# *Machine Learning Platform for Power Electronics Modeling*


PRESENTER:

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## ABSTRACT


Power magnetics are key components in power electronics systems. They determine the volume, size, and efficiency of power electronics and play important roles in renewable energy systems and transportation electrification. We developed neural network models to capture the behaviors of magnetic components across different temperatures, DC bias, frequency, and amplitude range. We explored novel ways of predicting the response waveform based on an excitation waveform and scalar parameters such as temperature and DC bias.


## RESEARCH QUESTION

Can we predict the B-H loop of power magnetics under different excitations using machine learning techniques? Can this process be automated for newly-collected data? Can this system outperform accepted empirical solutions?

## METHODS

1. Collect B-field (excitation) data and H-field (response) sequence data from a range of frequencies, amplitudes, and waveform shapes for materials under range of temperature and DC bias.
2. Construct Seq2Seq LSTM-based model to predict H-field sequence given B-field sequence and scalar parameters
3. Allowed model to train to minimum of convergence and 500 epochs, minimizing MSE loss
4. Compute cosine similarity between true/predicted response sequence, treat as vector in 128-space (time domain is 128 timesteps)

## RESULTS

- Trained on 236,624 excitation-response sequences with 85/10/5 train/validation/test split
- Converged after 341 epochs @ 46s/epoch (~4h20m)
- Avg. RMSE = 0.853, stddev = 0.651
- Avg. cosine similarity = 0.994, std. dev. = 0.015

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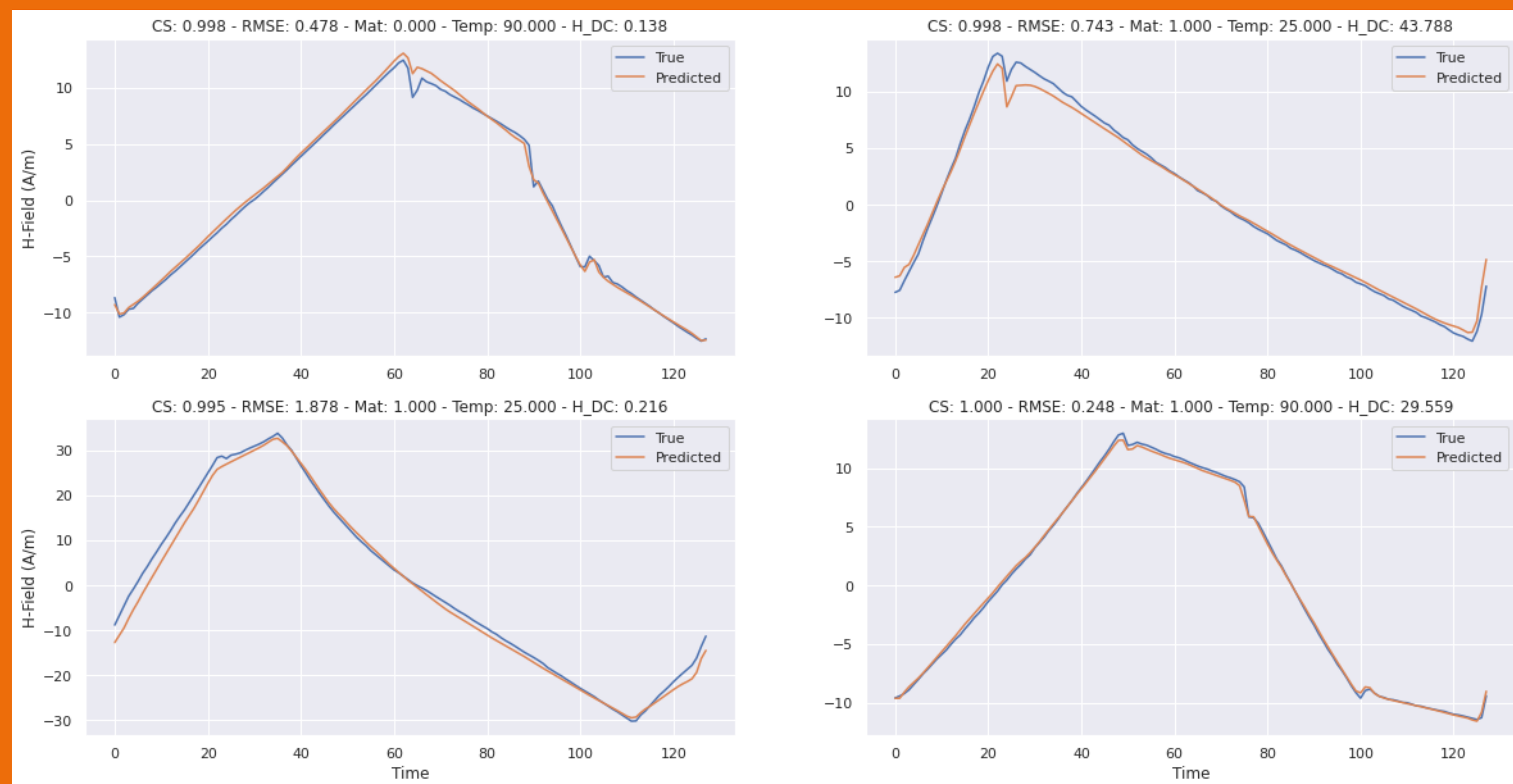
## REFERENCES


E. Dogariu, H. Li, D. Serrano López, S. Wang, M. Luo and M. Chen, "Transfer Learning Methods for Magnetic Core Loss Modeling," IEEE Workshop on Control and Modeling of Power Electronics (COMPEL), Cartagena de Indias, Colombia, 2021

H. Li, S. R. Lee, M. Luo, C. R. Sullivan, Y. Chen and M. Chen, "MagNet: A Machine Learning Framework for Magnetic Core Loss Modeling," IEEE Workshop on Control and Modeling for Power Electronics (COMPEL), 2020.


# **Seq2Seq LSTM autoencoders** can predict response waveform of power electronics given excitation, temperature, and DC bias to **over 99% accuracy.**




Predicting response sequence of device-under-test (DUT) to avg. validation cosine similarity of 0.9942 (std. dev. 0.015)

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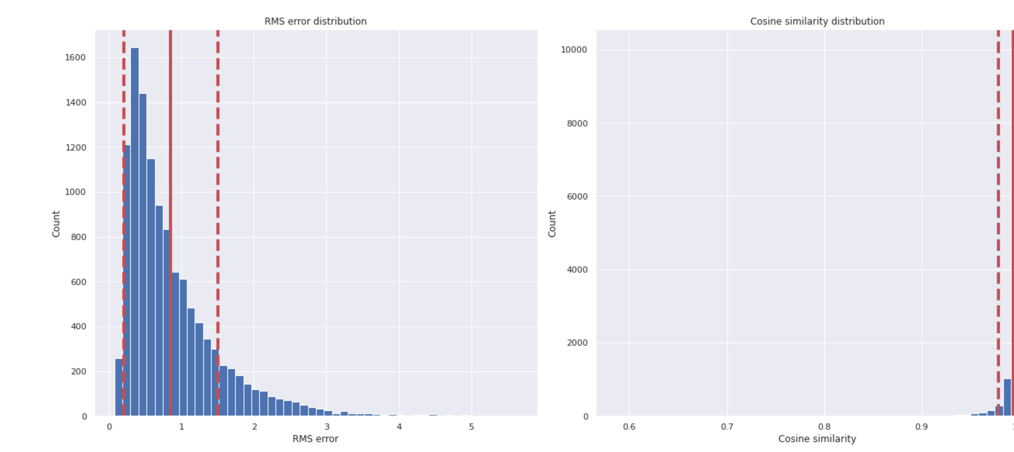
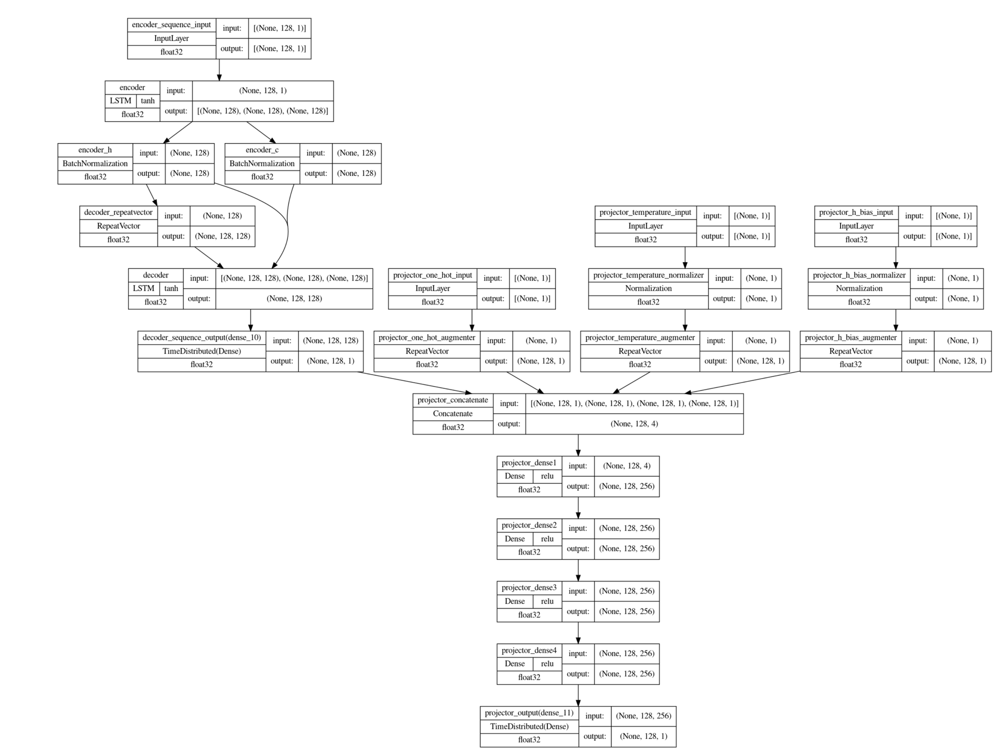
## MORE DETAILS

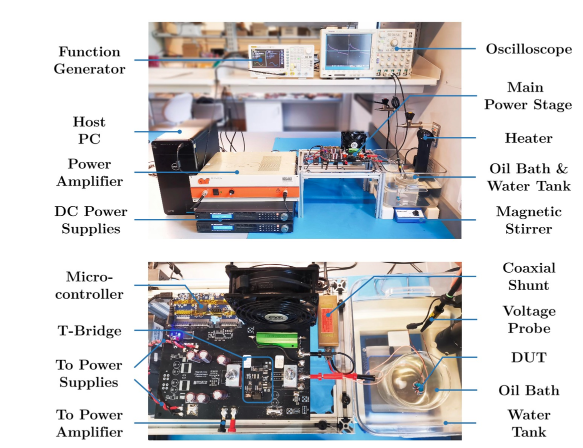
- Encoder → Decoder → Projector
- LSTM-based structure
- Data pre-processed to 128-timestep single-cycle from ~10 cycle sample
- Model outputs 128-timestep single cycle response prediction
- 397,698 trainable parameters, 518 non-trainable parameters





$$\text{cosine similarity} = S_C(A,B) := \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$

| Method | Core Loss ($P_v$) | #Param. |
|---|---|---|
| SE | $kf^{\alpha}\hat{B}^{\beta}$ | 3 |
| iGSE | $\frac{1}{T}\int_0^T k_i\|\frac{dB}{dt}\|^{\alpha}(\Delta B)^{\beta-\alpha}dt$ | 3 |
| i$^2$GSE | $\frac{1}{T}\int_0^T k_i\|\frac{dB}{dt}\|^{\alpha}(\Delta B)^{\beta-\alpha}dt + \Sigma_{l=1}^{n} Q_{rl}P_{rl}$ | 8 |
| ML | Neural Network | $\gg$10 |





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