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PHYSICS-INFORMED RECURRENT NEURAL NETWORKS

for the identification of a generic energy buffer system

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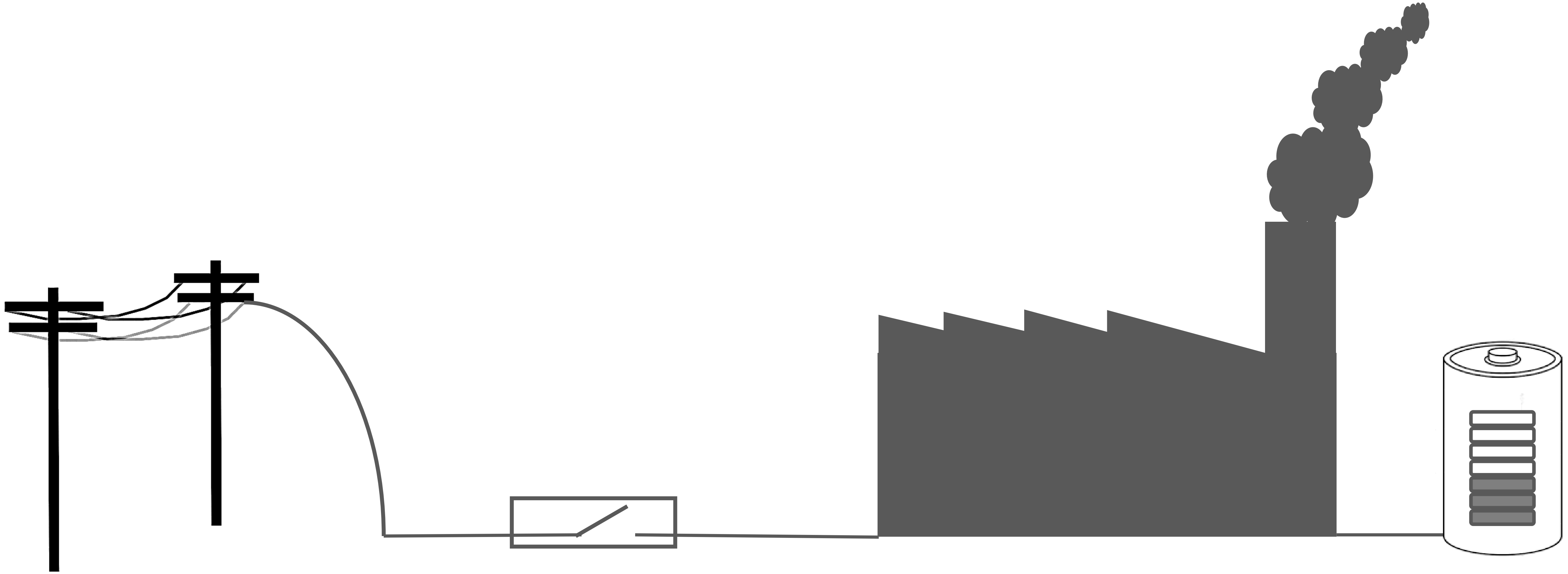
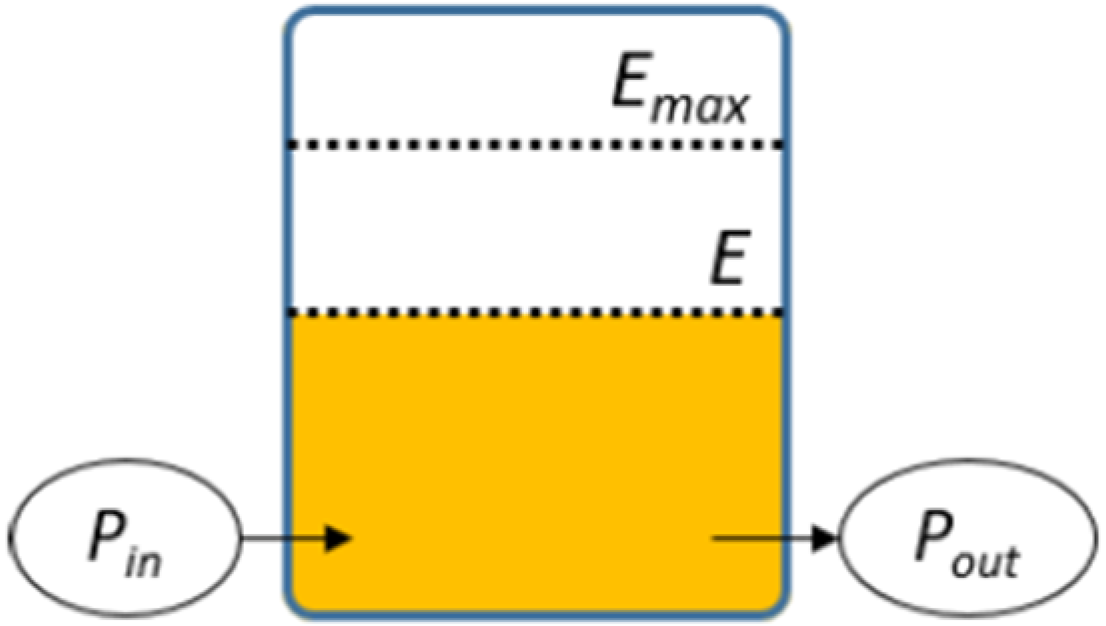
MOTIVATION



MOTIVATION

1. Physic rules: white-box model
2. Data-driven approaches: black-box model
3. Combination (1 and 2): grey-box model

GENERIC BUFFER SYSTEM



Generic buffer
(Used to represent
industrial processes in
form of virtual battery)

$$\frac{\partial m}{\partial t} = K(P_{out} - P_{in})$$

$$E = \frac{m - m_{min}}{K}$$

$$E_{min} \leq E \leq E_{max}$$

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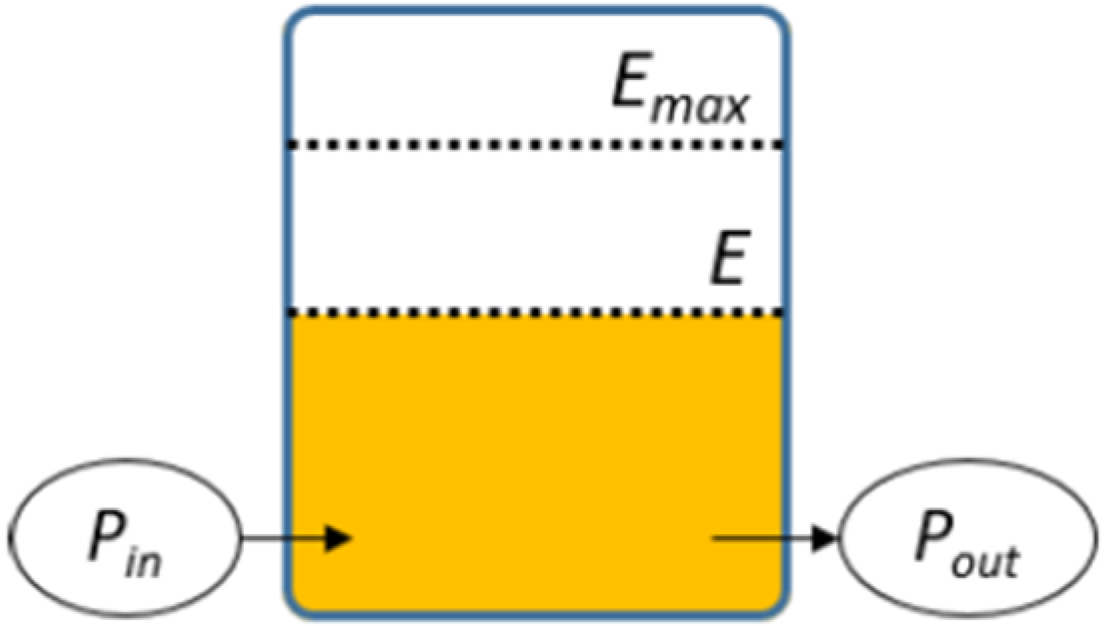

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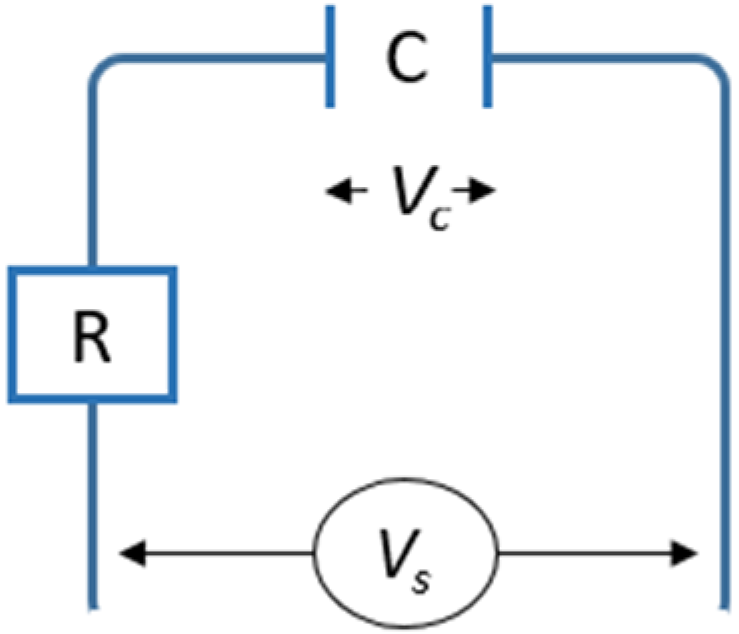

RC-circuit as a virtual battery
(V_s: Input voltage,
V_c: Capacitor voltage)

$$\frac{\partial V_c}{\partial t} = \frac{V_s - V_c}{RC}$$

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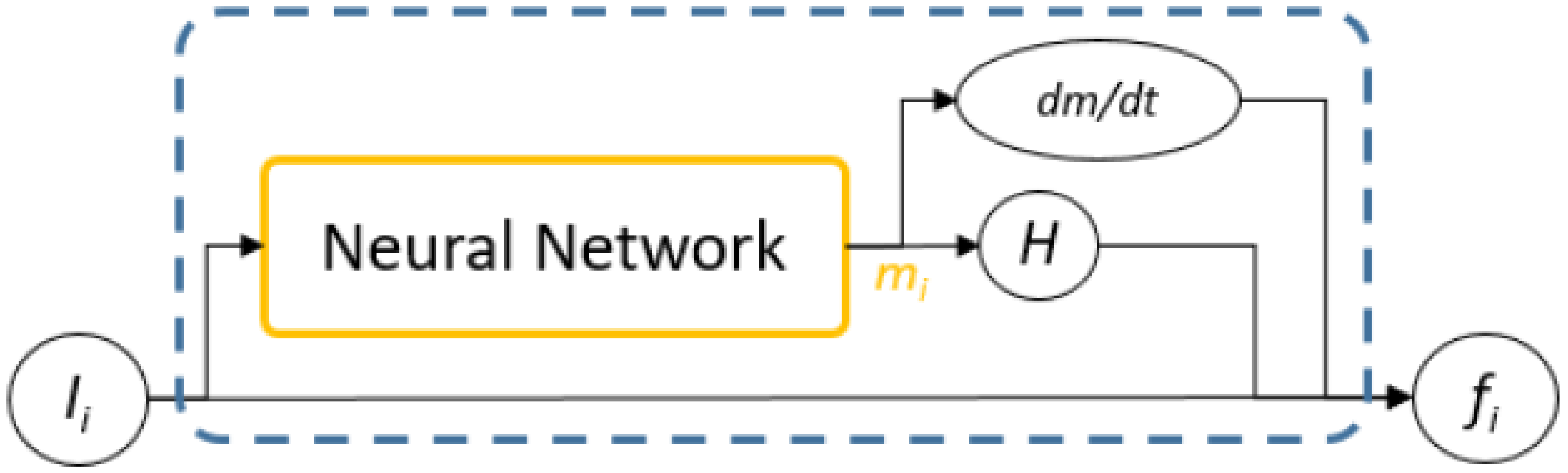
PHYSICS-INFORMED NETWORKS

PyNN: physics-informed neural networks

$$\frac{\partial m}{\partial t} + H(m;\lambda) = 0$$

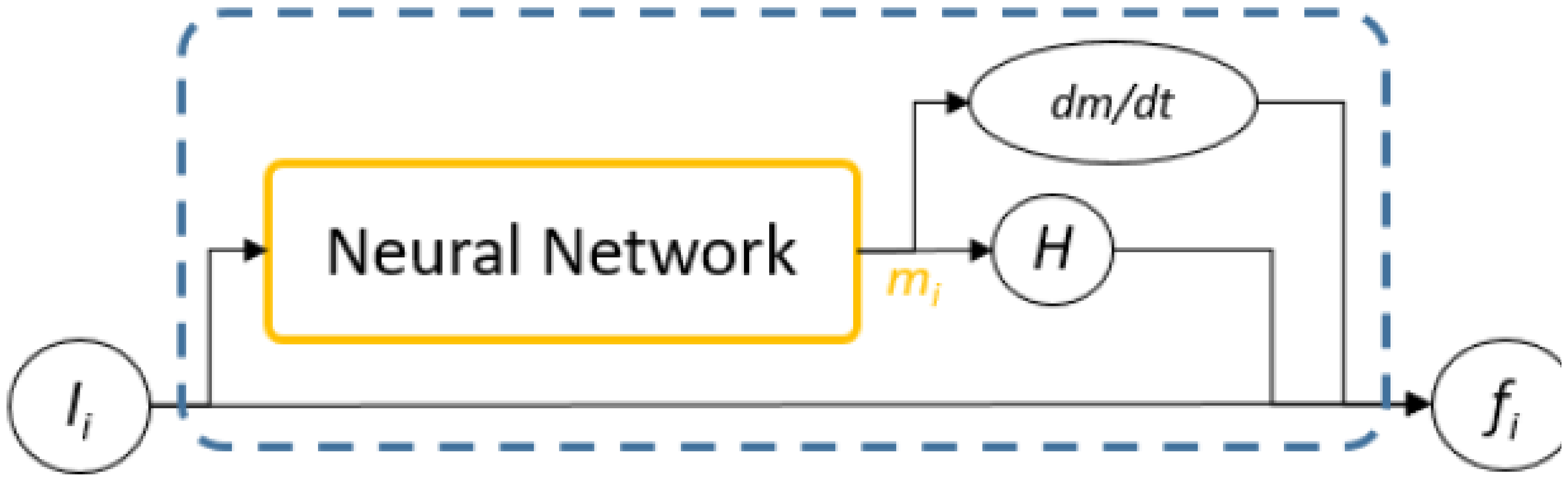
$$f = \frac{\partial m}{\partial t} + H(m;\lambda)$$

$$f = \frac{\partial V_c}{\partial t} - \frac{V_s - V_c}{RC}$$



PHYSICS-INFORMED NETWORKS

PyNN: physics-informed neural networks



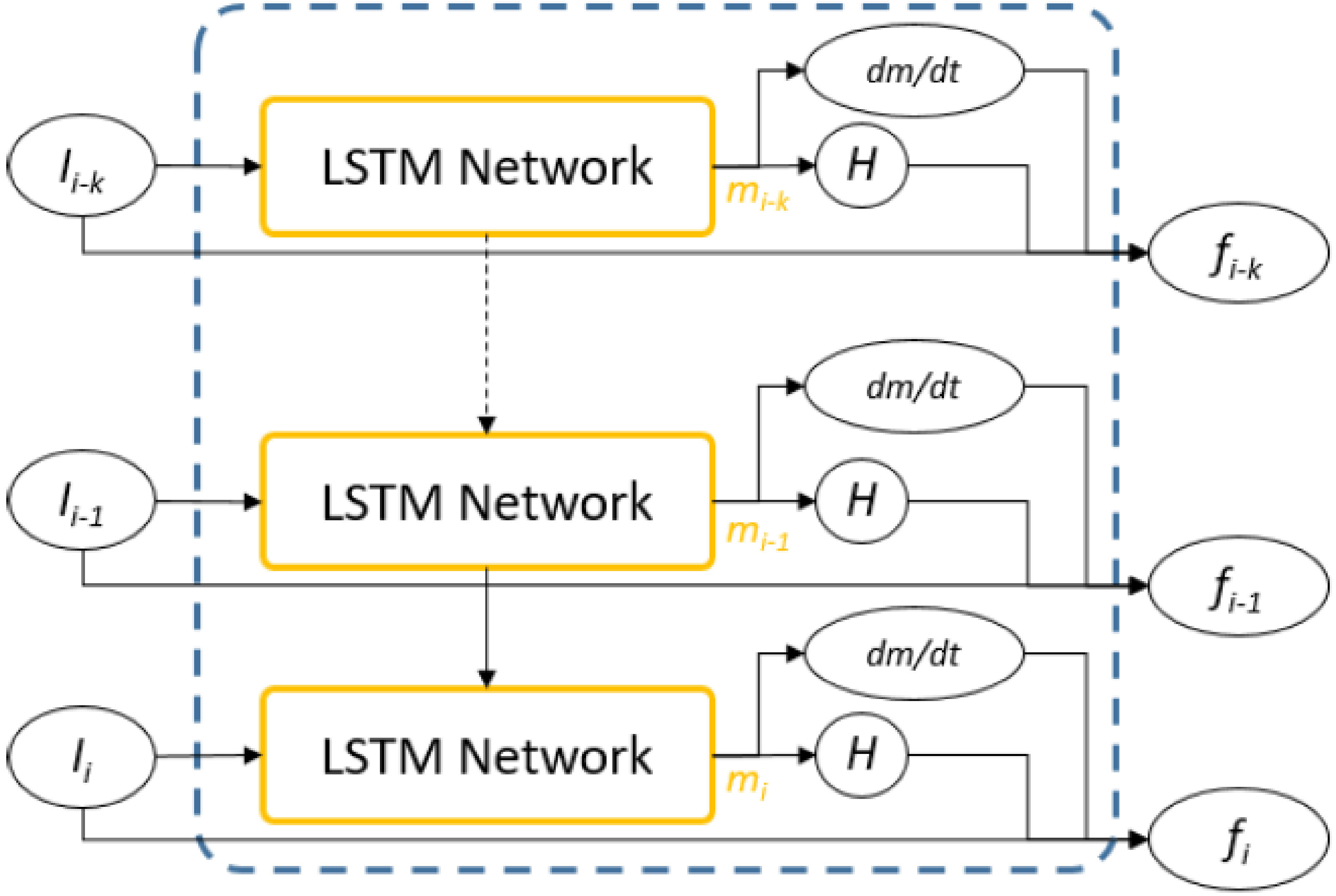
$$\widehat{m}_i^{PyNN} = PyNN(I_i;\theta)$$

$$\widehat{V}_{c,i}^{PyNN} = PyNN(R_i, C_i, V_{s,i}, t_i;\theta)$$

$$\widehat{f}_i^{PyNN} = \left(\frac{\partial \widehat{V}_c^{PyNN}}{\partial t}\right)_i - \frac{V_{s,i} - \widehat{V}_{c,i}^{PyNN}}{R_i C_i}$$

PHYSICS-INFORMED NETWORKS

PyLSTM: physics-informed long short-term memory networks



PHYSICS-INFORMED NETWORKS

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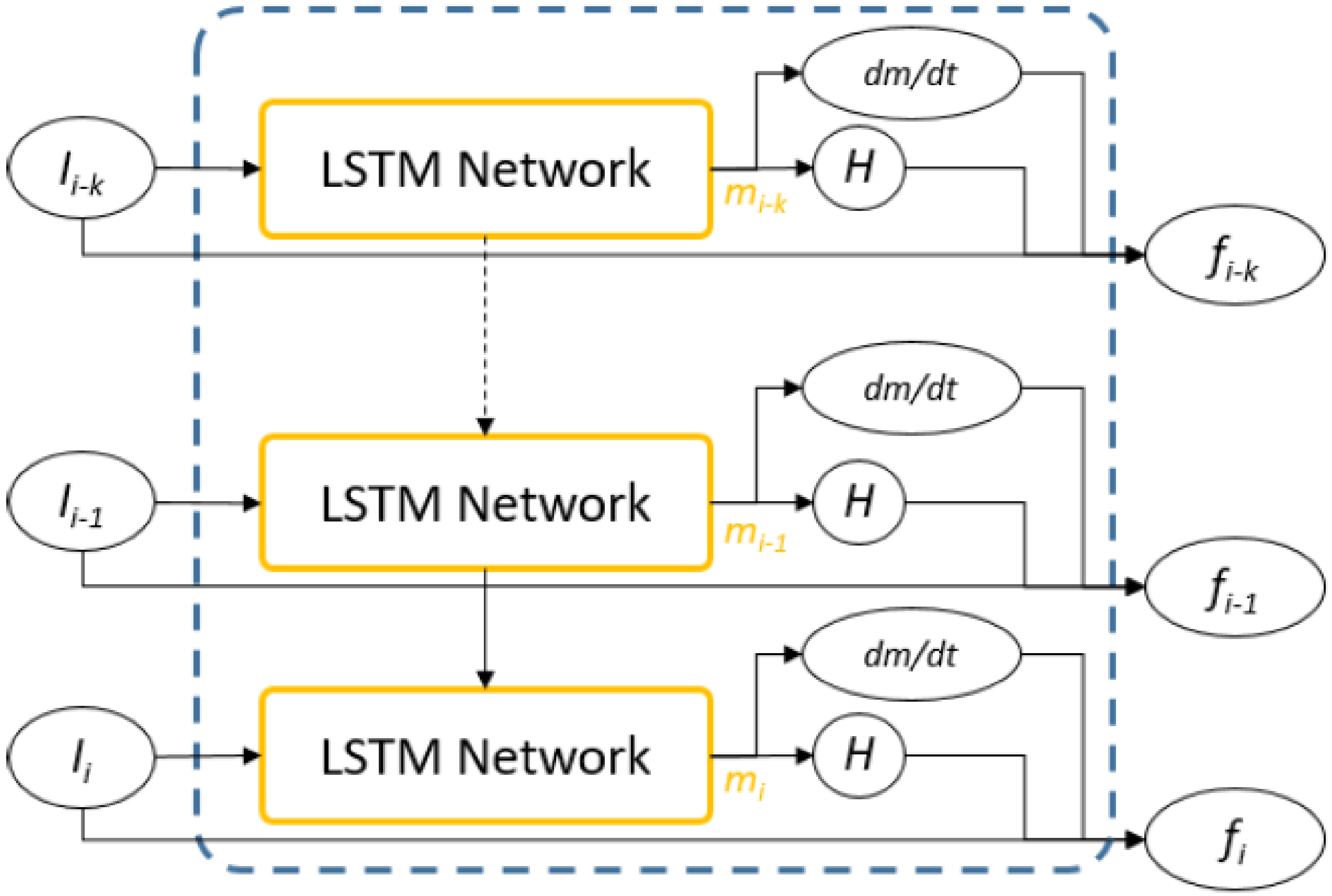

$$\widehat{m}_i^{PyLSTM} = PyLSTM(I_i, I_{i-1}, \ldots, I_{i-k}; \theta)$$

$$\widehat{V}_{c,i}^{PyLSTM} = PyLSTM(R_i, C_i, V_{s,i}, t_i, \ldots$$
$$\ldots, R_{i-k}, C_{i-k}, V_{s,i-k}, t_{i-k}; \theta)$$

EXPERIMENTAL DESIGN

- Training

$$L(W) = MSE_m + MSE_f + \Omega(W)$$
$$= \frac{1}{N}\sum_{i=1}^{N}(e_{m,i}^2 + e_{f,i}^2 + \lambda|W_i|^2)$$

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- Data simulation
  - ❑ Identifying voltage across the capacitor (Vc)
  - ❑ Data is simulated for 5000 seconds (100 observations/second) based on randomly chosen values

$$V_s \in \{0,1,2,3\}V; \mathrm{R} \in \{1,2,3\}\Omega; \mathrm{C} \in \{1,2,3\}F$$

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- Model configuration
  - ❑ Both architectures are fully connected networks with two hidden layers with 16 neurons in each layer.
  - ❑ We build a PyLSTM with the length k = 50 steps to make predictions for the next step. Two hidden layers of 16 LSTM cells each are utilized.
  - ❑ The 'teacher-forcing' training is used to train the LSTM network at each step.
  - ❑ Prediction with PyLSTM: the data id feed for the last k steps to make the prediction.

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- Evaluation

$$|e_i|_M = |V_{c,i} - \widehat{V}_{c,i}^M|$$

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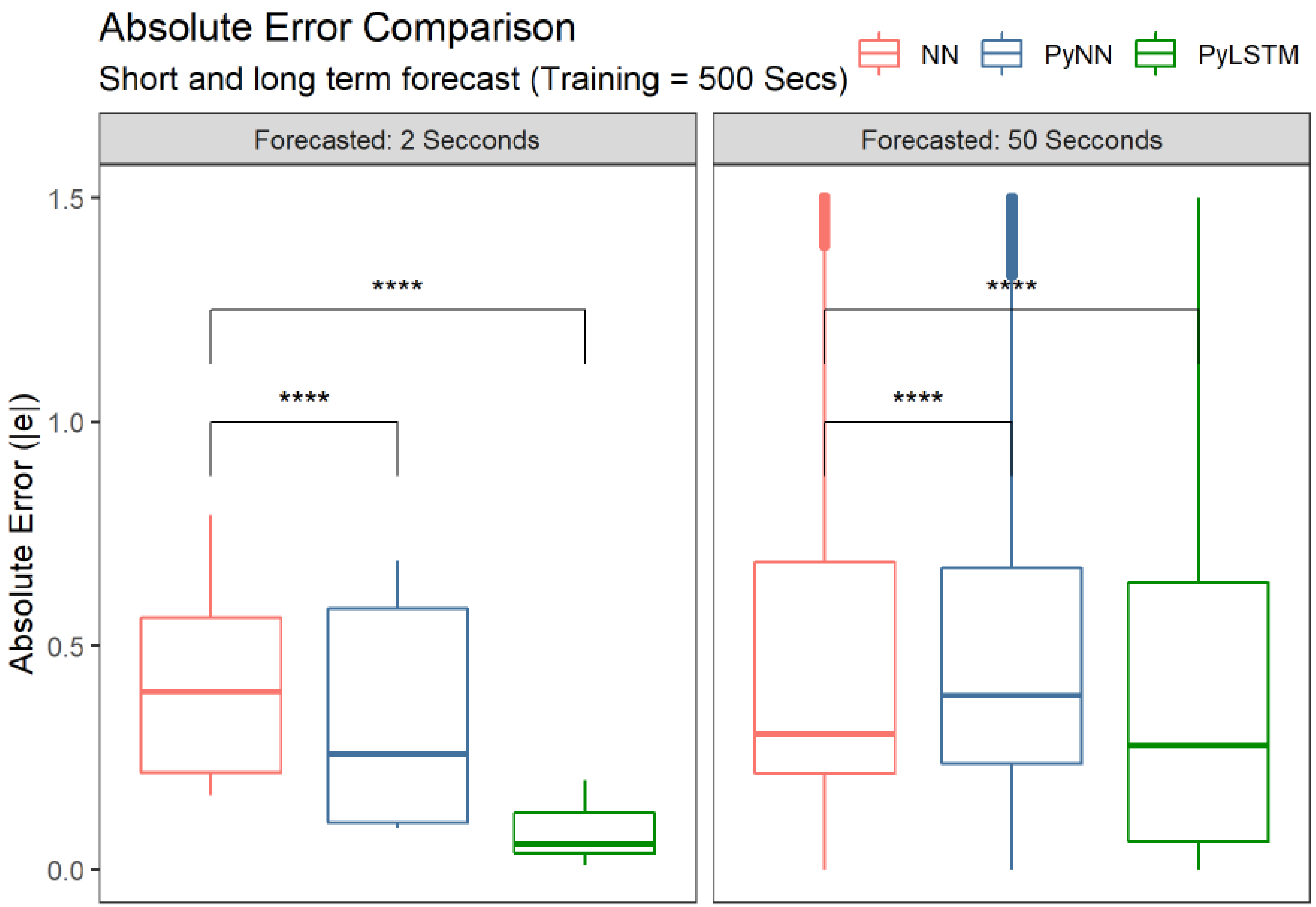
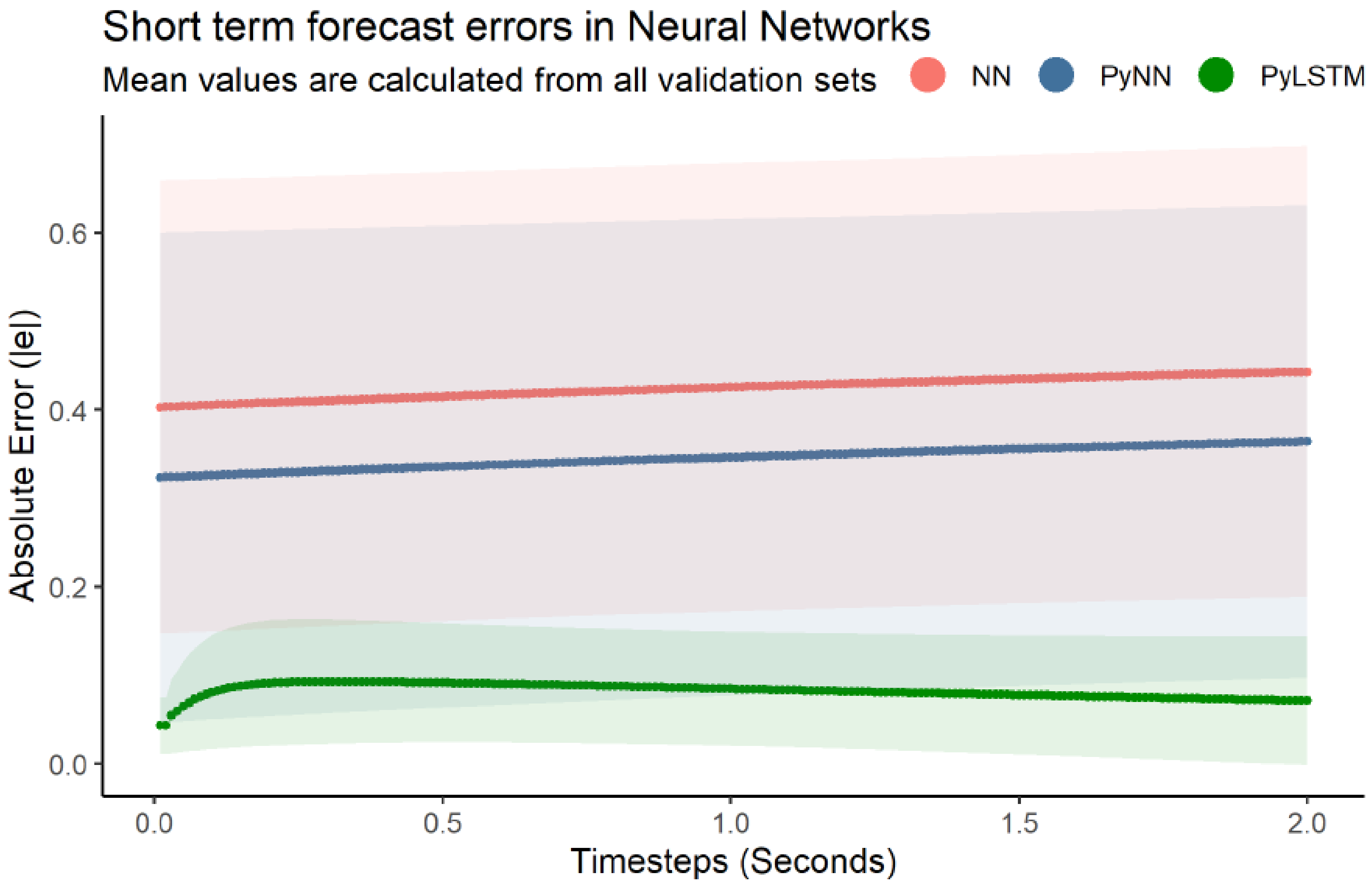
NUMERICAL RESULTS



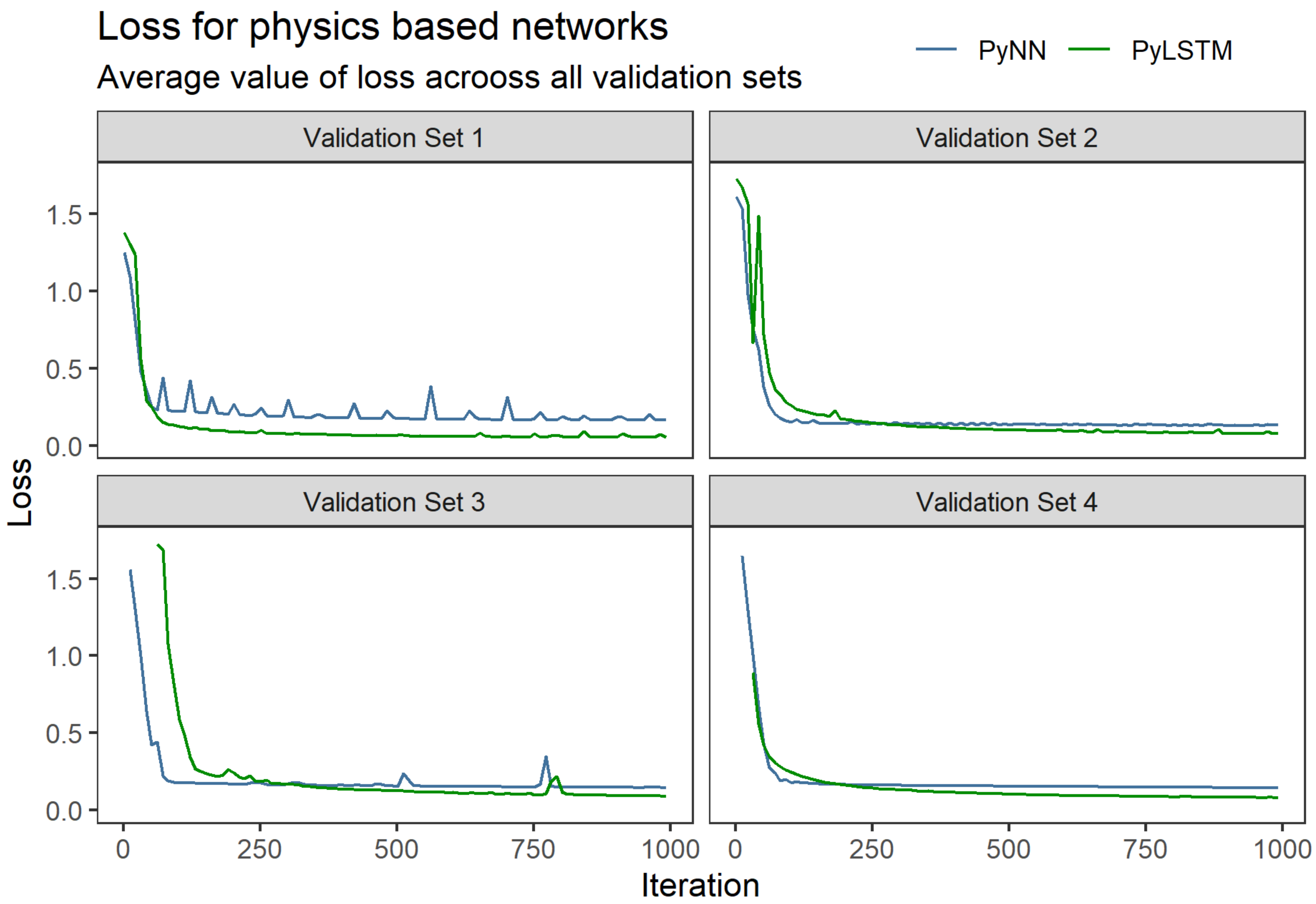
Absolute error distribution for short-term (2 s) and long-term predictions (50 s)

NUMERICAL RESULTS



Absolute error for short-term predictions.

NUMERICAL RESULTS



Loss per iteration for physics-informed models

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