A Compact Machine Learning Framework for Multi-Material Core Loss Modeling

Edward Deleu, Shukai Wang, Haoran Li, and Minjie Chen

Princeton University, Princeton NJ, USA

andlinger center for energy+the environment

Supported By:
Peter B. Lewis Fund for Student Innovation in Energy and the Environment;
Dede T. Bartlett P03 Fund for Student Research in Energy and the Environment

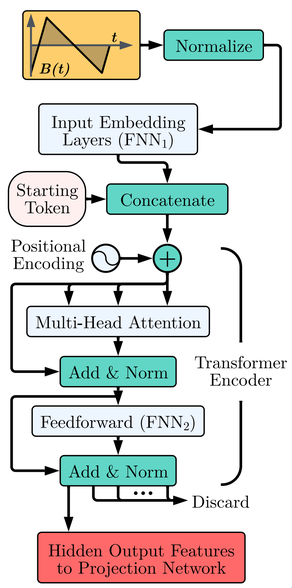
PRINCETON UNIVERSITY

Background

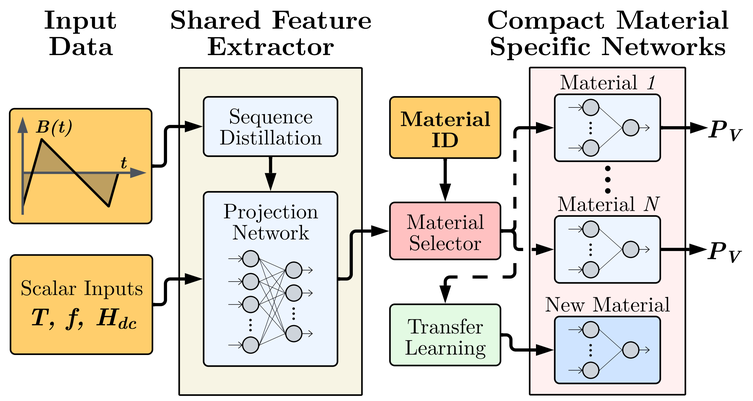
- Magnetic core loss modeling is challenging & impacted by many intertwined operating conditions
  - Temperature, frequency, DC-bias, & waveform shape
- No sufficient physics-based models exist: empirical methods like the Steinmetz Equation $\mathbf{P_V = k \cdot f^{\alpha} \cdot B^{\beta}}$ have limited accuracy and are outdated
- Current machine-learning methods require large network setups to cover all operating conditions, while only supporting a single material
  - Large datasets are required for each unique magnetic material, an unfeasible and hard to scale technique

Approach

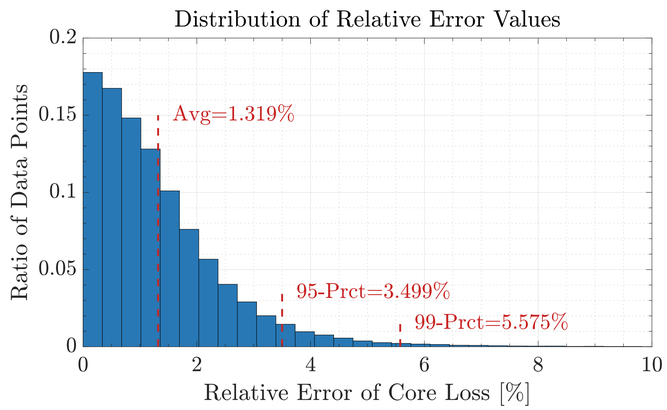
- Generalize much of core loss modeling between materials & create a shared framework
  - Individual materials require 100s of parameters instead of 10,000+ as in past methods
- Implement a transformer network to distill data between all materials (right)
- Expand to new materials using transfer learning to make compact mapping networks
  - Very little data is needed for expansion since the feature extractor remains fixed



Framework Setup

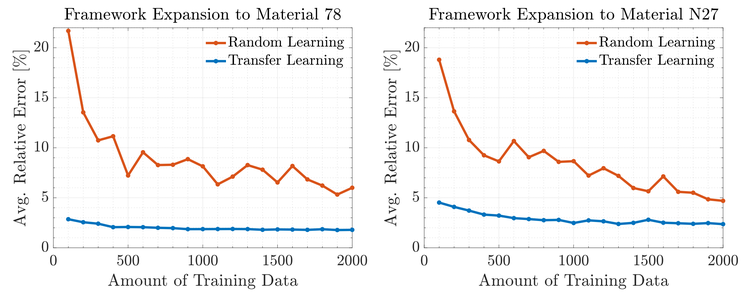


- The framework is trained with a variety of six magnetic materials, simultaneously, using data from the open-source MagNet database
  - Sinusoidal and triangular waveforms are over-sampled to overcome the imbalanced waveform distribution
  - After augmentation, there are 950k data sequences
- All materials impact the training of the shared feature extractor, while each material only impacts training for its own mapping network
- The framework produces highly accurate results on the previously unseen validation dataset (below)



Evaluation

- Consistent performance is achieved across all waveform types and materials from training
- The framework requires just 573 parameters per material, while the shared portion of the framework is 14,864 parameters
- Using the pre-trained feature extractor, the network achieves very low error expanding to new materials
  - Transfer learning provides significant benefits over randomly initializing the mapping networks, only requiring 100s of datapoints for exceptional results



Conclusion

- The proposed framework predicts core loss with extremely high accuracy while being exceedingly compact and easily expandable to materials not seen during training
  - The framework learns to distill flux-density sequences in a manner generalized between all materials, removing material-specific impacts through data normalization
- Expanding the framework requires very little data, saving designers time collecting experimental data