Evaluating deep neural networks for Newtonian noise subtraction

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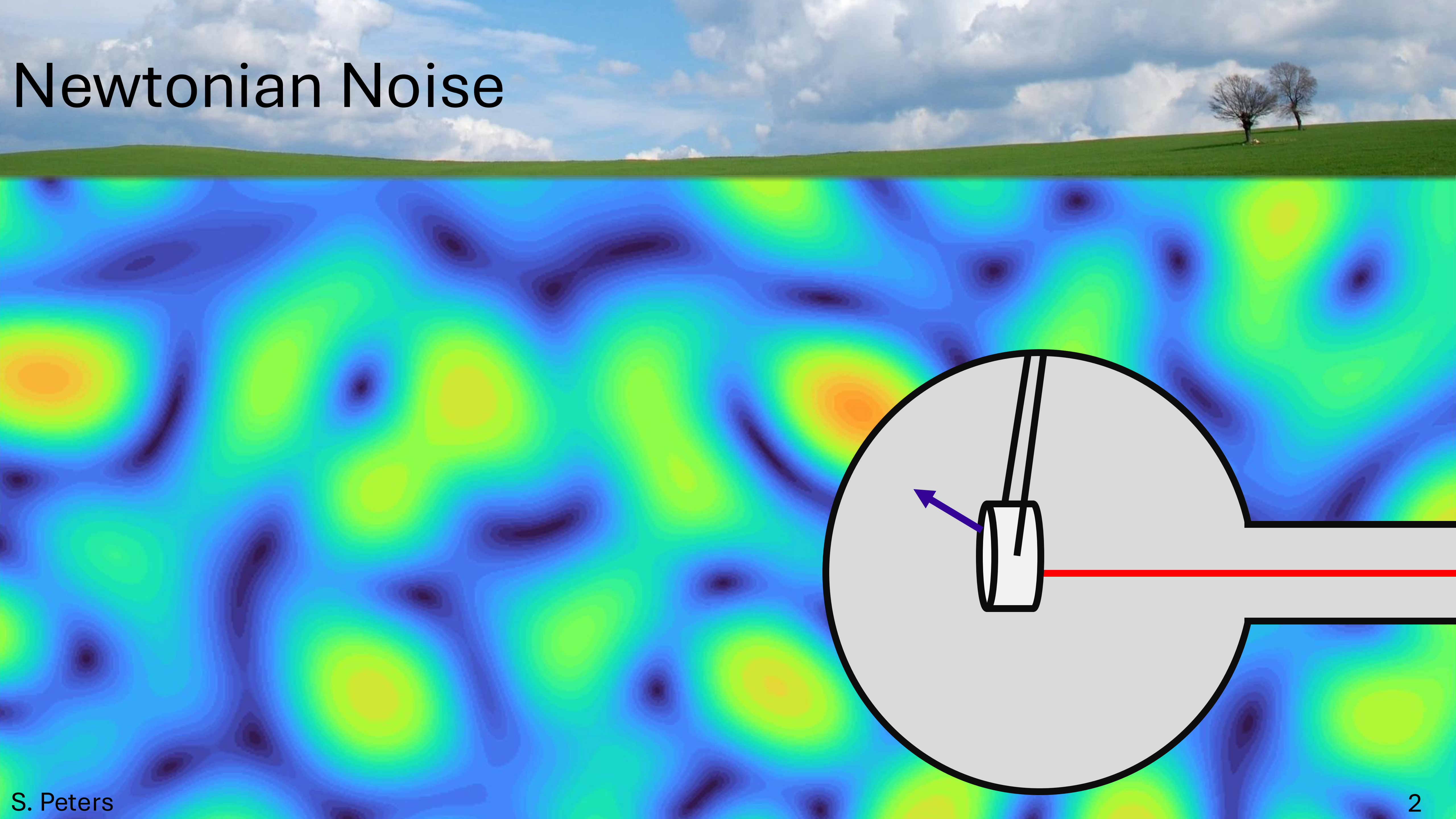
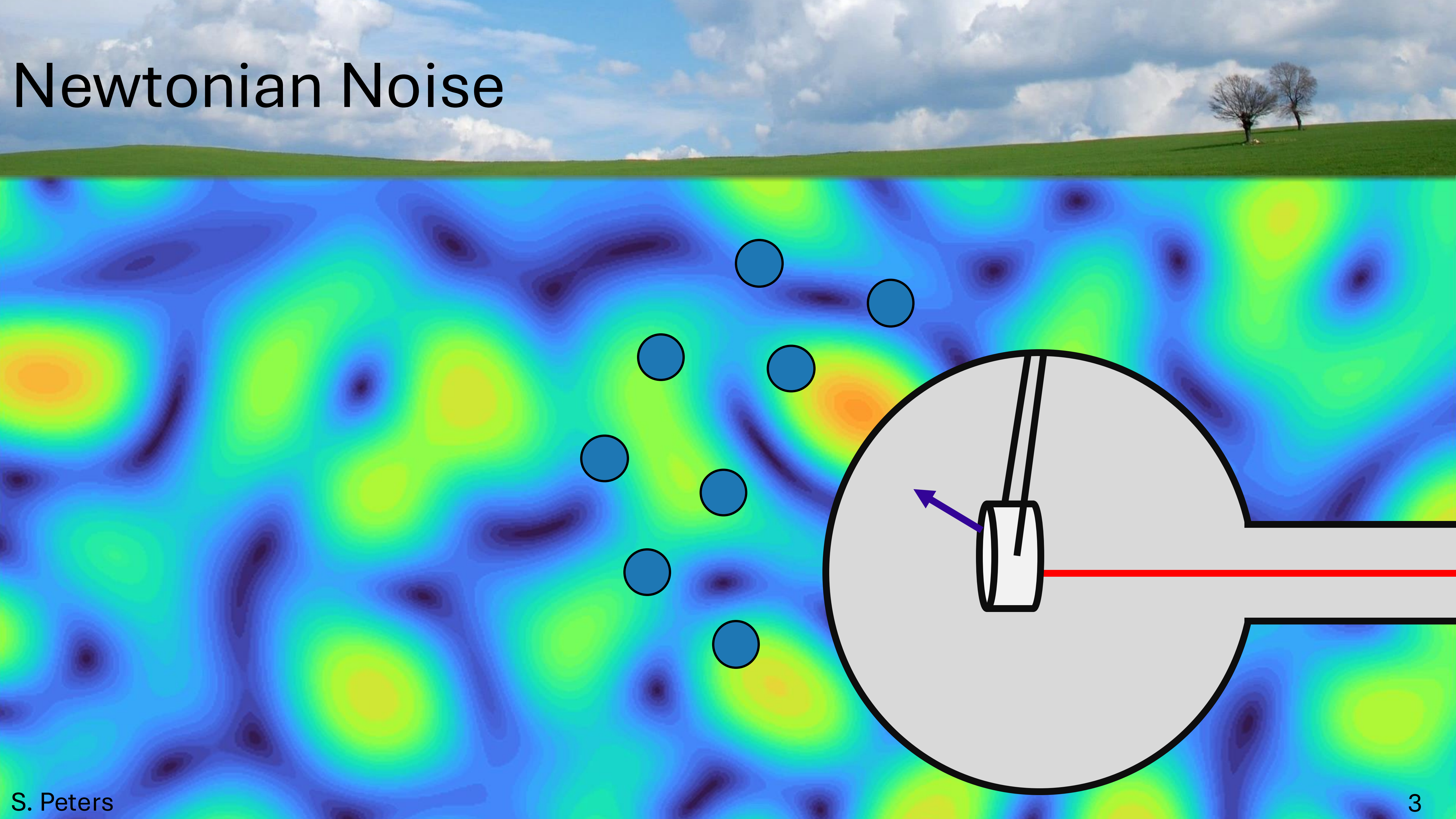
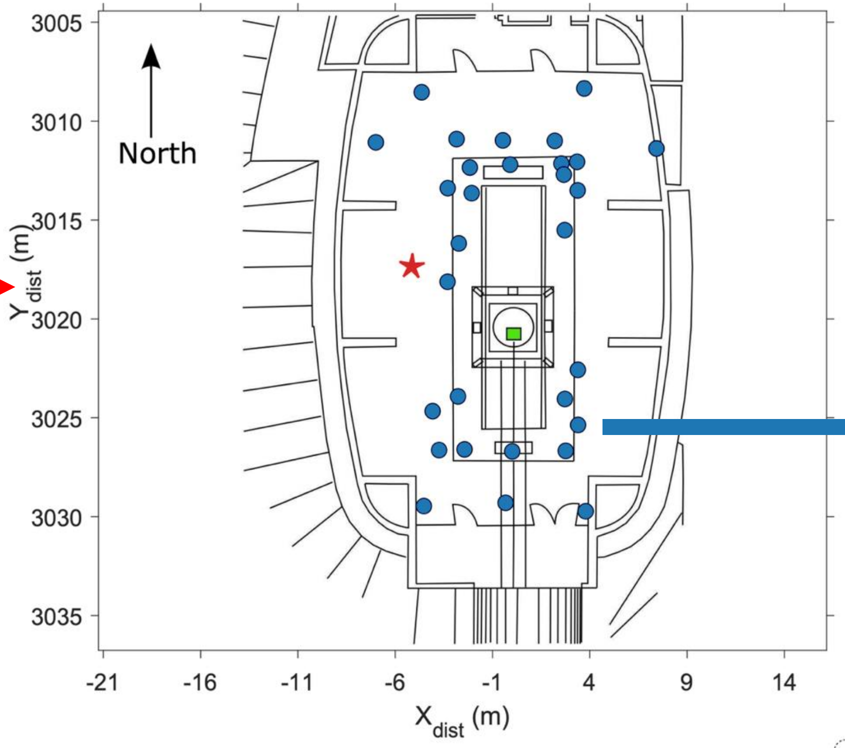
Newtonian Noise



Newtonian Noise



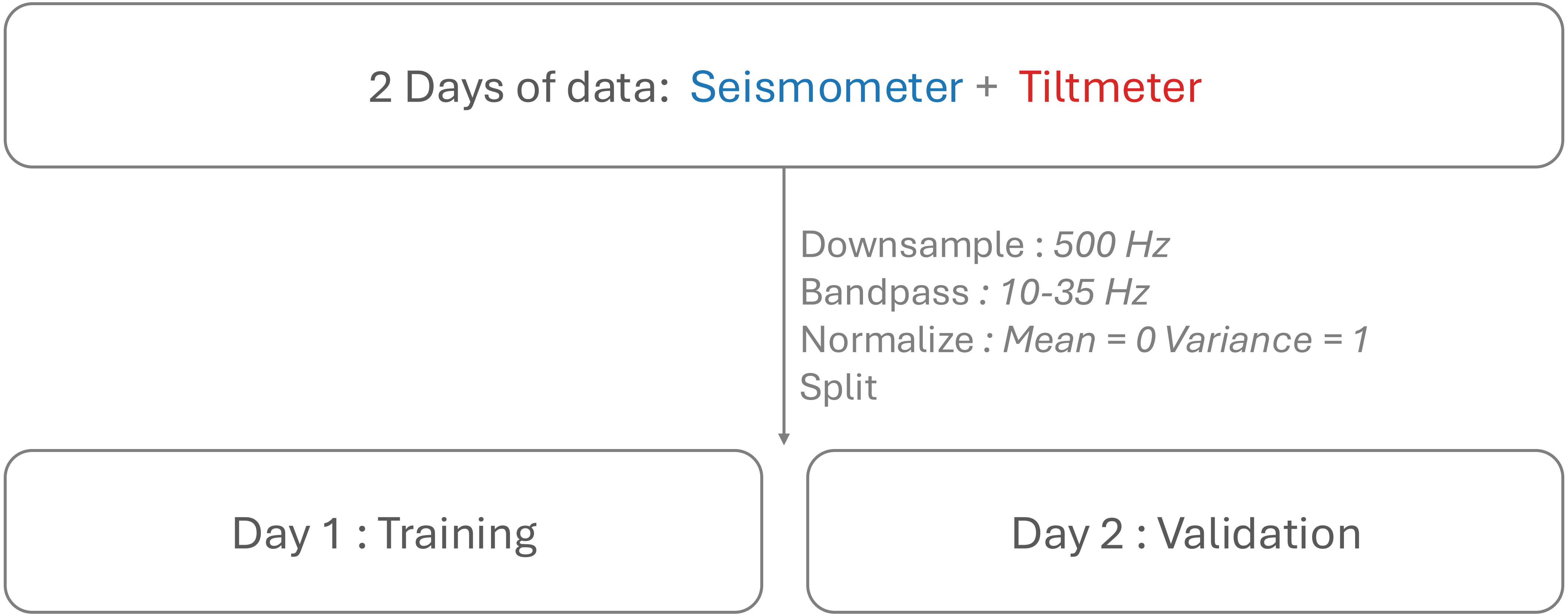
Using Virgo Data



24 Seismometers
1 Tiltmeter (proxy for Newtonian Noise)

"Adaptive algorithms for low-latency cancellation of seismic Newtonian-noise at the Virgo gravitational-wave detector". S. Koley, J. Harms, et al.

Preprocessing



Wiener Filter vs Deep Neural Networks

Optimal **linear** filter for **stationary** noise

$$\hat{y}(t) = \sum_{i=1}^{N} \sum_{\tau=0}^{L-1} h_i(\tau) \cdot x_i(t-\tau)$$

Theoretical cancellation performance
(frequency domain)

$$R(\omega) = 1 - \frac{\vec{C}_{\mathrm{SN}}^{\dagger} \, \mathbf{C}_{\mathrm{SS}}^{-1} \, \vec{C}_{\mathrm{SN}}}{C_{\mathrm{NN}}}$$

Learn a **non-linear** mapping from inputs to output using data

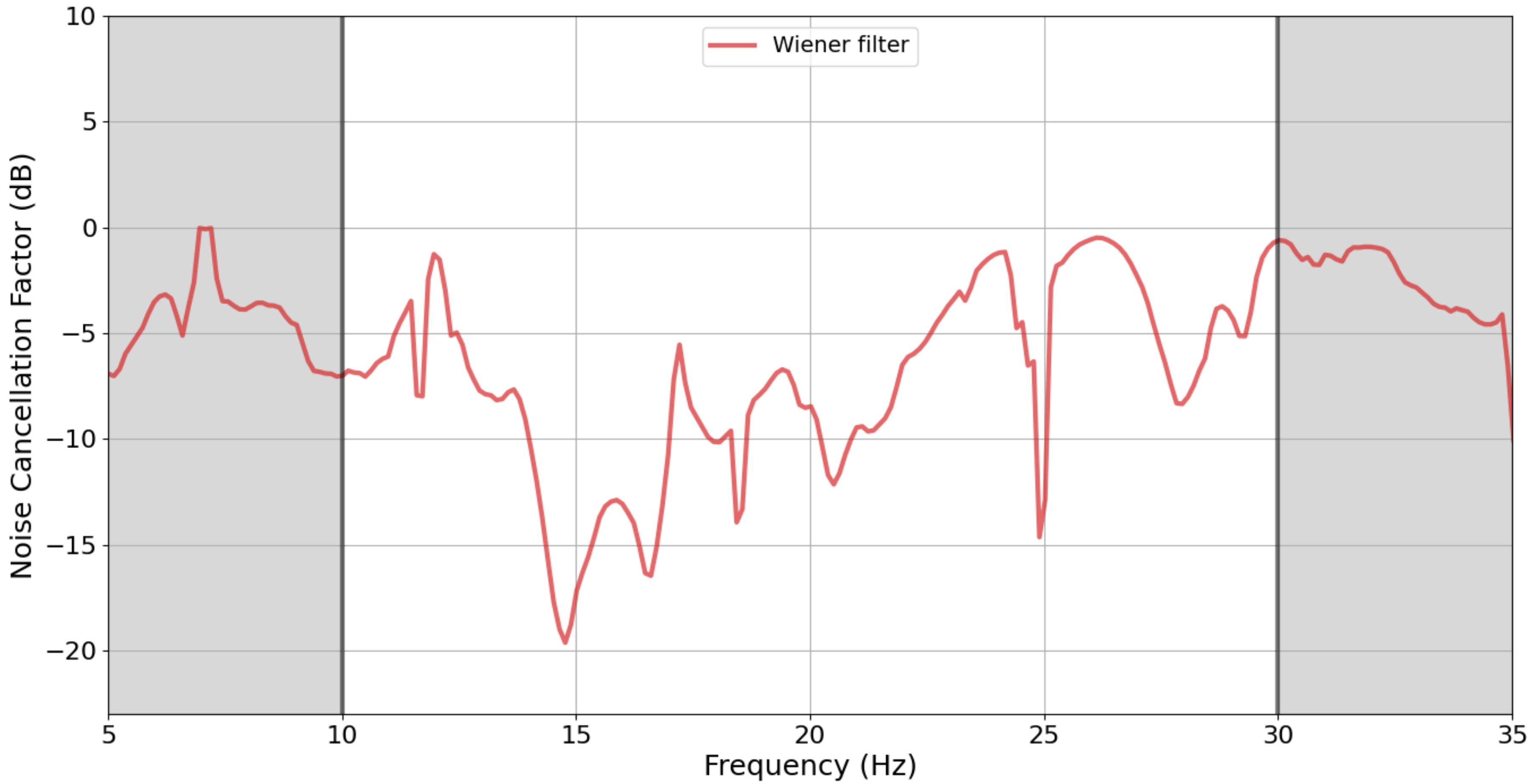
$$\hat{y}(t) = f_\theta\left(\{x_i(t-\tau)\}_{i,\tau}\right)$$

$$\text{with } i = 1, \ldots, N \quad \text{and} \quad \tau = 0, \ldots, L{-}1$$

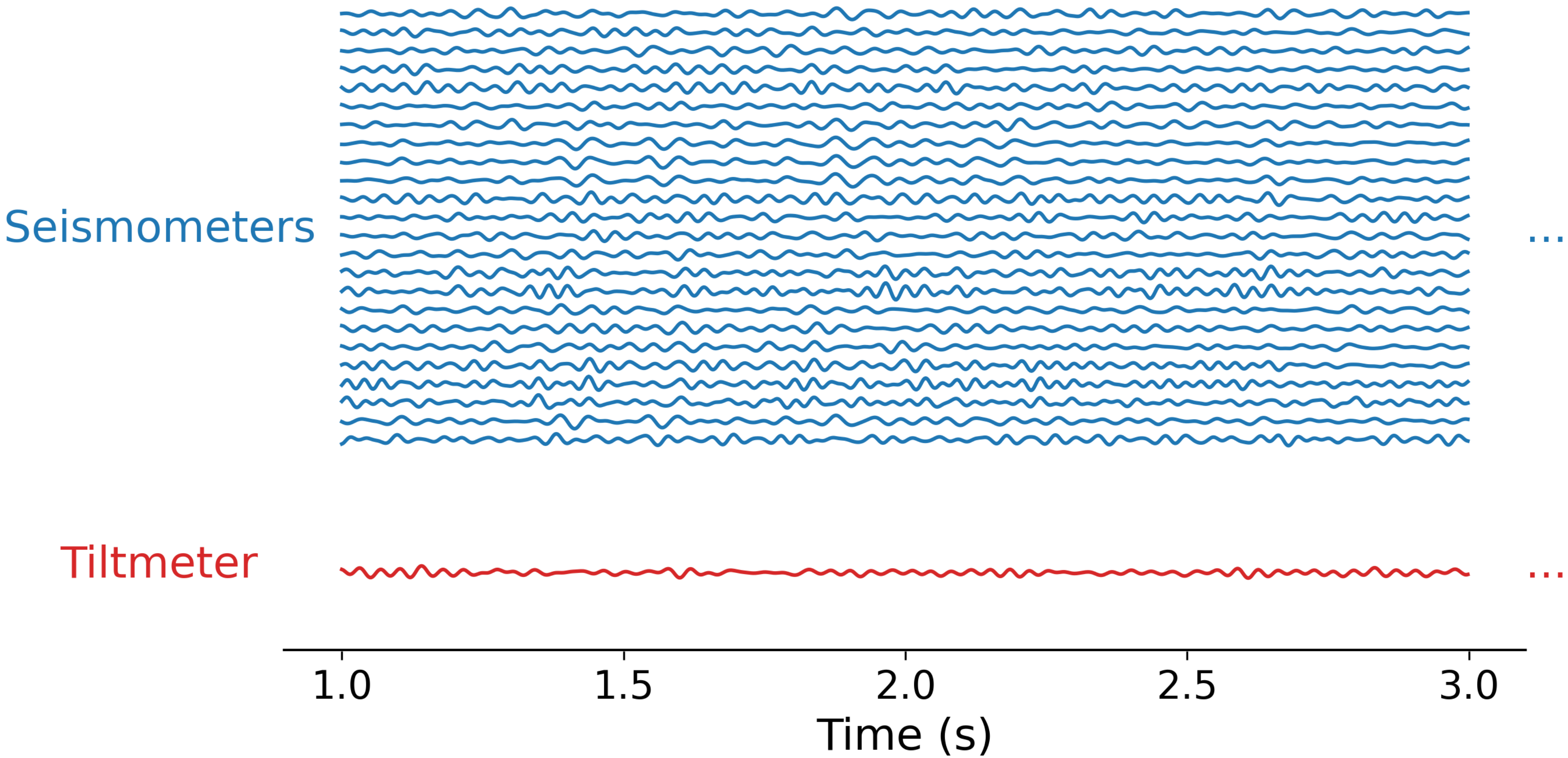
Wiener Filter

Theoretical cancellation performance
(frequency domain)

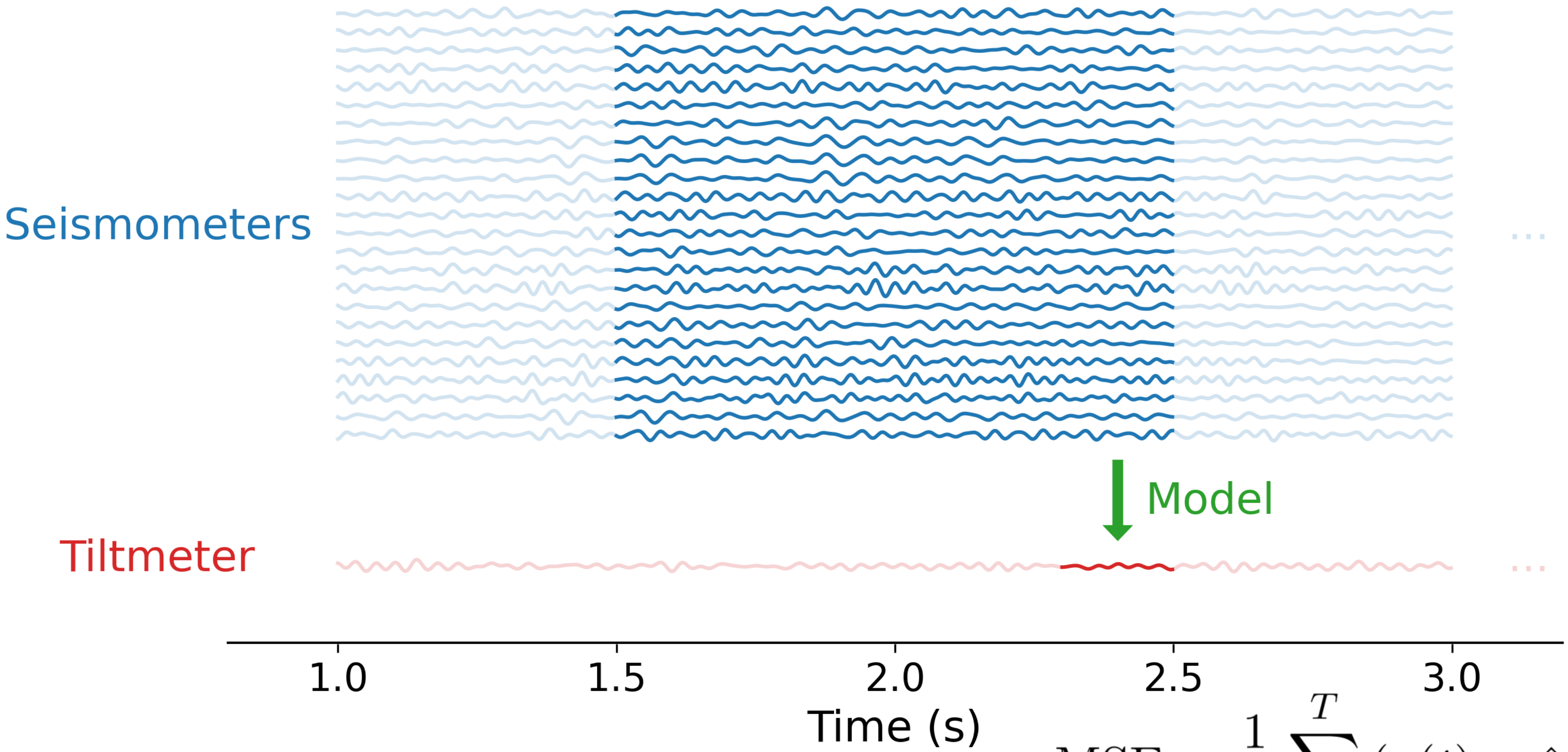
$$R(\omega) = 1 - \frac{\vec{C}_{\mathrm{SN}}^{\dagger}\, \mathbf{C}_{\mathrm{SS}}^{-1}\, \vec{C}_{\mathrm{SN}}}{C_{\mathrm{NN}}}$$



Training Deep Neural Networks: *Dataset*



Training Deep Neural Networks: *Dataset*

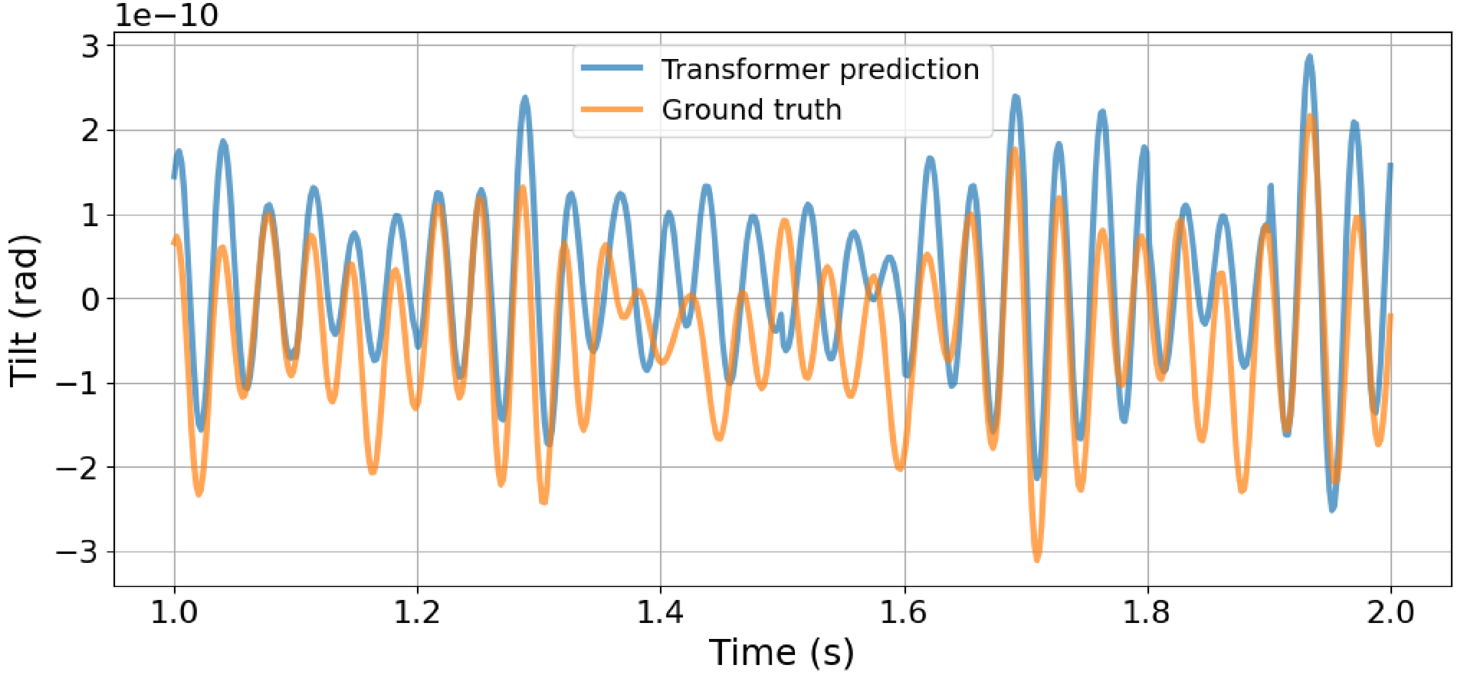


$$\mathrm{MSE} = \frac{1}{T}\sum_{t=1}^{T}\left(y(t) - \hat{y}(t)\right)^2$$

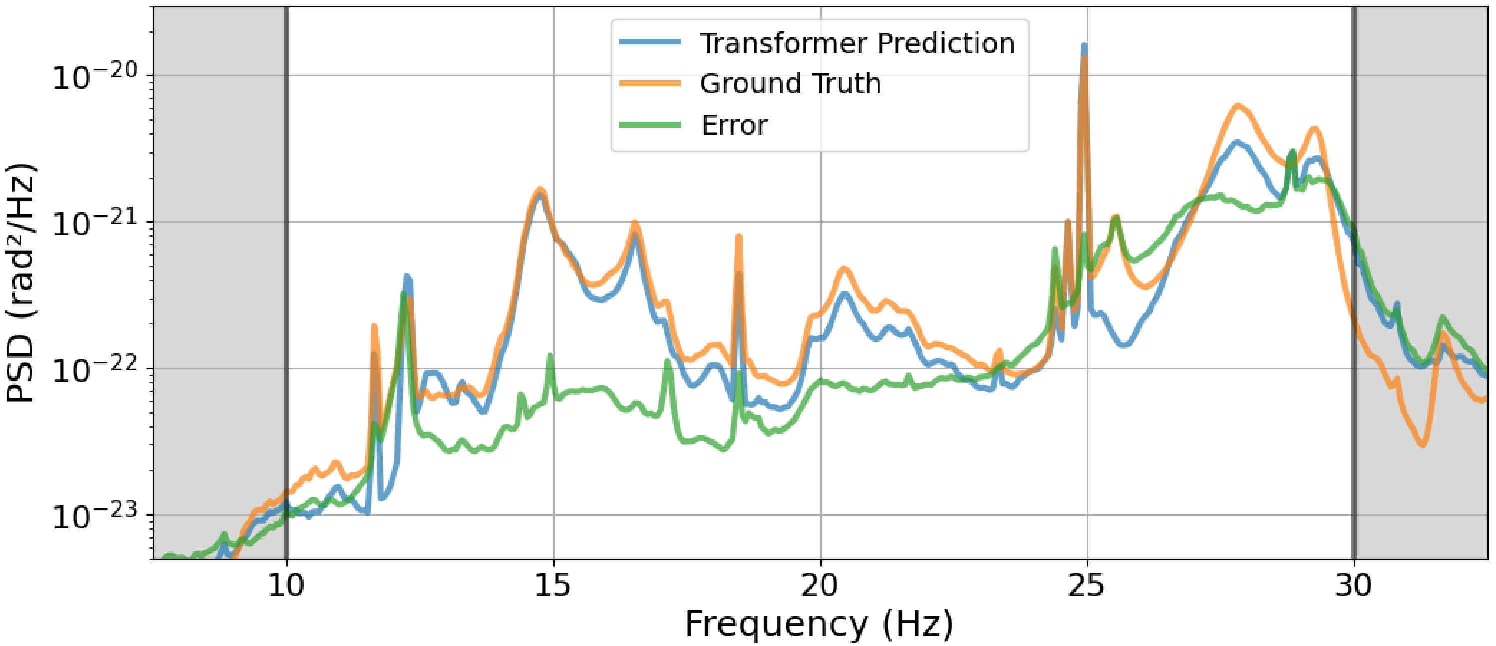
Training Deep Neural Networks: *Models*

• Convolutional Neural Network (CNN)	42 000 parameters
• Long Short Term Memory (LSTM)	217 000 parameters
• Transformer	3 000 000 parameters

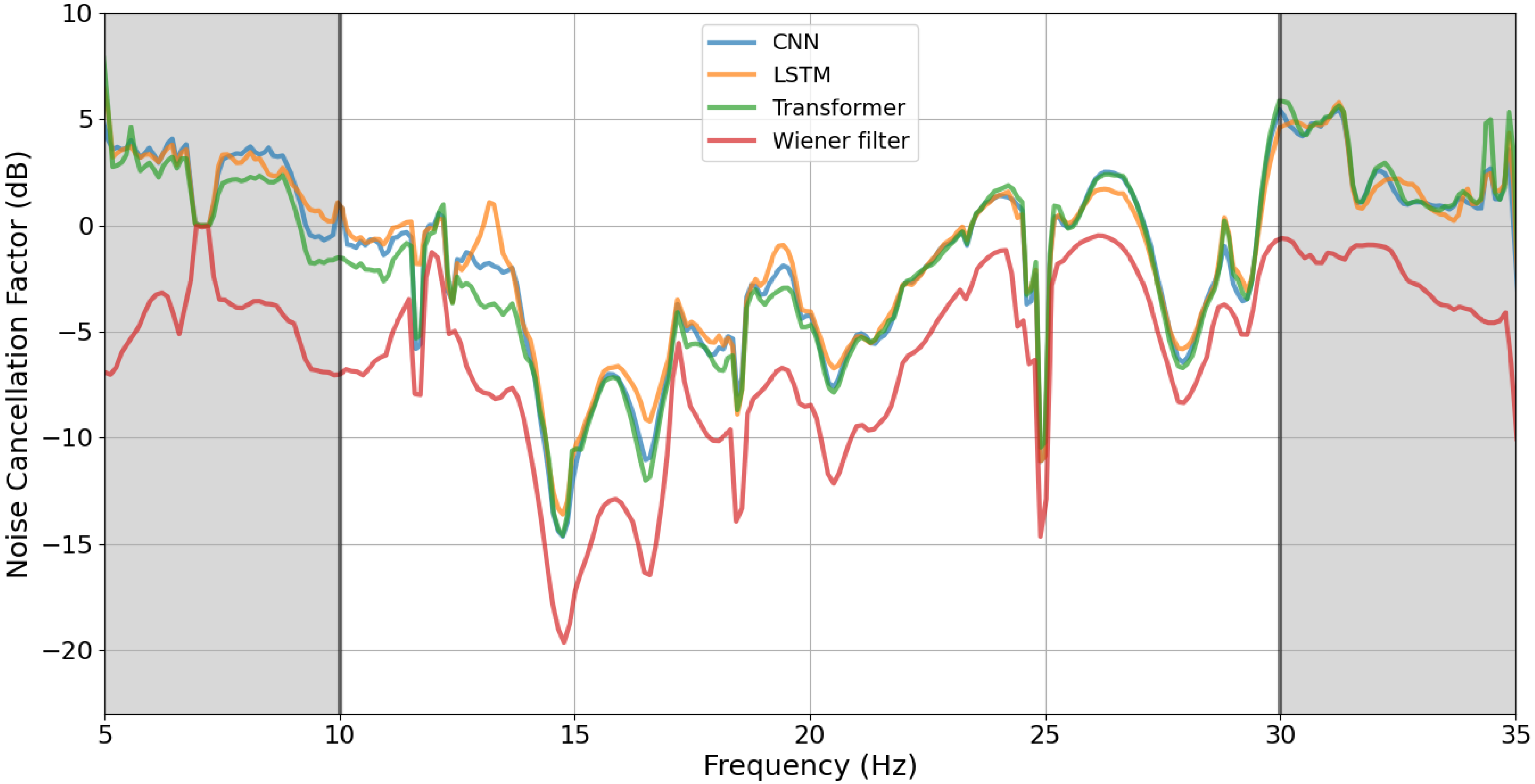
Results



$$e(t) = y(t) - \hat{y}(t)$$

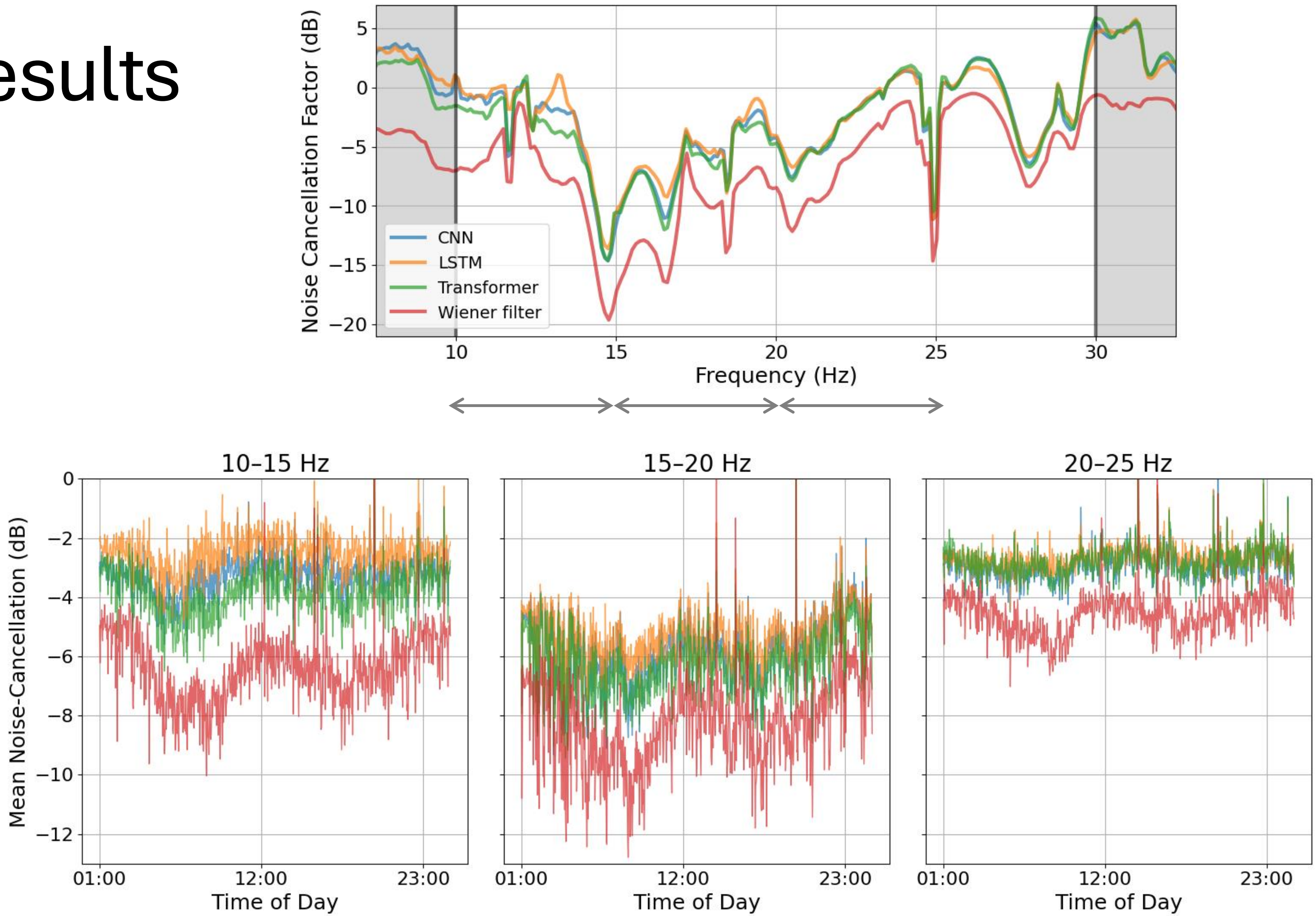


Results



CNN
LSTM
Transformer
Wiener filter
Noise Cancellation Factor (dB)
Frequency (Hz)
10
5
0
−5
−10
−15
−20
5
10
15
20
25
30
35

Results



Noise Cancellation Factor (dB)
5
0
−5
−10
−15
−20
10
15
20
25
30
Frequency (Hz)
CNN
LSTM
Transformer
Wiener filter
10–15 Hz
15–20 Hz
20–25 Hz
Mean Noise-Cancellation (dB)
0
−2
−4
−6
−8
−10
−12
01:00
12:00
23:00
Time of Day

Discussion

Our current Neural Networks do not outperform the Wiener Filter

↓

Optimal **linear** filter for **stationary** noise

↓

One frequency band does not affect the others

Further test: can Neural Networks exploit non-linearity:

Use seismometer data bandpassed between 50-200 Hz
to predict tiltmeter data between 10-30 Hz

→ *Converges to predicting the mean, confirming model limitations*

Discussion

- Either our current neural networks are not architectured to leverage the non-linearity :

  Further test: Use a spectral loss → *Difficulties converging*

  Solution: Use a spectral model (e.g. Seismonet)

- Either there is no non-linearity or non-stationarity :

  Test on a different dataset

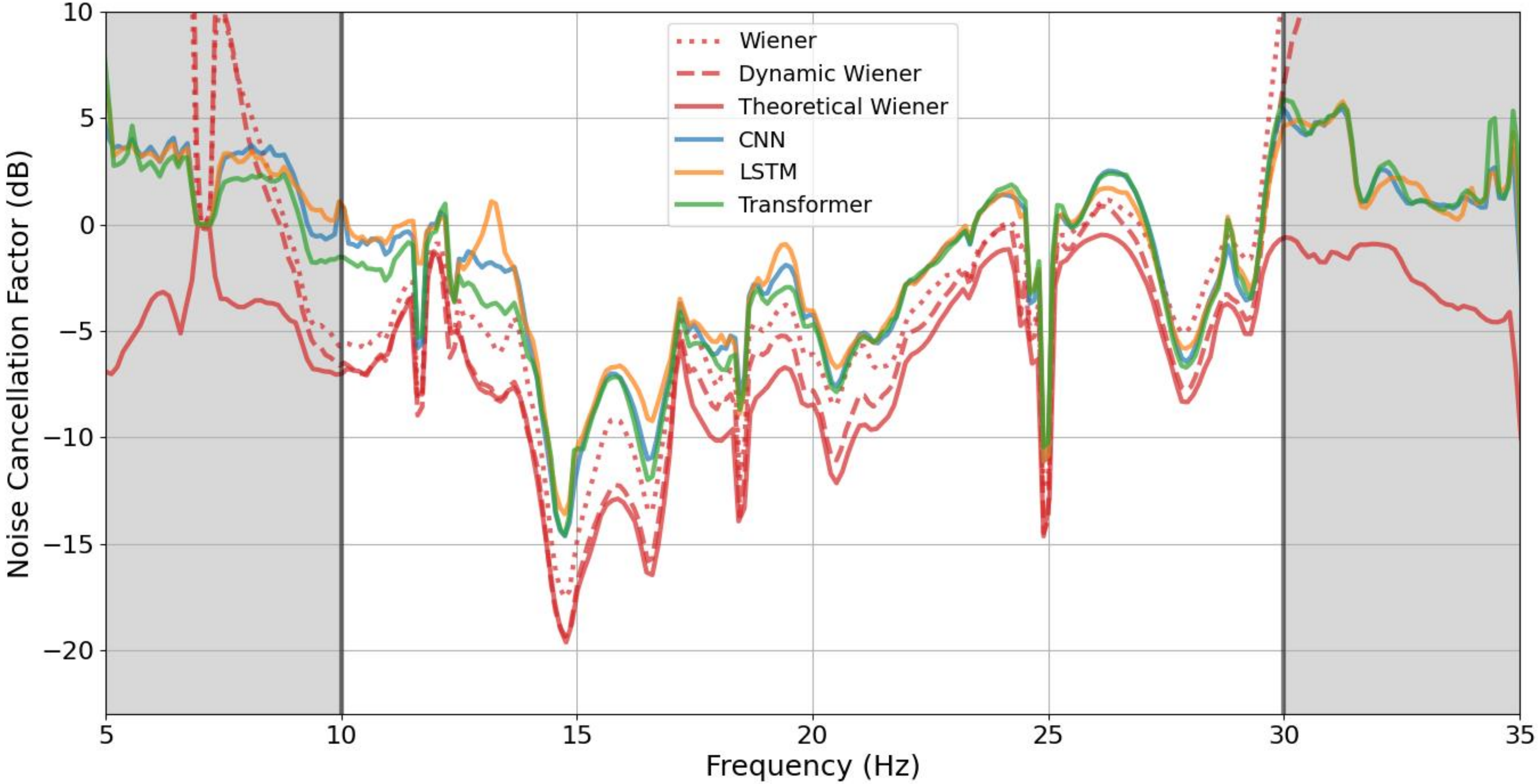
  Train on wiener-filtered data

"*A study of deep neural networks for Newtonian noise subtraction at Terziet in Limburg—the Euregio Meuse-Rhine candidate site for Einstein Telescope*". V. van Beveren, et al.

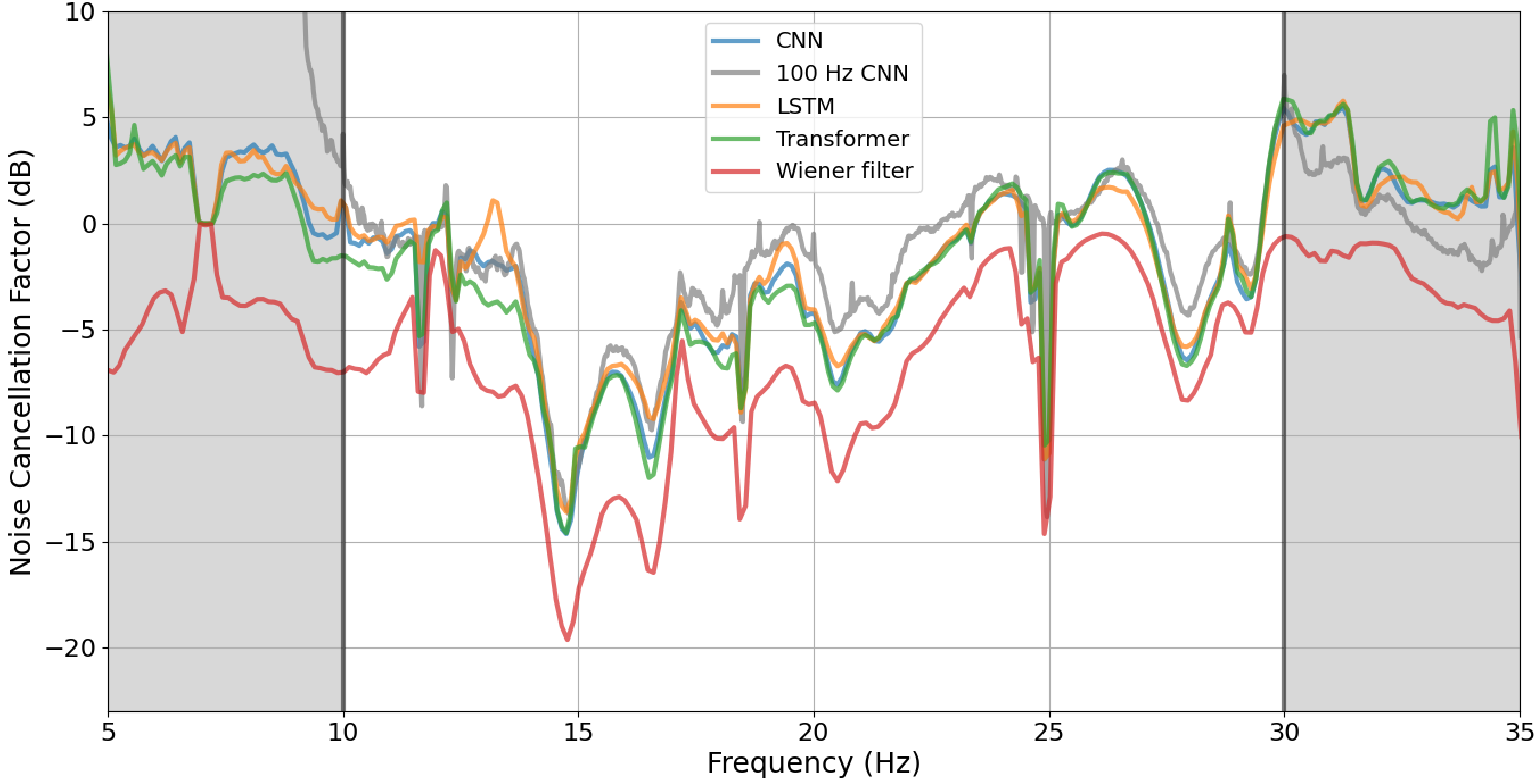
Conclusion

- Benchmarked different neural networks against the optimal linear filter on real data

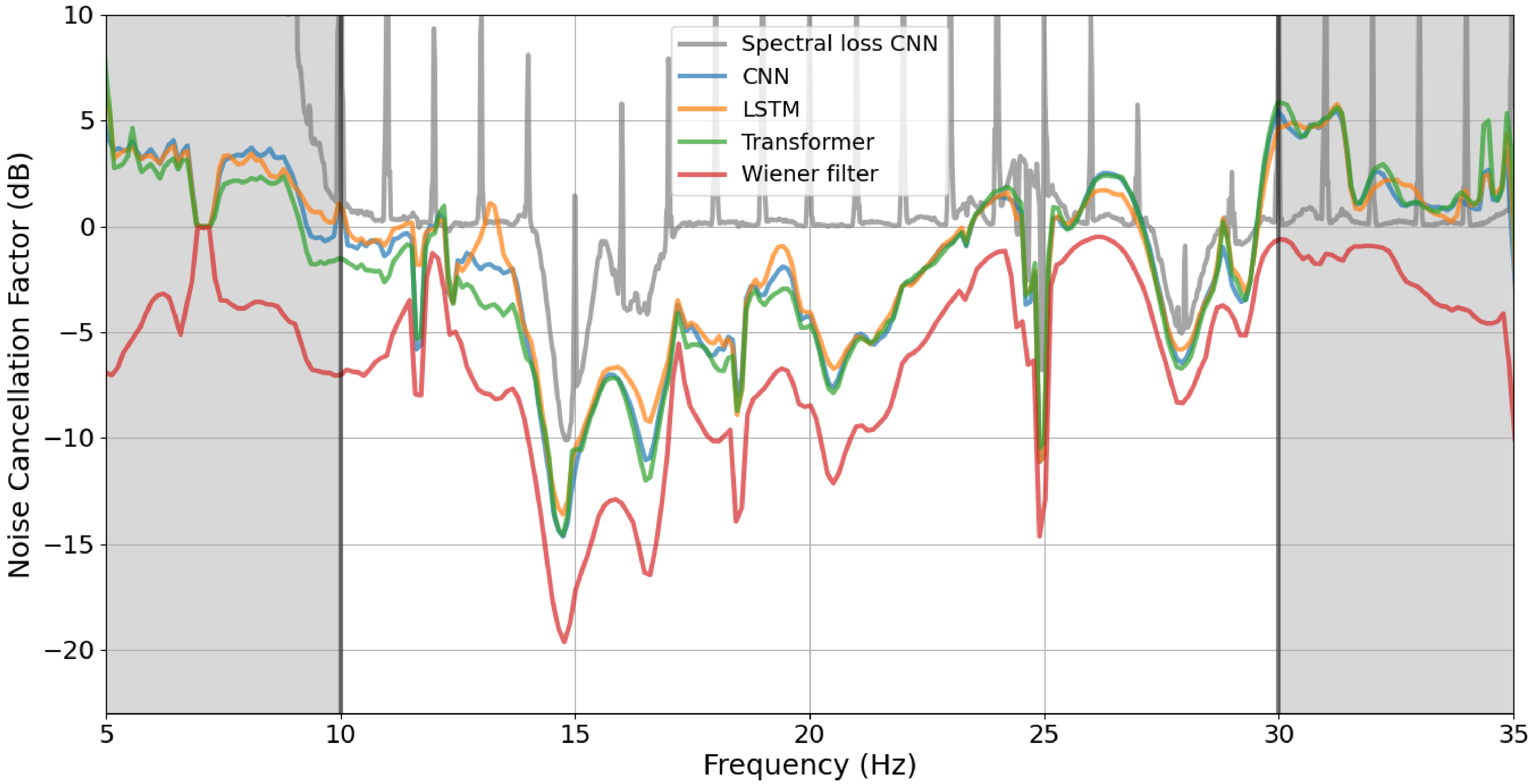
- Modular framework to train different models :
  - Change the parameters easily (input and output length, model,…)
  - Ready for forecasting (online NN substraction)



Wiener
Dynamic Wiener
Theoretical Wiener
CNN
LSTM
Transformer
Noise Cancellation Factor (dB)
Frequency (Hz)
10
5
0
−5
−10
−15
−20
5
10
15
20
25
30
35



CNN
100 Hz CNN
LSTM
Transformer
Wiener filter
Noise Cancellation Factor (dB)
Frequency (Hz)
10
5
0
−5
−10
−15
−20
5
10
15
20
25
30
35



Noise Cancellation Factor (dB)
10
5
0
−5
−10
−15
−20
5
10
15
20
25
30
35
Frequency (Hz)
Spectral loss CNN
CNN
LSTM
Transformer
Wiener filter