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MagNet Challenge 2023: An Open-Source Collaborative Research Initiative for Data Driven Power Magnetics Modeling

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ABSTRACT
This paper summarized the advancements and results of MagNet Challenge 2023, an open-source collaborative research initiative for data-driven power magnetics material modeling. MagNet Challenge 2023 was jointly hosted by Princeton University and Dartmouth College as the first IEEE Power Electronics Society International Challenge on Design Methods in Power Electronics, and have received industrial support from Google and Enphase Energy. The competition spanned from February 2023 to February 2024 and welcomed participation from 39 undergraduate and graduate student teams worldwide. Participants were tasked with developing software algorithms that can learn from provided training data and subsequently competed on undisclosed testing data. The competition yielded a collection of publicly disclosed software algorithms and tools designed to capture the distinct loss characteristics of power magnetic materials. The MagNet Challenge attempts to bridge power electronics domain knowledge with state-of-the-art advancements in artificial intelligence, machine learning, pattern recognition, and signal processing. Benefited from the transparent and collaborative open-source culture, the MagNet Challenge had greatly improved the accuracy and reduced the size of data-driven power magnetics models. The models and tools created for various materials were meticulously documented and shared within the broader power electronics community.

KEYWORDS
Open-Source, Data-Driven Methods, Machine Learning, Artificial Intelligence, Power Magnetics, Modeling

I. MAGNET CHALLENGE 2023 OVERVIEW

MAGNETIC components account for more than 30 % of both the cost and losses in nearly all power converters [1], [2]. The performance of these magnetic components poses a significant bottleneck in advancing high-performance power electronics. Magnetic components are becoming increasingly sophisticated with different portion of the core excited by different waveforms [3], and dc-bias [4] with geometry [5] and temperature [6] impact. While circuit simulation tools have expedited integrated circuit design, and numerical field simulation tools have deepened our understanding of intricate component geometries, progress in modeling and simulating power magnetic material characteristics has been lagging.

Fundamentally, Maxwell's equations can precisely describe the linear behavior of conductors at high frequencies. Finite element models have the potential to largely capture the geometry and thermal impact. The challenge lies in the highly nonlinear nature of magnetic materials and the considerable variation in magnetic component-level behaviors arising from the material properties and manufacturing processes [7]. Despite advancements in physical theory elucidating core loss phenomena, it falls short in predicting these occurrences with practical accuracy for real-world materials. Existing magnetic material modeling tools either oversimplify and lack accuracy, or rely on experimental measurements in post-design and fabrication.

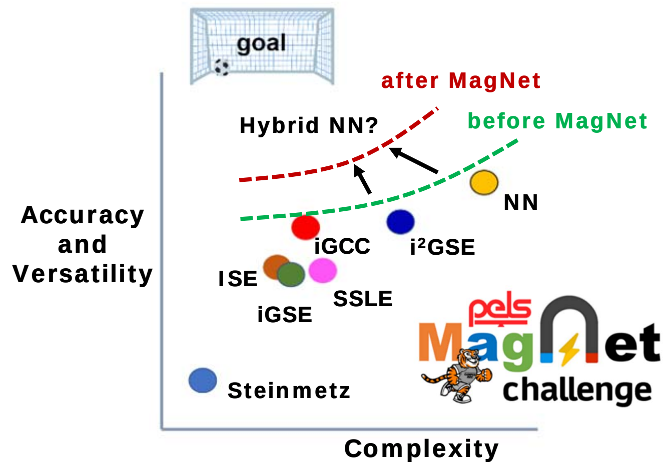

FIGURE 1. The vision and mission of MagNet Challenge 2023. The open-source initiative aims at developing less complex, more versatile, and more accurate data driven power magnetics models.

Designing high-performance magnetic components is difficult. It requires long development cycles and extensive engineering expertise. It may take an experienced engineer a few weeks or more to design one version of a reasonably good magnetic component, and usually, several design iterations are needed. The power electronics community would greatly benefit from a rapid and precise method for modeling the complex behaviors of magnetic materials, especially tools that can be integrated with circuit simulations or finite element analysis.

A majority of commonly used methods of modeling core losses in power magnetics are based on the empirical Steinmetz equation (SE) [8]. Steinmetz parameters may vary dramatically across the magnetics operating range. As power loss increases, the temperature of magnetic materials also increases, which is not well captured in the Steinmetz modeling framework. Despite several modifications and upgrades to the original SE (e.g., MSE [9], NSE [10], ISE [11], SSLE [12], CWH [13], iGCC [14], iGSE [15], i^{2}GSE [16]) – usually by adding new parameters to the SE framework – these curve-fitting methods have limited accuracy and cannot be smoothly expanded to cover more influences. Upgrading the Steinmetz modeling framework is an important start to revolutionizing the design flow for power magnetics.

Another important task for describing power magnetic materials is to model the B–H loops [17]–[20]. As a material signature, the B–H loop can be used to estimate the power loss, and can be used in analytical or numerical tools to analyze the behaviors of magnetic components, such as inductance variation, saturation, and coupling. Existing hysteresis modeling frameworks (e.g., the Preisach model [21] and the Jiles-Atherton model [22]) are generally developed based on empirical equation-based methods. There are opportunities of upgrading the B-H modeling methods with modern neural network methods [23], [24].

As illustrated in Fig. 1, a modeling framework that can better leverage modern data-driven methods to improve the model accuracy, model versatility, and to reduce the model size is the goal of the MagNet Challenge 2023.

A. MagNet Challenge 2023 Motivations

"It's time to upgrade the Steinmetz equation!" – Steinmetz's equation (SE) is an empirical equation used to calculate the power loss (typically referred to as core losses) per unit volume in magnetic materials when subjected to external sinusoidal magnetic flux. The earliest version was proposed by Charles Steinmetz in 1890s. Typically, the SE is written as:

$$P_{\mathrm{v}} = k \times f^a \times B_{\mathrm{ac}}^b, \tag{1}$$

where P_{v} is the time average power loss per unit volume in mW/cm^3, f is the frequency in kHz, and B_{ac} is the peak magnetic flux density in mT; k, a, and b, known as the Steinmetz coefficients or Steinmetz parameters, are generally found empirically from the material's B–H hysteresis curve by curve fitting. In the past decades, the most noticeable upgrade to the Steinmetz equation is the improved generalized Steinmetz equation [25], often referred to as iGSE, which calculates losses with any flux waveform using only the parameters needed for the original equation. The iGSE can be expressed as:

$$P_{\mathrm{v}} = \frac{1}{T}\int_0^T k_i \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^a (\Delta B^{b-a})\mathrm{d}t. \tag{2}$$

Here, ΔB is the peak-to-peak flux density in T, and k_i is defined by $k_i = \frac{k}{(2\pi)^{a-1}\int_0^{2\pi}|\cos\theta|^a 2^{b-a}\mathrm{d}\theta}$ while a, b, and k are the same coefficients used in the original Steinmetz equation. The iGSE is still widely used in academia and industry because most other models require parameters that are not usually given by manufacturers and that engineers are not likely to measure. The i^{2}GSE method [16] further improved the iGSE by adding 5 more parameters to the original 3 Steinmetz parameters to achieve higher accuracy. A key limitation of these models is that they do not capture the impact of flux dc-bias and temperature.

The MagNet Challenge 2023 aims to challenge the existing Steinmetz equation-based core loss modeling framework with the support of a massive amount of measurement data covering different materials across a wide range of frequencies, waveform shapes, and temperatures. We seek novel and elegant equations or data-driven algorithms to develop new tools and advance the entire power electronics society's understanding of magnetic core characteristics, especially core loss. The key questions we tried to answer when designing the challenge rules include:

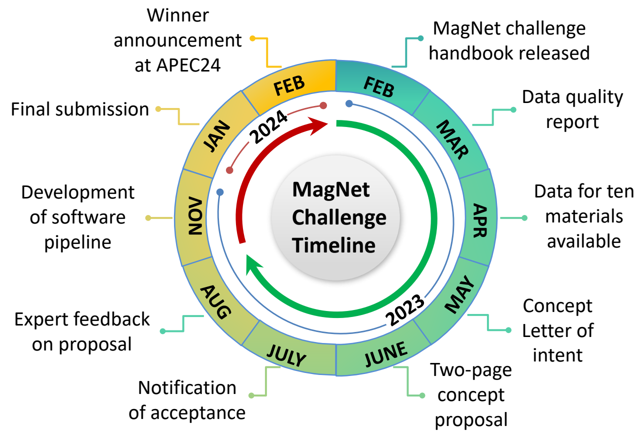

FIGURE 2. The 1-year timeline of the MagNet Challenge 2023 from February 2023 to February 2024.

- Shall we use **one uniform modeling framework (e.g., the SE framework) or explore many different modeling frameworks** for modeling a wide range of materials under different purposes?
- **How accurate is accurate enough** for power magnetics modeling, considering sample-to-sample variation, temperature and geometry dependence, dc-bias, and other operating conditions?
- **What is the minimum number of parameters** one model need to include to describe a particular power magnetics material across a wide operation range?
- **What is the best framework** for modeling power magnetics considering different design goals (e.g., for core loss modeling, B–H loop modeling, hand calculation, SPICE simulation, or finite element analysis)?
- How can we visualize the data and develop explainable data-driven models to **advance the physical understanding** of power magnetics?
- **How much data do we need** to train a good magnetic material model across a wide operation range? How to sample the operation space and reduce the dimension?

These are just example questions one may ask when developing a new data-driven framework for modeling power magnetic material characteristics. Modeling core loss is our focus in MagNet Challenge 2023. B–H loop information was provided as training data, but predicting B–H loops was beyond the scope of this challenge. To answer these questions, we designed the following three competition tracks:

- **Model Performance Track**: Develop a systematic approach to learn from a large-scale amount of existing data for pre-existing materials, and apply this approach to model new materials with new data, and make accurate predictions.
- **Concept Novelty Track**: Develop new concepts for power magnetic core loss and B-H loop modeling, including but not limited to fundamental physics mechanisms and hypothesis, as well as data and signal processing methods, tools and algorithms.

TABLE 1. Sizes of the training and testing datasets for the 10 materials used in competition round #1.

Material	3C90	3C94	3E6	3F4	77
Training	108494	113691	6996	50630	29986
Testing	5000	5000	5000	5000	5000
Material	78	N27	N30	N49	N87
Training	24091	42948	14134	41168	142871
Testing	5000	5000	5000	5000	5000

† Each data point represents the measured B–H loop information at a particular operating point.
‡ Three different types of excitations (sinusoidal, triangle, and trapezoidal) are included for each material in both the training and testing sets.

- **Software Engineering Track**: Develop code and software systems with high readability, reusability, and versatility for open-source development. Enhanced human-computer interface for rapid design iteration.

By participating in the MagNet Challenge 2023, all teams automatically enter the above three tracks and compete on model performance, size and software engineering. Figure 2 shows the timeline of MagNet Challenge 2023. The MagNet Challenge attracted a community of international researchers to explore the important questions together. By submitting the code and the results to MagNet Challenge 2023, the intellectual property is disclosed to the public.

B. MagNet Challenge 2023 Rules and Data Preparation

The goal of MagNet Challenge 2023 is to develop intelligent software tools that can learn and predict core loss information with efficient data usage. For each magnetic material of interest, student teams were asked to develop a MATLAB or Python function that takes the following three floating-point inputs for modeling power magnetic materials in steady state:

- A single-cycle arbitrary flux density waveform in 1024-step: $B(t)$ (unit: T).
- An operation frequency: f (unit: Hz).
- A temperature: T (unit: degree C).

and produce the following output:

- An average volumetric core loss estimation (floating point): P_{v} (unit: W/m^3).

Due to lack of high quality data, dc-bias [4] and geometry impact [5] are not included in MagNet Challenge 2023. Student teams are encouraged to consider dc-bias information which may be included in future competitions.

Figure 3 shows an example data point used in the MagNet Challenge 2023. The training data includes the B-H loop time sequences, frequency f, and temperature T. The final outcome of the model is a callable function:

$$P_{\mathrm{v}} = f(B(t), f, T). \quad (3)$$

TABLE 2. Sizes of the training and testing datasets for the 5 materials used in competition round #2.

Material	3C92	T37	3C95	79	ML95S
Training	2432	7400	5357	580	2013
Testing	7651	3172	5357	7299	3738

† The training and testing datasets were strategically sampled in particular ways to examine the model performance from different angles.

The data used for the MagNet Challenge 2023 comes from the MagNet Project [7], [23], [24]. The challenge included two rounds of competitions: a pre-test round which allows the teams to get familiar with the data and the competition rules, and a final-test round which determines the teams' final ranking. Each training data point is offered as a pair of single-cycle $B(t)$ and $H(t)$ time sequences, with 1024-steps at different frequencies f and temperatures T. The area of the B–H loop determines the volumetric core loss P_{v}. Note different numerical integration algorithms for calculating the B–H loop areas may result in very different core loss estimation results, especially if the B–H curve is non-smooth (e.g., due to non-sinusoidal excitation or nonlinear material behavior). The testing data points include $B(t)$, f, and T, but do not include $H(t)$ or P_{v}. The datasets used for the pre-test phase and the final-test phase are:

- Round #1 Training: A large amount of training data for 10 materials: {**3C90, 3C94, 3E6, 3F4, 77, 78, N27, N30, N49, N87**}.
- Round #1 Testing: Randomly sampled testing data for the same 10 materials: {**3C90, 3C94, 3E6, 3F4, 77, 78, N27, N30, N49, N87**}.
- Round #2 Training: Strategically sampled training data for 5 materials: {**3C92, T37, 3C95, 79, ML95S**}.
- Round #2 Testing: The rest data for the same 5 materials used in Round #2 training: {**3C92, T37, 3C95, 79, ML95S**}.

Table 1 and Table 2 list the size of the dataset made available for each material. As documented in [7], [23], the MagNet dataset covers a frequency range between 50 kHz to 500 kHz, and a flux density range between 10 mT to 300 mT, with sinusoidal, triangular, and trapezoidal waveforms. The maximum measurement error is generally controlled below 20% across the full operation range [7], making it attractive to developing core loss models with an average error below 10 % (i.e., pushing for high model accuracy by increasing the model complexity and the number of model parameters).

The names of the materials used in the round #2 competition were kept confidential from the student teams to ensure competition fairness. The datasets for the 5 materials used in the round #2 competition were strategically sampled to test the model performance from 5 different ways:

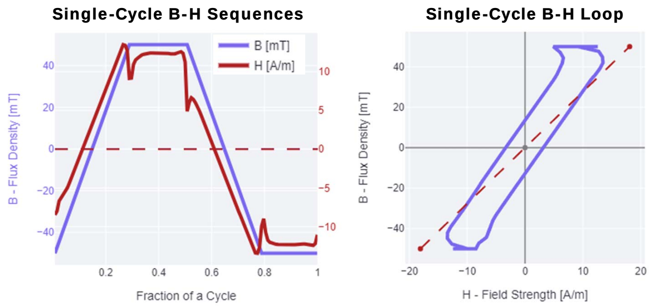

FIGURE 3. An example data point offered in the MagNet Challenge 2023. This data point describes the B–H loop of N87 material operating at 25°C, 200 kHz, and zero dc bias under a trapezoidal excitation. The volumetric core loss is 113.64 kW/m^3. Over 2,000,000 data points like this is available in the MagNet database for 15 different materials.

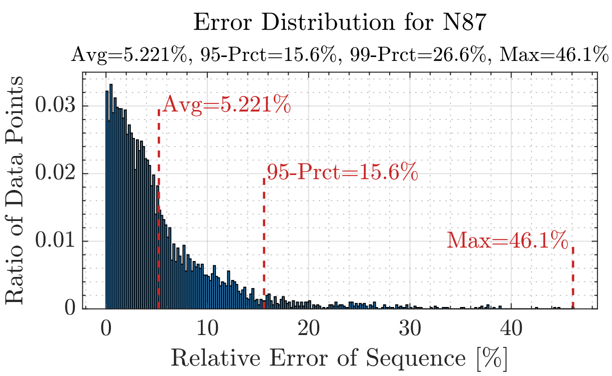

FIGURE 4. The histogram of the prediction error of an example model, together with labeled average, 95$^{\text{th}}$ percentile error, and maximum error.

- **3C92** (Material A) is a material which looks very similar to the 10 materials available in the first round training set. It was used to set up a "tiny data challenge", in which only a small dataset was offered for training, and a large dataset was reserved for testing.
- **T37** (Material B) is a broadband material which looks fairly different from the 10 materials available in the previous training set. It was used to set up a "new material challenge", in which a large dataset was offered for training, and a small dataset was reserved for testing.
- **3C95** (Material C) is a material used for testing temperature dependence. It was used to set up a "temperature challenge", in which the testing dataset includes temperature which were not covered in the training dataset.
- **79** (Material D) is a material used for testing waveform dependence. It was used to set up a "waveform challenge", in which the training set only has very limited data points for trapezoidal waveform excitation, while the testing set has lot of data points for trapezoidal waveform.
- **ML95S** (Material E) is a material used for testing frequency and flux density dependence. It was used to set up a "frequency and flux density challenge", in which the training set only has very limited data points for a few frequency and flux density operating points, while the testing set has lots of data points which were not covered in the training set.

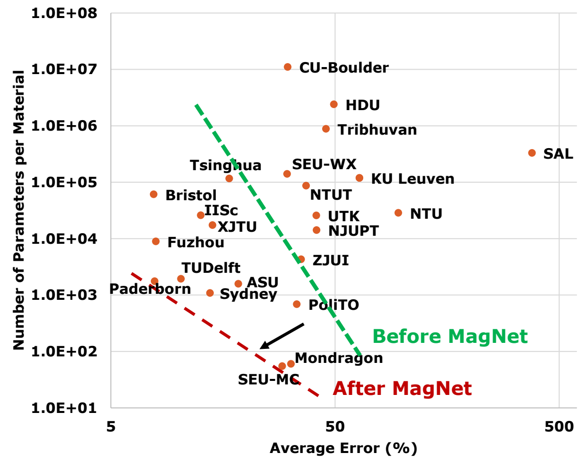

FIGURE 5. Average 95$^{\text{th}}$ percentile error across the 5 materials, and average model number of parameters (size) of the 24 final submissions, together with the state-of-the-art (SOTA) Pareto fronts before and after the MagNet Challenge 2023, estimated using the results reported in [23] as a benchmark. The minimum average 95$^{\text{th}}$ percentile error reaches 7 %, and the smallest model parameter size reaches 60. Both the model sizes and average errors are greatly reduced as a result of the community effort in MagNet Challenge 2023.

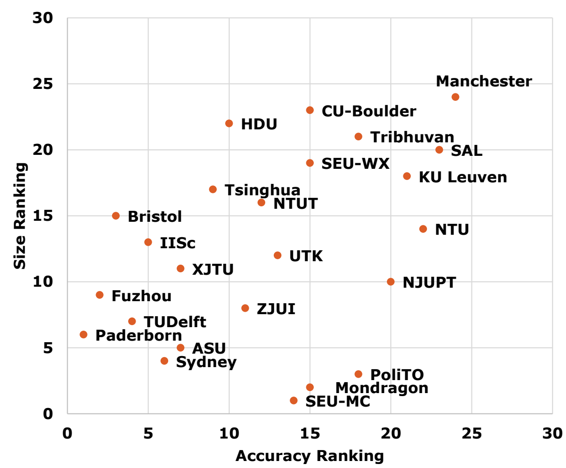

FIGURE 6. Model accuracy and model size ranking of the 24 teams which qualified for the final competition. Note the differences on the model accuracy is usually very small among the winning teams, and the differences on the model size is usually large among the winning teams.

C. MagNet Challenge 2023 Final Results

The MagNet Challenge 2023 focused on core loss prediction. The absolute percentage error ϵ of the core loss prediction is defined as:

$$\epsilon = \frac{|P_{\text{v}}^{\text{measured}} - P_{\text{v}}^{\text{predicted}}|}{P_{\text{v}}^{\text{measured}}} \times 100\%. \tag{4}$$

Here $P_{\text{v}}^{\text{measured}}$ is the measured volumetric core loss, $P_{\text{v}}^{\text{predicted}}$ is the predicted volumetric core loss. The his-

TABLE 3. MagNet Challenge 2023 Methodology Summary.

Team Name	Method	Model Size	Methodology Highlights
ASU	Black-Box Data-Driven	1576	Systematic transfer learning and model optimization
Bristol	Black-Box Data-Driven	90653	Systematic transfer learning and model optimization
Fuzhou	Black-Box Data-Driven	8914	Thorough neural network exploration based on deep physical insights
HDU	Black-Box Data-Driven	2396048	Systematic neural network implementation
KU-Leuven	Black-Box Data-Driven	118785	Generative advisory neural network development
NJUPT	Black-Box Data-Driven	9728	Systematic neural network implementation
NTU	Black-Box Data-Driven	28564	Systematic neural network implementation
NTUT	Black-Box Data-Driven	86728	Systematic neural network implementation
Tribhuvan	Black-Box Data-Driven	1033729	Systematic neural network exploration
Tsinghua	Black-Box Data-Driven	116061	Systematic neural network implementation
TU-Delft	Black-Box Data-Driven	1419	Systematic neural network implementation and multi-objective optimization
UTK	Black-Box Data-Driven	23000	State-of-the-art neural network exploration
XJTU	Black-Box Data-Driven	17342	Systematic neural network implementation
ZJUI	Black-Box Data-Driven	4285	Systematic neural network implementation
CU-Boulder	Grey-Box Hybrid	11012900	Binary-tree neural network and trustworthy-oriented machine learning
IISc	Grey-Box Hybrid	25923	Waveform classification and neural network development
Paderborn	Grey-Box Hybrid	1755	Residual CNN with physics-informed extensions (intermediate B-H reconstruction layer)
PoliTO	Grey-Box Hybrid	610	Hybrid neural network model with equation based methods for trustworthy
SAL	Grey-Box Hybrid	329537	Systematic neural network exploration
SEU-WX	Grey-Box Hybrid	139938	Hybrid neural network model with physical insights
Sydney	Grey-Box Hybrid	1084	Hybrid neural network model with physical insights, excellent software engineering
Manchester	White-Box Equation-Based	N/A	Physics-oriented model exploration
Mondragon	White-Box Equation-Based	60	Fully automated multi-dimensional curve-fitting
SEU-MC	White-Box Equation-Based	81	Multi-dimensional curve-fitting with physical insights

togram of ϵ for each material is then plotted with the average, the 95^{th} and 99^{th} percentile, and the maximum errors labeled as in Fig. 4. The 95 % percentile error was used to rank the accuracy of different models. Based on our evaluation of sample-to-sample variation of power magnetic components [7], we anticipate a 95^{th} percentile error of less than 10 % as competitive for magnetic core loss modeling.[1]

It is important to quantify the model size. We define the model size as the total number of parameters that one model needs to remember to describe the characteristics of each material. The complexity of algorithms, such as model structure, iteration loops, layers of neuron networks, do not count as parameters. MagNet Challenge 2023 was designed to encourage models with more computation and less memory usage.

39 teams from 18 countries registered to the MagNet Challenge 2023. 24 teams stayed until the end and submitted the final results. A complete list of the participating teams in the two rounds of competition are provided in the Appendix.

[1]The normalization in (4) might led towards a data bias overemphasizing samples with very low absolute losses since the estimation error (numerator) typically does not scale linearly with the target value (denominator). While operation points with low losses (i.e., low load) are typically of less interest when design magnetic components for power electronics, alternative performance metrics might be considered in future challenges.

Figure 5 shows the average 95^{th} percentile error and model size of the final submissions. The winning models use about 1,000 parameters to achieve less than 10 % average 95^{th} percentile error. Fig. 6 lists the accuracy ranking and size ranking of the 24 teams. The 7 final winners of the MagNet Challenge 2023 are:

- Model Performance 1^{st} Place: Paderborn University
- Model Performance 2^{nd} Place: Fuzhou University
- Model Performance 3^{rd} Place: University of Bristol
- Excellent Innovation 1^{st} Place: University of Sydney
- Excellent Innovation 2^{nd} Place: TU-Delft
- Excellent Innovation 3^{rd} Place: Mondragon University
- Software Engineering Award: University of Sydney.

The 9 honorable mention teams are:

- Arizona State University
- Indian Institute of Science
- Xi'an Jiaotong University
- Zhejiang University-UIUC
- University of Tennessee
- Politecnico di Torino
- Southeast University SEU-WX
- Southeast University SEU-MC
- Tsinghua University

TABLE 4. MagNet Challenge 2023 final results: 95$^{\rm th}$ percentile error and model size of the 24 teams qualified for the final competition.

Material	3C92		T37		3C95		79		ML95S	
Team Name	**% Error**	**# Size**	**% Error**	**# Size**	**% Error**	**# Size**	**% Error**	**# Size**	**% Error**	**# Size**
ASU	9.6	1576	5.6	1576	8.5	1576	55.3	1576	13.5	1576
Bristol	8.5	90653	2	90653	4.5	90653	15.9	16449	8	16449
Fuzhou	4.9	8914	2.2	8914	2.9	8914	20.7	8914	9	8914
HDU	16	2396048	3.7	2396048	6.8	2396048	201.4	2396048	19.3	2396048
KU-Leuven	72.4	118785	58	118785	66.1	118785	71.3	118785	53.7	118785
NJUPT	45.9	9728	6.9	29600	26.4	21428	59.4	1740	68.4	8052
NTU	99.8	28564	88.7	28564	93.7	28564	99.3	28564	97.8	28564
NTUT	19.9	86728	7.4	86728	7.7	86728	65.9	86728	85.1	86728
Tribhuvan	24.5	1033729	8	1033729	8.9	1033729	67.9	276225	118.7	1033729
Tsinghua	13.1	116061	6.4	116061	9.3	116061	29.9	116061	25.7	116061
TU-Delft	7.2	1419	1.9	2197	3.5	2197	29.6	1419	9.1	2454
UTK	15.6	23000	4.3	23000	9.3	23896	79.2	32546	98	25990
XJTU	12.4	17342	3.8	17342	10.7	17342	30	17342	14.1	17342
ZJUI	15.5	4285	6.1	4285	10.1	4285	67.9	4285	77	4285
CU-Boulder	40.5	11012900	7.8	11012900	25.2	11012900	44.1	11012900	36.3	11012900
IISc	4.6	25923	2.8	25923	6.8	25923	39.5	25923	9.3	25923
Paderborn	4.8	1755	2.2	1755	3.4	1755	22.2	1755	6.6	1755
PoliTO	32.1	610	33.4	760	27.7	748	47.1	700	28.5	610
SAL	351.2	329537	138.7	329537	439.5	329537	810.1	329537	152.8	329537
SEU-WX	26.1	139938	12.9	139938	15.6	139938	79.1	139938	19.1	139938
Sydney	10	1084	3.7	1084	5	1084	30.7	1084	19.9	1084
Manchester	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Mondragon	21.3	60	7.9	60	14.4	60	93.9	60	21.5	60
SEU-MC	38.8	81	6.9	56	21	61	50.5	23	28.2	53

Table 4 listed ther 95$^{\rm th}$ percentile error and size of the models developed by each team for each of the 5 testing materials. The competition handbook, tutorials, supporting documents, training and test datasets, final submitted reports, presentation slides, meeting recordings, and the submitted models can be found at: https://github.com/minjiechen/magnetchallenge. Paderborn University and the University of Sydney are developing tools and systems to further disseminate the outcomes of the MagNet Challenge.

II. MAGNET CHALLENGE 2023 RESEARCH FINDINGS

The MagNet Challenge offered an opportunity for student teams to explore a wide range of data-driven methods for power magnetics modeling, and the outcomes of the challenge quantitatively verified the fundamental tradeoff between model size and model accuracy. Most teams centered their strategy around modern machine learning methods. A few of them are focusing on physics or equation-based methods. Evaluating a wide variety of different methods with a strategically designed database leads to a better understanding on the strengths and weaknesses of different strategies.

Note all the descriptions about these models are developed based on their performance and novelty ranking in MagNet Challenge 2023. Although the rules of the MagNet Challenge were carefully designed to reflect the opportunities and challenges in the real application scenario, a winning model in the MagNet Challenge may or may not necessarily perform well in real-world application scenarios.

A. Grey-Box Hybrid Approach

One widely-adopted data-driven approach in MagNet Challenge 2023 is the grey-box neural network approach, for its excellent capability of balancing model accuracy and model size. The neural network architectures are designed with guidelines from physical understanding and explainable logics. Fig. 7 shows the HARDCORE architecture developed by **Paderborn University** [26]. The architecture starts from feature engineering on the $B(t)$ waveform, followed by a B–H loop estimation block implemented as 1-D convolutional neural network (CNN). The core loss predicted by the B–H loop area calculation is then corrected by a data-driven model which produces the final prediction. This model is highly compact (with 1755 parameters) but also delivers very high prediction accuracy across all five testing materials.

The Magnetization Mechanism-Inspired Neural Networks (MMINN) architecture developed by **University of Sydney** also achieved good balance between model size and

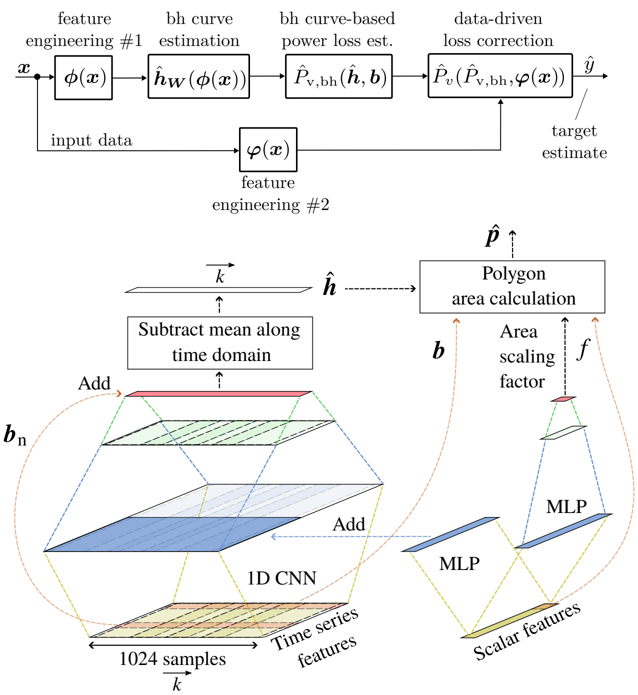

FIGURE 7. Overview of the HARDCORE architecture developed by Paderborn University, which leads to excellent model accuracy and compact model size.

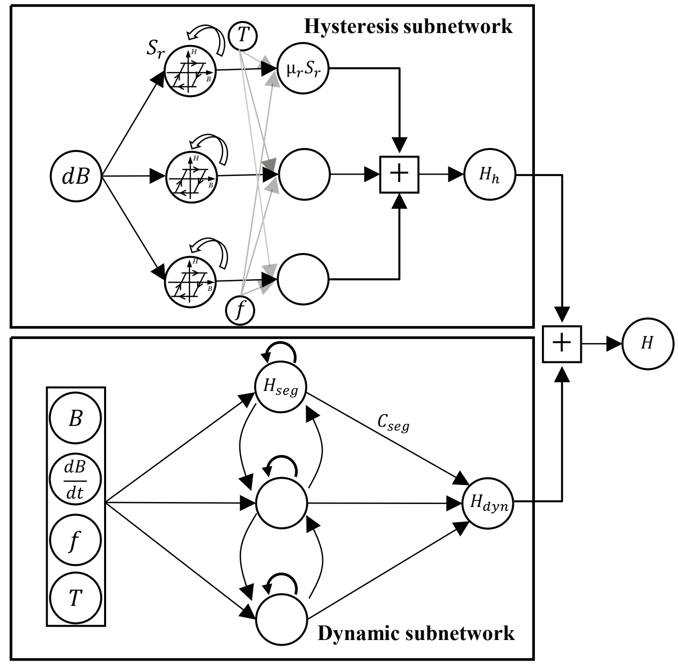

FIGURE 8. The MMINN architecture developed by University of Sydney.

model accuracy. MMINN is designed to capture the fundamental magnetization process of magnetic materials at the microscopic-level. As illustrated in Fig. 8, MMINN comprises two subnetworks for capturing hysteresis (i.e., the magnetization of magnetic domains) and dynamic (i.e., the eddy current of the core material owing to the electromagnetic induction) behaviors, and has the potential to be extended to capturing more complex dynamic core loss profiles when more data is available. The compact MMINN model only needs 1000 parameters and performed well on the accuracy test.

The model proposed by the team from **Politecnico di Torino** tried to apply different modeling methods to different excitation waveforms to minimize the model size. SVM regression were used to model sinusoidal excitations and neural networks were used to model triangle excitations. Composite waveform hypothesis was then used to convert the results predicted by the neural network trained with triangle data for trapezoidal excitations.

The model presented by the team from **Indian Institute of Science** followed a similar strategy. Three different neural networks are trained for three different waveform excitations. The model achieved very high accuracy on four materials (except for **79**) with a relatively large number of parameters.

The team from **University of Colorado Boulder** selected random forest algorithms as the core of their strategy. Random forest algorithms prioritize rapid computation over parameter size as compared to other previously mentioned neural network methods.

The **Southeast University SEU-WX** team presented an interesting Physics-Inspired Multimodal Feature Fusion Cascaded Network (PI-MFF-CN), which was developed based on micromagnetism and the associated Landau-Lifshitz-Gilbert (LLG) equation, and is trained by embedding physical mechanisms in the gradient learning process of the network. As shown in Fig. 9, a multimodal feature fusion method then combines the advantages CNN and fully connected neural network (FCNN) to learn mixed sequence scale data. Although not ranking high in the competition, this method represents a deep exploration of hybrid data-driven and physics-based models.

The teams from **Nanjing University of Posts and Telecom.**, **University of Manchester**, and **Tribhuvan University** also explored equation based methods with novel insights and promising outcomes.

B. Black-Box Data Driven Approach

The model developed by **Fuzhou University** fully exploited the potential of encoder-projector-decoder based architecture, together with deep understanding about the data and the principles of core loss modeling. The sequence-to-scalar transformer model offers smaller size compared to sequence-to-sequence models. The pretraining and fine-tuning strategy further improves the accuracy of the model when facing cases with limited data.

The **University of Bristol** team adopted a long-short-term-memory (LSTM) architecture to process the time sequences, followed by a Feedforward Neural Network (FNN) for merging frequency and temperature information. The outstanding model performance comes from the deep understanding and engineering practice on transfer learning. As illustrated in

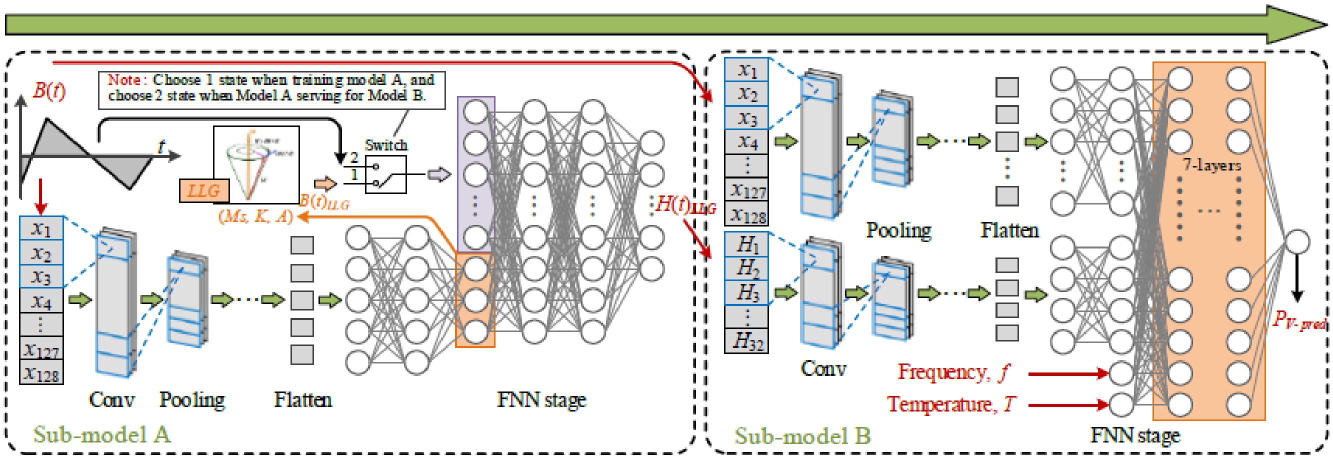

FIGURE 9. The two-stage PI-MFF-CN architecture developed by Southeast University SEU-WX.

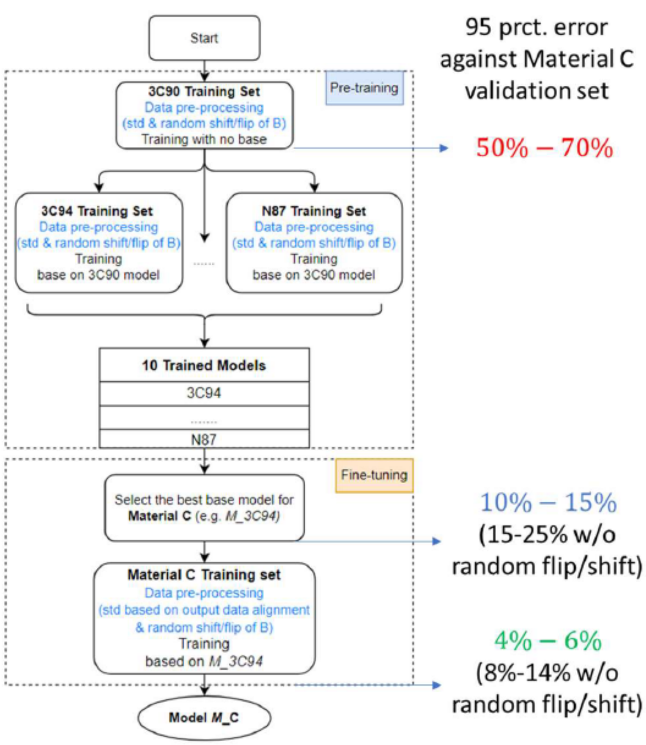

FIGURE 10. Transfer learning strategy from University of Bristol.

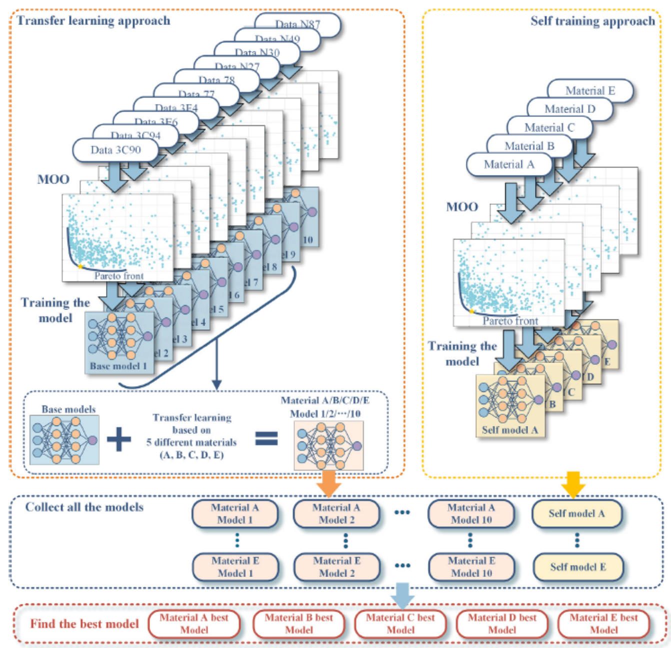

FIGURE 11. The multi-material transfer learning and multi-objective optimization method proposed by TU Delft.

Fig. 10, the transfer learning process enables the model to achieve high performance even with very limited available data for a new power magnetic material. This model needed a lot of parameters, but achieved high performance across all five materials.

The **Delft University of Technologies** team proposed an excellent strategy for multi-material transfer learning and model multi-objective optimization (MOO). As illustrated in Fig. 11, the MOO approach allows the model to precisely select the right parameter size to balance model size and accuracy. The optimization shows that a total number of 1,000 parameters is a good balancing point between model size and accuracy, which was validated when comparing all winning models in the MagNet Challenge 2023.

The **University of Tennessee Knoxville** team introduces the state-of-the-art machine learning concepts – Attention-based U-Net architecture, to the MagNet Challenge 2023. U-Net is a neural network architecture widely used for image segmentation. The team specifically designed a U-Net architecture to adapt to the intricate and varying nature of magnetic materials and operational environments. The large U-Net model excelled for **3C92**, **T37**, and **3C95**, but didn't perform well for **79** and **ML95S**.

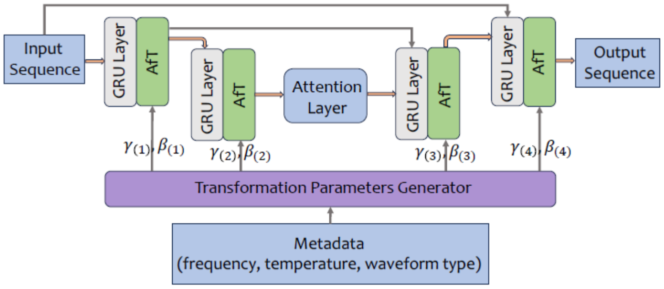

FIGURE 12. **The U-Net architecture developed by University of Tennessee Knoxville, representing an out-of-the-box attempt by using state-of-the-art neural network architecture.**

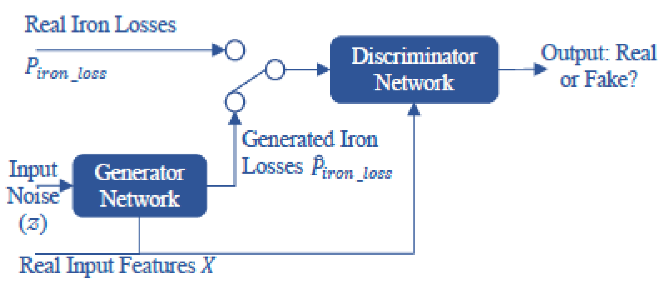

FIGURE 13. **The cGANET architecture developed by KU Leuven.**

The teams from **Arizona State University**, **Xi'an Jiaotong University**, **Tsinghua University**, **National Taipei University of Technology**, **Nanyang Technological University**, **Hangzhou Dianzi University**, and **Silicon Austria Labs** also presented a variety of neural network architectures (combinations of ViT, CNN, FCNN, LSTM, and Transformer) together with systematic training and fine-tuning strategies for cross-modeling of many materials. Some of these models' performance are very good and the model sizes are small.

The **KU-Leuven** team introduced a novel Conditional Generative Adversarial Network (cGANET) model which explores the possibility of training an adversarial neural network to improve the trustworthyness of a traditional neural network approach. It has the potential to ensure bounded safety for data-driven methods to predict trustworthy results.

C. White-Box Equation-based Approach

The most successful equation-based attempt in the MagNet Challenge 2023 is the ci2GSE method developed by the team from **Mondragon University**. The method is a combination of the original true Steinmetz Equation (tSE), the improved Generalized Steinmetz Equation (iGSE), the composite waveform hypothesis (CWH), and the improved improved Generalized Steinmetz Equation (i2GSE). For each temperature point, the ci2GSE uses 9 parameters to describe the core loss a three step trapezoidal excitation as:

$$P_\mathrm{v} = D \times \left(e^{k'_1 + a_1 \ln\left|\frac{\mathrm{d}B}{\mathrm{d}t}\right| + b_1 \ln \Delta B} + e^{k'_2 + a_2 \ln\left|\frac{\mathrm{d}B}{\mathrm{d}t}\right| + b_2 \ln \Delta B}\right) + f \times e^{k'_\mathrm{rel} + a_\mathrm{rel} \ln|t_\mathrm{rel}| + b_\mathrm{rel} \ln \Delta B} \quad (5)$$

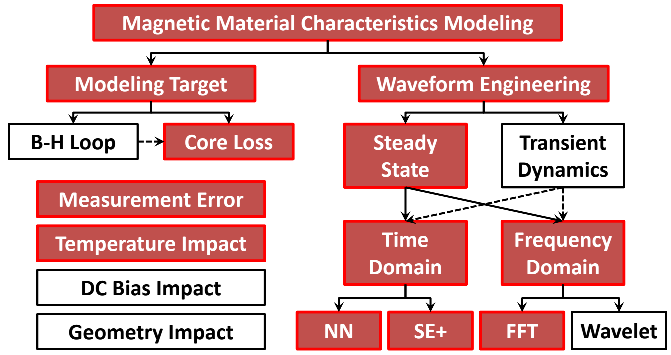

FIGURE 14. **Roadmap of the MagNet challenge with addressed topics marked in red boxes, and future topics marked in white boxes.**

where k'_1, k'_2, k'_rel, a_1, a_2, a_rel, and b_1, b_2, b_rel are the Steinmetz parameters used to describe the core losses in the three sub-sections of the piece-wise linear waveforms (e.g., triangle and trapezoidal excitations). The core losses during the relaxation time are captured. In addition, six additional parameters p_{00}, p_{10}, p_{01}, p_{20}, p_{11} and p_{02}, are used to fit the sinusoidal core loss data into the three dimension f, ΔB, and P_v plane. The curve-fitting was performed for each temperature. The total number of parameters needed to describe the material characteristics at four temperature points are $(9+6)\times 4 = 60$. The curve-fitting algorithm was implemented in Excel and was fully automated. The average 95^{th} percentile error of this method is about 15 %, which is impressive for only 60 parameters.

Another impressive equation-based approach was developed by the **Southeast University SEU-MC** team employing the vector magnetic circuit theory to predict core loss. The theory is developed based on lumped circuit analysis and is very similar to the Laithwaite magnetic equivalent circuit model. The model on average used 60 parameters to describe each material, and reach a similar accuracy as that of the Mondragon model. However, the model tuning process is not fully automated.

III. MAGNET CHALLENGE ROADMAP

The ultimate goal of the Magnet Challenge is to explore and compare a wide range of modeling strategies for power magnetic components, and to optimize and automate power magnetic design. To this end, we believe that the future Magnet model should be:

- **Accuracy:** to reach a high level of model accuracy (as accurate as the data accuracy and sample-to-sample variation) and repeatability for magnetics modeling in the design, development, and manufacturing process, and to precisely reflect the multi-scale and multi-physics nature of power magnetics modeling.
- **Compactness:** to achieve efficient model training, rapid simulation, and effective optimization. This is particularly important given the lack of sufficient high-quality publicly available training data and the potentially

huge design space (materials, geometries) and model operating space (excitation waveforms, temperatures, frequencies, peak flux densities, etc.) of magnetic components. A simpler model generally means a smaller number of model parameters and a more efficient usage of measurement data.

- **Generality, consistency, and versatility**: a good power magnetic component model should be applicable to a wide range of application scenarios with minimum limitations, and be consistent with other existing component models (e.g., semiconductor models and capacitor models) for high fidelity design and simulation, and be versatile so that it can be adjusted for different design purposes (e.g., trading model simplicity for accuracy).

Fig. 14 shows the strategic roadmap of the MagNet Challenge in the near future, including the topics that MagNet Challenge 2023 has covered, and the topics MagNet Challenge 2024 intents to cover. This roadmap is in line with the above-mentioned characteristics of the future Magnet model, with a particular focus on the generality of the model. For example, MagNet Challenge 2023 prioritizes model accuracy and simplicity for periodic steady state, major-loop, and zero dc-bias type of excitation waveforms. The excitation frequency is limited in the tens to hundreds kilo-Herz range at sparse temperature points (four points only). In the future, more complicated excitation profiles (e.g., transient excitations with minor-loop and non-zero dc bias), wider operation range (e.g., frequency range up to a few Megahertz), transient operation (e.g., magnetic components in switched-mode ac-dc converters) and geometry impacts will need to be explored.

The winning models in the MagNet Challenge 2023 only perform well under the designated training and testing scenario, and are not necessarily the most appealing modeling strategies. Better models and better interpretations are still to be found. The potential technologies that will be explored in future Magnet Challenges may include:

- **Data Engineering:** In MagNet Challenge 2023, the data acquisition is performed by the Challenge organizer and manage and distributed in a centralized way. Data acquisition should be standardized and be rigorously cross-validated and certified across institutions. For data-driven methods, the quality of a model is fundamentally limited by the quality of data. In future challenges, an open-source, transparent, community-driven data management strategy may ensure the sustainable development of the community.
- **Model Framework:** The MagNet Challenge 2023 explored Black-Box Data Driven methods, White-Box Equation-based methods, and Grey-Box Hybrid methods were explored. A majority of student teams performed time domain analysis. Frequency domain methods are under explored. The machine learning frameworks are rapidly evolving and it is still early to identify the best strategy for modeling power magnetics. Modeling frameworks that can be naturally expanded and updated to cover many different materials under a unified framework worth exploration. Modeling frameworks that can naturally interface with large-language models also deserve their roles.
- **Data Visualization:** Power magnetics modeling is naturally complex and has high dimension. Systematically compressing, filtering, and visualizing the high-dimension data for human interpretation is critical for advancing the human-data interface and enabling new data-driven applications.
- **Physical Insights and Better Materials**: Although the MagNet Challenge 2023 didn't intent to close the loop for advancing physical understanding of power magnetics, many teams attempted (e.g., UTK, Manchester, SEU-MC). With larger data size, better data quality, more powerful data-driven models, and better human-data interface, we hope the MagNet Challenge can ultimately lead to enhanced physical understanding of power magnetics, and better magnetic material and component design.

IV. CONCLUSION

This paper summarizes the key progress and major outcomes of the MagNet Challenge 2023, an International Challenge on Design Methods in Power Electronics supported by IEEE Power Electronics Society, Google, and Enphase Energy. The critical outcomes and performance ranking of the challenges are streamlined and highlighted.

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APPENDIX: MagNet Challenge 2023 Participating Teams

The 39 undergraduate and graduate teams that registered for the MagNet Challenge 2023 include:

1) Aalborg University, Denmark
2) Arizona State University, USA
3) Cornell University Team 1, USA
4) Cornell University Team 2, USA
5) Federal University of Santa Catarina, Brazil

6) Fuzhou University, China
7) Hangzhou Dianzi University, China
8) Indian Institute of Science, India
9) Jinan University, China
10) Katholieke Universiteit Leuven, Belgium
11) Mondragon University, Spain
12) Nanjing University of Posts and Telecom., China
13) Nanyang Technological University, Singapore
14) Nation Taipei University of Technology, Taiwan
15) Northeastern University, USA
16) Paderborn University, Germany
17) Politecnico di Torino, Italy
18) Purdue University, USA
19) Seoul National University, Korea
20) Silicon Austria Labs, Austria
21) Southeast University SEU-WX, China
22) Southeast University SEU-MC, China
23) Tribhuvan University, Nepal
24) Tsinghua University, China
25) Delft University of Technology, Netherland
26) University of Bristol, UK
27) University of Colorado Boulder, USA
28) University of Kassel, Germany
29) University of Manchester, UK
30) University of Nottingham, UK
31) University of Sydney, Australia
32) University of Tennessee, USA
33) University of Twente Team 1, Netherland
34) University of Twente Team 2, Netherland
35) University of Wisconsin-Madison, USA
36) Universidad Politécnica de Madrid, Spain
37) Xi'an Jiaotong University, China
38) Zhejiang University, China
39) Zhejiang University-UIUC, China

The 24 teams that qualified for the round #2 competition and submitted the final results are:

1) Arizona State University (**ASU**), USA
2) Fuzhou University (**Fuzhou**), China
3) Hangzhou Dianzi University (**HDU**), China
4) Indian Institute of Science (**IISc**), India
5) Katholieke Univ. Leuven (**KU Leuven**), Belgium
6) Mondragon University (**Mondragon**), Spain
7) Nanjing Univ. of Posts and Telecom. (**NJUPT**), China
8) Nanyang Technological University (**NTU**), Singapore
9) National Taipei Univ. of Technology (**NTUT**), Taiwan
10) Paderborn University (**Paderborn**), Germany
11) Politecnico di Torino (**PoliTO**), Italy
12) Silicon Austria Labs (**SAL**), Austria
13) Southeast University (**SEU-WX**), China
14) Southeast University (**SEU-MC**), China
15) Tribhuvan University (**Tribhuvan**), Nepal
16) Tsinghua University (**Tsinghua**), China
17) Delft Univ. of Technology (**TU-Delft**), Netherland
18) University of Bristol (**Bristol**), UK
19) University of Colorado Boulder (**CU-Boulder**), USA
20) University of Manchester (**Manchester**), UK
21) University of Sydney (**Sydney**), Australia
22) University of Tennessee Knoxville (**UTK**), USA
23) Xi'an Jiaotong University (**XJTU**), China
24) Zhejiang University-UIUC (**ZJUI**), China

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