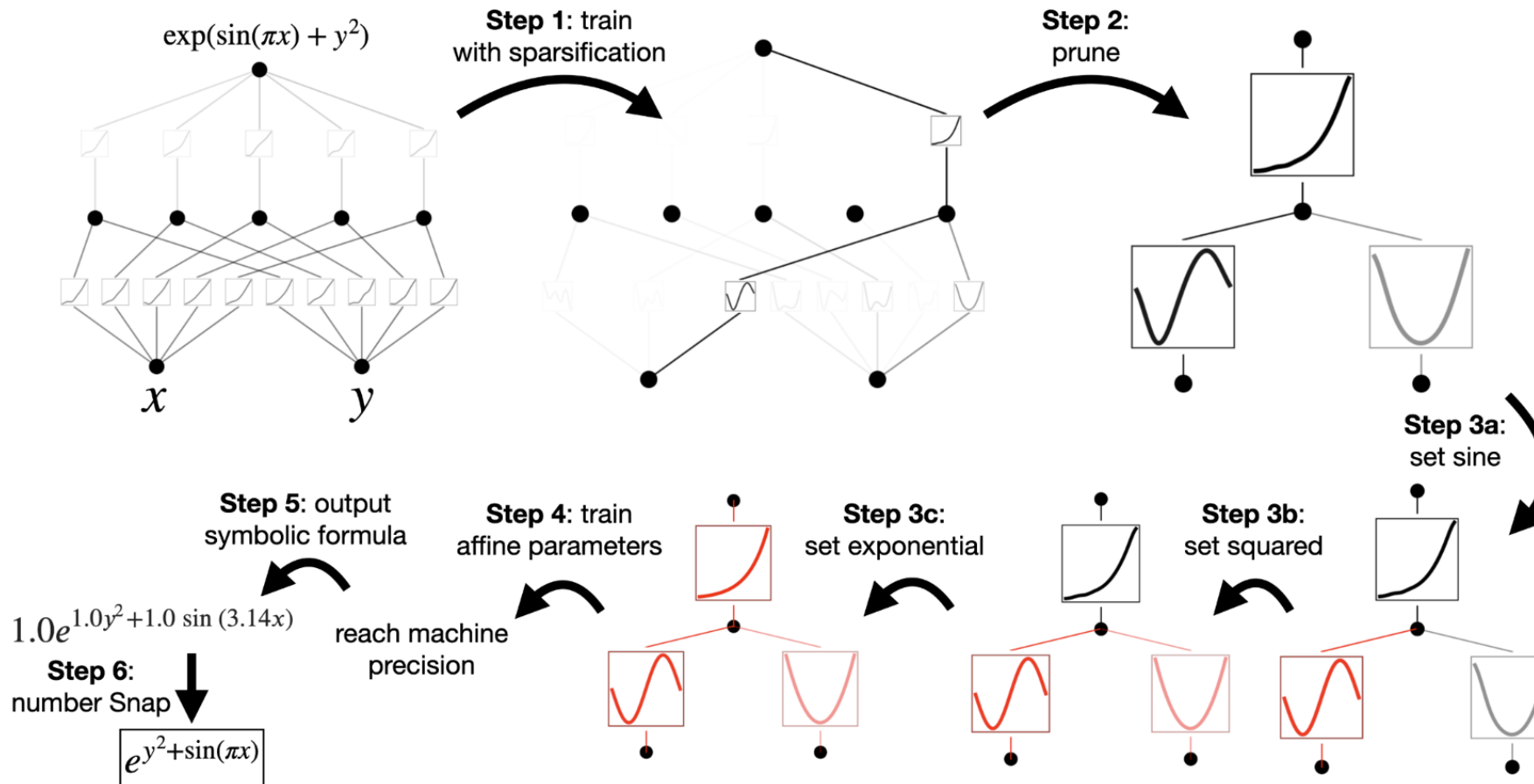


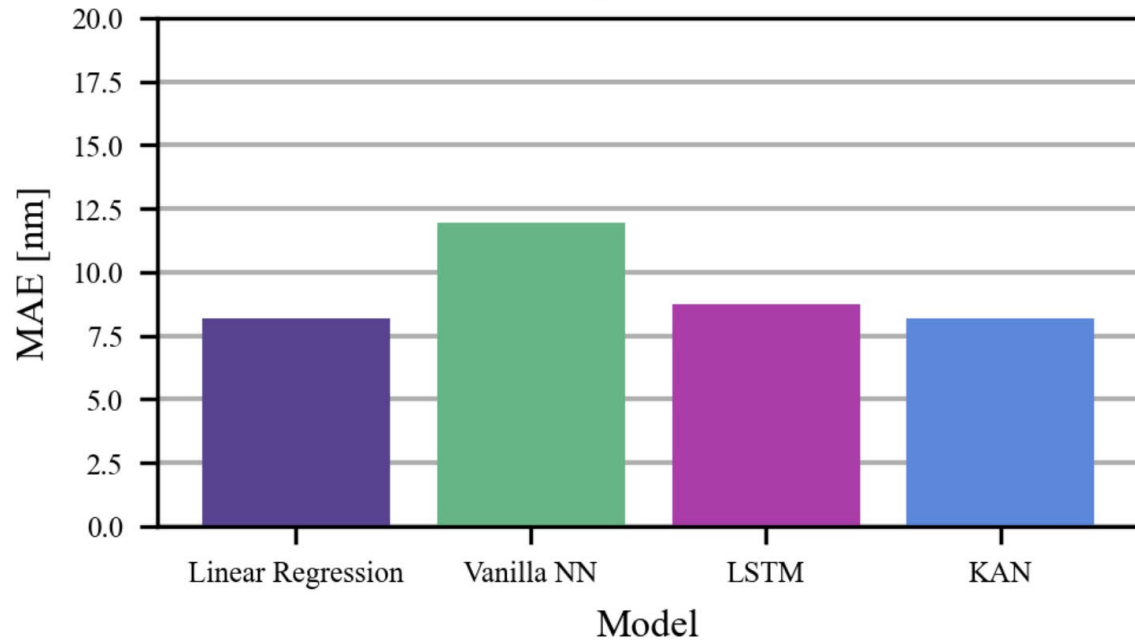
Figure 2.4: An example of how to do symbolic regression with KAN.

<https://arxiv.org/abs/2404.19756>

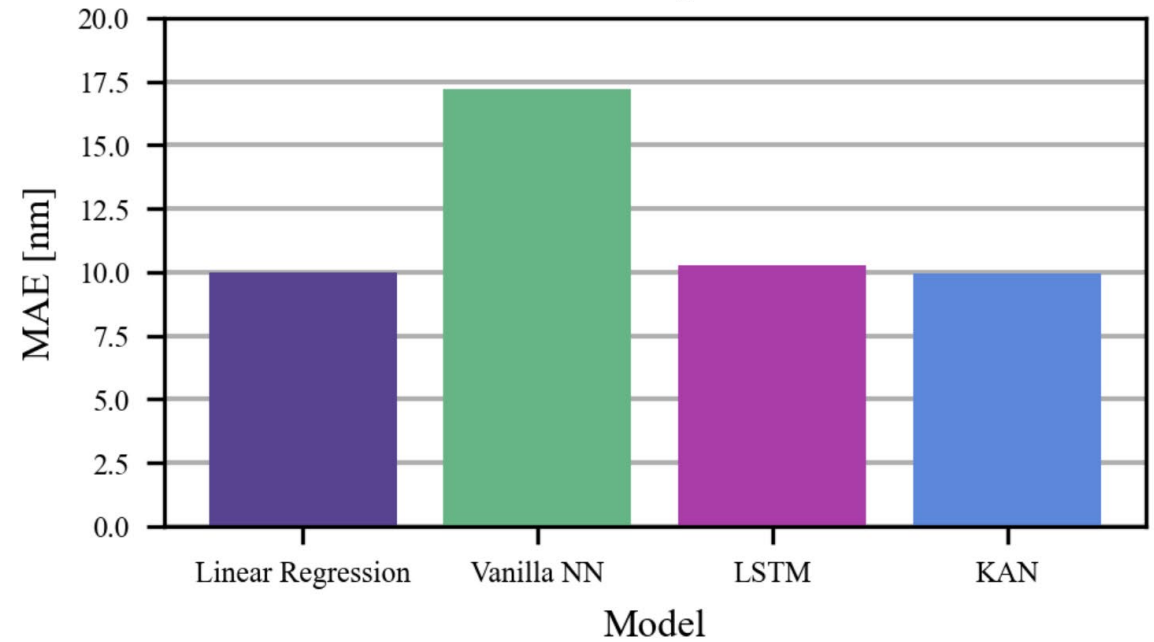
Metrics

Metrics for Hysteresis and Creep Prediction

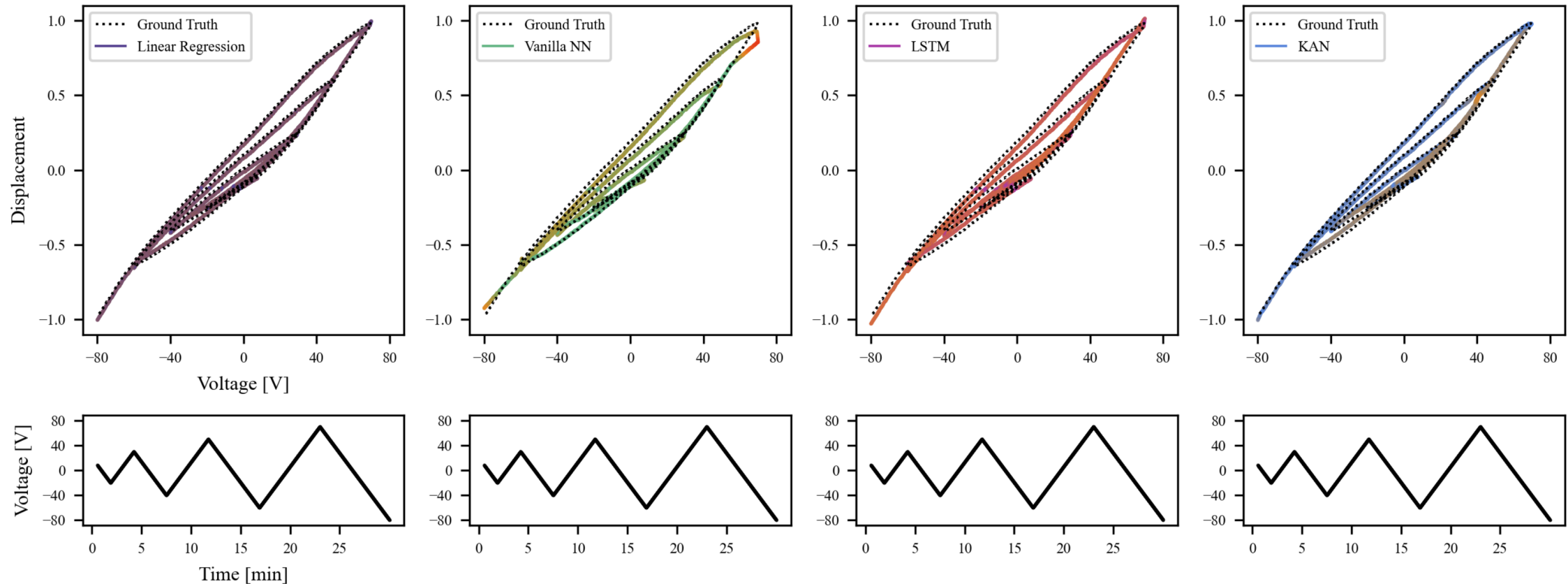
Hysteresis



Creep

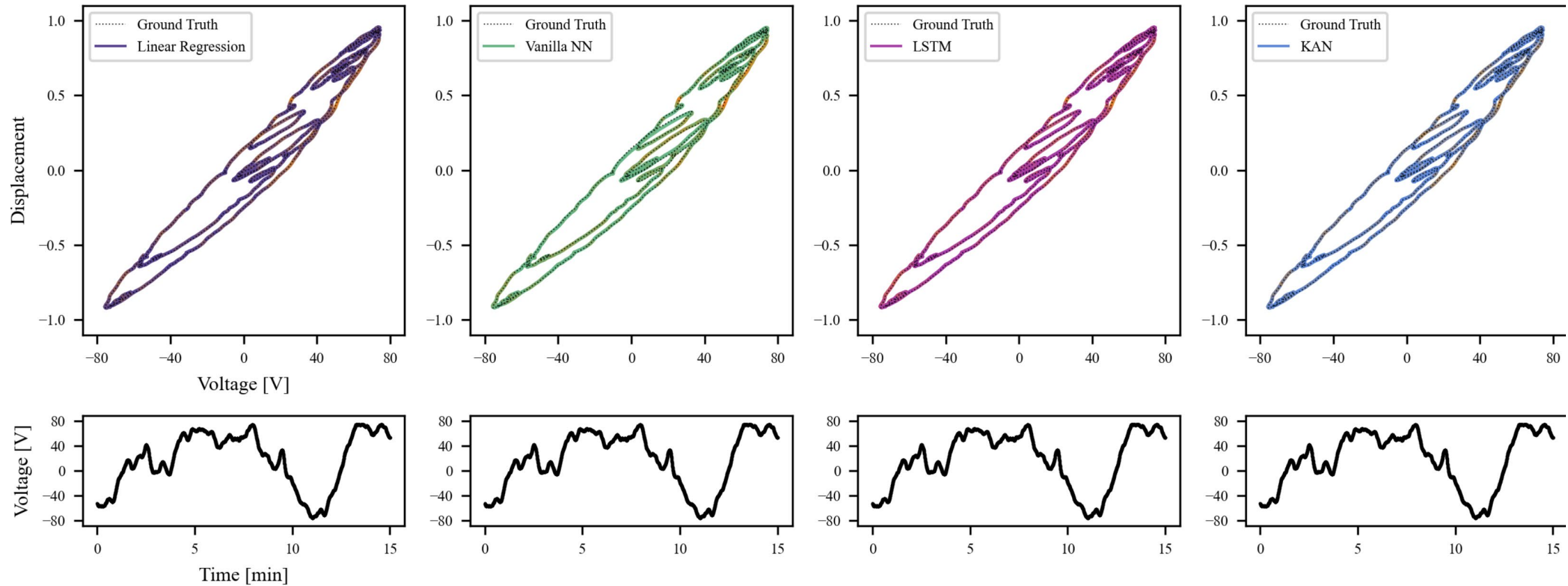


Evaluation: Hysteresis



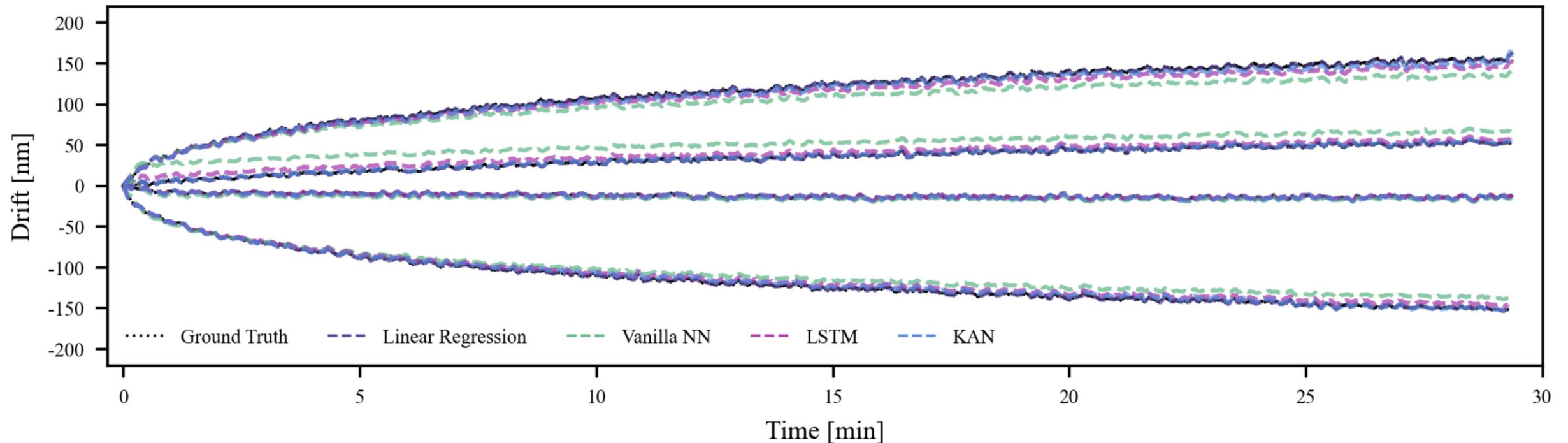
- Turning points pose a problem for neural network

Evaluation: Hysteresis



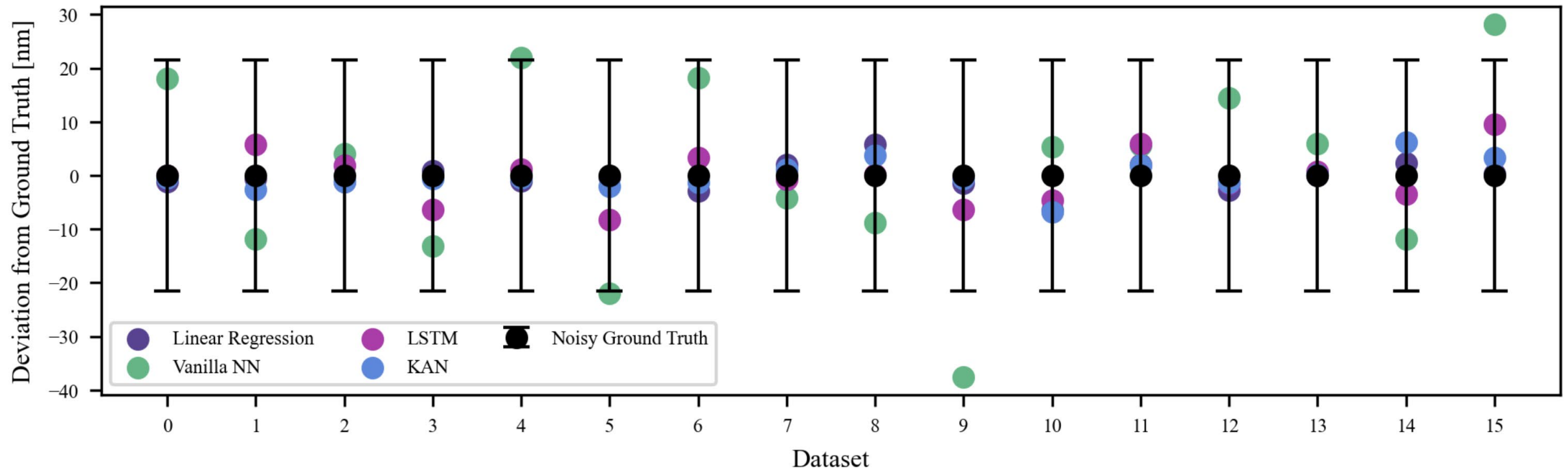
Evaluation: Creep

- Vanilla NN and LSTM deficate slightly
- KAN near perfect



Evaluation: Creep

- Endposition + encoder noise characteristic



Outlook

- Create an inverse model to compensate the effects
- Extend model to predict voltage for goal position
- Integrate models into the controller of the manipulators