1st IEEE International Challenge in Design Methods for Power Electronics

2023 PELS-Google-Enphase-Princeton MagNet Challenge

MagNet 2023

Executive Summary, January 26, 2024

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"It's time to upgrade the Steinmetz Equation"
– in 100-year honor of Prof. Charles P. Steinmetz (1865-1923)

- Do you like Steinmetz Equation?

$$P_v = k \times f^a \times B^b$$

  - Yes, but can be better!
  - Perhaps the **weakest** link in power electronics.
  - Not much physics, not accurate.
  - No waveform, temperature, dc-bias, etc.
  - Better first-principle physical models?
  - More accurate & capable data-driven models?

Charles Steinmetz
(1865-1923)

- If not, how can we improve/upgrade it?
  - **Improve - Stay within the Steinmetz framework?**
    - ✓ Leverage all the existing explanation and carry the historical understanding / data / knowledge about core loss.
  - **Upgrade - Jump outside of the Steinmetz framework?**
    - ✓ Try machine learning or other more advanced signal processing methods for modeling magnetics.
  - **Data is ready / tools are ready / need a community**

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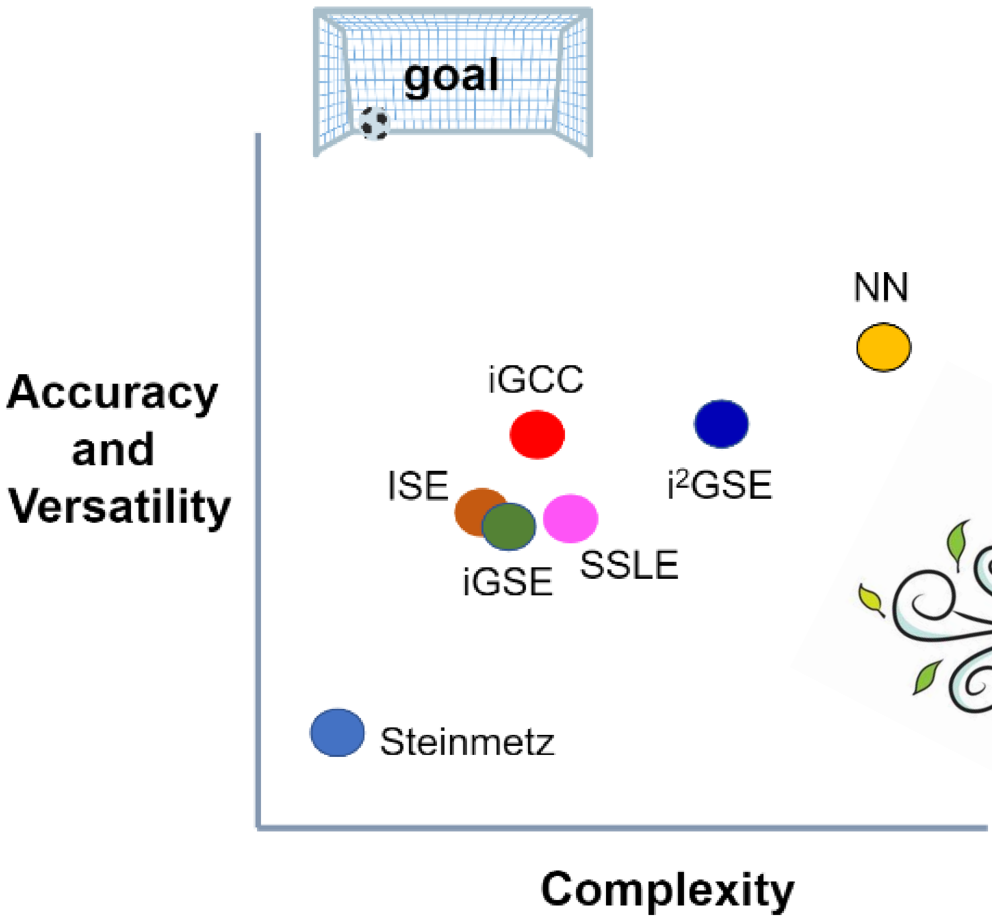
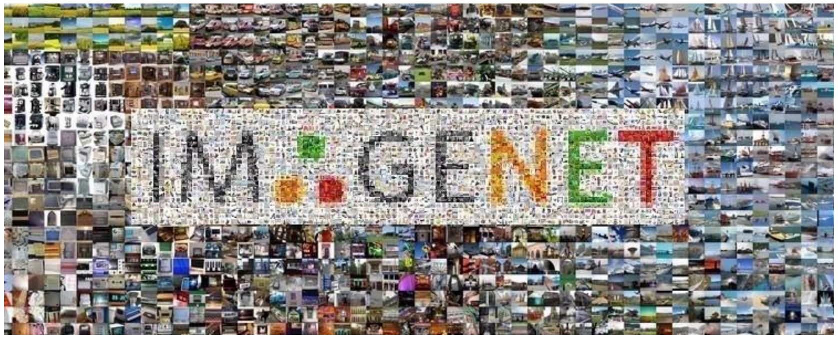
Equation-based Methods vs. Data Driven Methods



Leverage advanced computing/ML

ImageNet Challenge → MagNet Challenge



High Quality Open-Source Image Data (>14M images in 20k categories)

https://www.image-net.org/challenges/LSVRC/

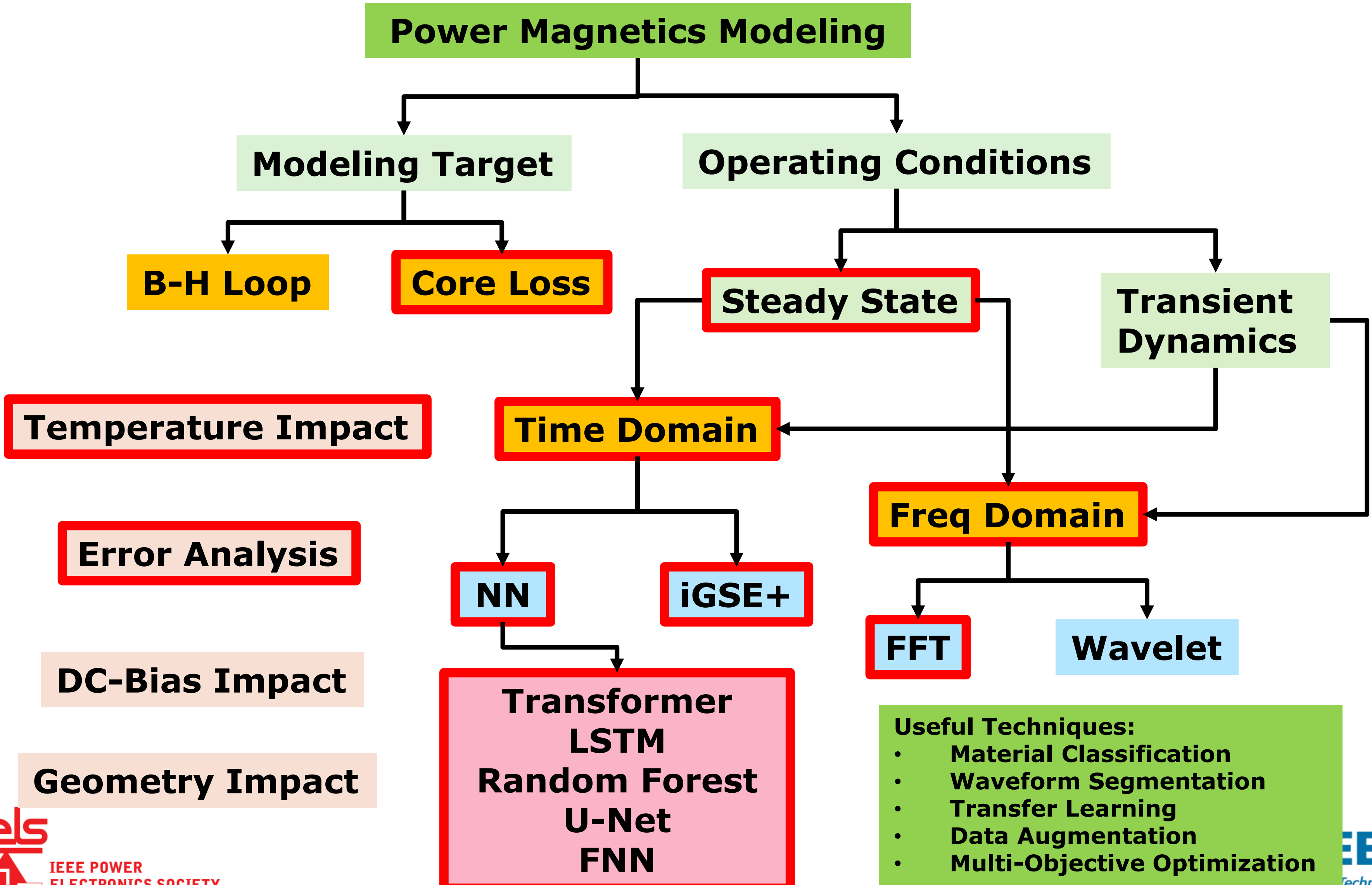
High Quality Open-Source Magnetics Data (>2M B-H loops for 15 materials)

https://mag-net.princeton.edu

- **An opportunity to promote open-source culture in power electronics.**
- **Unify next generation power electronics engineers who can USE advanced machine learning / software tools as a community**

- Open
- Transparent
- Inclusive
- Education
- Research
- Standard

Methodology Summary



Useful Techniques:
- Material Classification
- Waveform Segmentation
- Transfer Learning
- Data Augmentation
- Multi-Objective Optimization

Competition Rules of MagNet Challenge

- MagNet 2023 rule: understand the core loss dependency on waveform, temperature and frequency, and ***systematically*** develop a Python/MATLAB function for each material as the an "interactive" datasheet (like SPICE model for MOSFETs).

$$\boxed{P_v = function\,\{B(t), frequency, temperature\}}$$

Input Information

$B(t)$: *Single-cycle 1024-step waveform*	*in mT*
f: *Excitation frequency*	*in kHz*
T: *Operating temperature*	*in °C*

Output Information

P_v: *Volumetric Core Loss*

Winning Criteria:

- Model Accuracy (% error)
- Model Size (# of parameters)
- Novelty (concept / strategy)
- Software Engineering
- Potential to become a standard method???

MagNet Challenge Timeline

March 2023: Launched MagNet Challenge

- **Advance** data driven methods for modeling power magnetics
- **Bridge** power electronics and machine learning
- **Promote** open-source culture in power electronics

July 2023: Registration (40 teams from 17 countries)

- Denmark, USA, Brazil, China, India, Belgium, Spain, Singapore, Taiwan
- Germany, Italy, South Korea, Austria, Nepal, Netherland, UK, Australia

August 2023: Tutorials (#1 to #4, hundreds of participants)

November 2023: Qualification (25 teams from 14 countries)

- USA, China, India, Belgium, Spain, Singapore, Taiwan
- Germany, Italy, Austria, Nepal, Netherland, UK, Australia

December 2023: Final Submission (24 teams from 14 countries)

- USA, China, India, Belgium, Spain, Singapore, Taiwan
- Germany, Italy, Austria, Nepal, Netherland, UK, Australia

January 2024: Review and Code Evaluation

February 2024: Final Winner Announcement

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MagNet Challenge Registrations

- 40 Universities from 18 Countries
- Denmark, USA, Brazil, China, India, Belgium, Spain, Singapore, Taiwan, Germany, Italy, South Korea, Austria, Nepal, Netherland, UK, Australia

- Aalborg University, Aalborg, Denmark
- Arizona State University, Tempe AZ, USA
- Cornell University Team 1, Ithaca, USA
- Cornell University Team 2, Ithaca, USA
- Federal University of Santa Catarina, Brazil
- Fuzhou University, Fuzhou, China
- Hangzhou Dianzi University, Hangzhou, China
- Indian Institute of Science, Bangalore, India
- Jinan University, Guangzhou, China
- KU Leuven, Leuven, Belgium
- Mondragon University, Hernani, Spain
- Nanjing University of Posts and Telecom., China
- Nanyang Technological University, Singapore
- Nation Taipei University of Technology, Taiwan
- Northeastern University, Boston MA, USA
- Paderborn University, Paderborn, Germany
- Politecnico di Torino, Torino, Italy
- Princeton University, Princeton NJ, USA (host)
- Purdue University, West Lafayette IN, USA
- Seoul National University, Seoul, Korea
- Silicon Austria Labs, Graz, Austria
- Southeast University Team 1, Nanjing, China
- Southeast University Team 2, Nanjing, China
- Tribhuvan University, Latipur, Nepal
- Tsinghua University, Beijing, China
- TU Delft, Delft, Netherland
- University of Bristol, Bristol, UK
- University of Colorado Boulder, Boulder CO, USA
- University of Kassel, Kassel, Germany
- University of Manchester, Manchester, UK
- University of Nottingham, Nottingham, UK
- University of Sydney, Sydney, Australia
- University of Tennessee, Knoxville, USA
- University of Twente Team 1, Enschede, Netherland
- University of Twente Team 2, Enschede, Netherland
- University of Wisconsin-Madison, Madison WI, USA
- Universidad Politécnica de Madrid, Madrid, Spain
- Xi'an Jiaotong University, Xi'an, China
- Zhejiang University, Hangzhou, China
- Zhejiang University-UIUC, Hangzhou, China

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MagNet Challenge Final Submissions

- Arizona State University, Tempe AZ, USA US
- Fuzhou University, Fuzhou, China CN
- Hangzhou Dianzi University, Hangzhou, China CN
- Indian Institute of Science, Bangalore, India IN
- KU Leuven, Leuven, Belgium BE
- Mondragon University, Hernani, Spain ES
- Nanjing University of Posts and Telecom., Nanjing, China CN
- Nanyang Technological University, Singapore SG
- National Taipei University of Technology, Taipei, Taiwan TW
- Paderborn University, Paderborn, Germany DE
- Politecnico di Torino, Torino, Italy IT
- Silicon Austria Labs, Graz, Austria AT
- Southeast University Team 1, Nanjing, China CN
- Southeast University Team 2, Nanjing, China CN
- Tribhuvan University, Lalitpur, Nepal NP
- Tsinghua University, Beijing, China CN
- TU Delft, Delft, Netherland NL
- University of Bristol, Bristol, UK GB
- University of Colorado Boulder, Boulder CO, USA US
- University of Manchester, Manchester, UK GB
- University of Sydney, Sydney, Australia AU
- University of Tennessee, Knoxville, USA US
- Xi'an Jiaotong University, Xi'an, China CN
- Zhejiang University-UIUC, Hangzhou, China CN

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MagNet 2023 Organizing Team

MagNet 2023 co-Chairs:

- Minjie Chen, Princeton, USA
- Charles Sullivan, Dartmouth, USA

Executive Committee:

- Haoran Li, Princeton, USA
- Thomas Guillod, Dartmouth, USA
- Shukai Wang, Princeton, USA
- Diego Serrano, Princeton, USA

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- Johann Kolar, ETH Zurich, Switzerland
- Dragan Maksimovic, CU Boulder, USA
- SY Ron Hui, NTU, Singapore

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- David Schumacher, Enphase, USA

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- Matt Wilkowski, EnaChip, USA
- George Slama, Wurth Elektronik, USA
- Edward Herbert, PSMA, USA
- Jens Schweickhardt, Germany
- Ziwei Ouyang, DTU, Denmark
- Alex Hanson, UT Austin, USA

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- Shirley Pei, University of Bath, UK
- Subham Sahoo, Aalborg, Denmark
- Miroslav Vasic, UPM, Spain

PELS Signee:

- Pat Wheeler – PELS VP
- Mario Pacas – PELS VP
- Dehong Xu – PELS VP
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- Liucheng Chang - President

PRINCETON UNIVERSITY

ENPHASE.

Google

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MagNet Challenge $50,000 Budget

Model Performance 1st Place $10,000	**Model Novelty** 1st Place $10,000	**Outstanding Software Engineering** $5,000
Model Performance 2nd Place $5,000	**Model Novelty** 2nd Place $5,000	**Honorable Mention** $1,000 x 9
Model Performance 3rd Place $3,000	**Model Novelty** 3rd Place $3,000	

Open-Source Matlab/Python Package

- Award winning teams are invited to join an open-source community effort to develop a standard MagNet Matlab/Python software package for modeling the 15 materials and extend it beyond.

Intellectual Property

- MagNet Challenge has no restrictions on intellectual property.
- We encourage open-source culture and open-source licenses.
- Presenting the models to MagNet team is considered as public disclosure.
- Student teams should take actions before disclosure if IP protection is needed.

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Competition Rules

Goal: A systematic method to develop an accurate and compact model for a new power magnetics material.

Step 1: Method Development

- Practice Dataset: Massive Data for 10 Old Materials

  3C90 / 3C94 / 3E6 / 3F4 / 77 / 78 / N27 / N30 / N49 / N87

Step 2: Method Verification

- Training Dataset: Limited Data for 5 New Materials
- Testing Dataset: Massive Data for 5 New Materials
- Sampled in particular ways to test models from different angles

	"tiny data challenge"	"special material challenge"	"temperature challenge"	"waveform challenge"	"f and B challenge"
# Data Points	**Material A (3C92)**	**Material B (T37)**	**Material C (3C95)**	**Material D (79)**	**Material E (ML95S)**
Training Data	2432 (101/694/1637)	7400 (364/2253/4783)	5357 (215/1679/3463)	580 (145/400/35)	2013 (57/667/1289)
Testing Data	7651 (334/2174/5143)	3172 (147/980/2045)	5357 (212/1751/3394)	7299 (61/2247/4991)	3738 (107/1205/2426)

***Total # (sine / triangle / trapezoidal)**

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Performance Overview

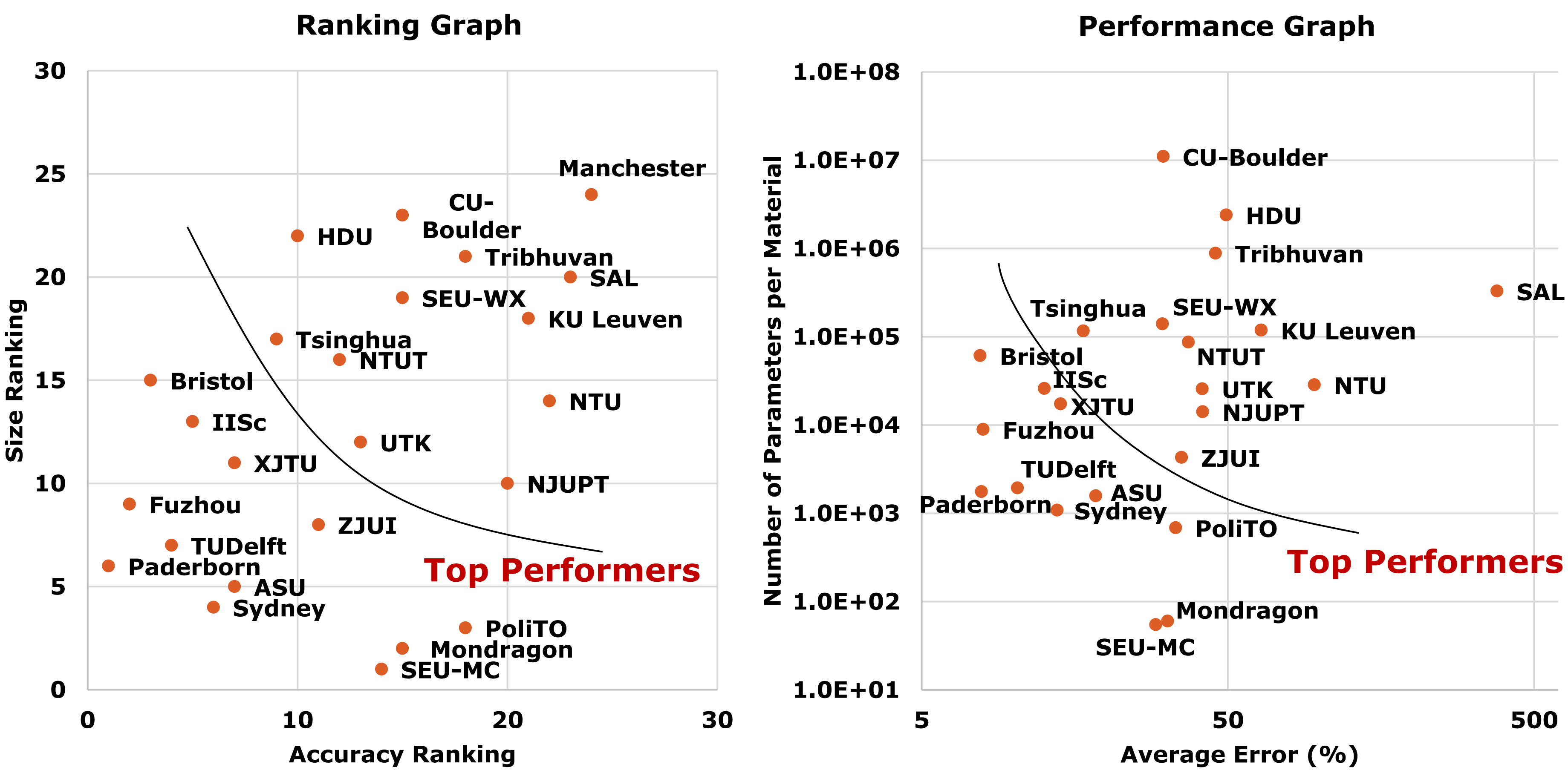
		"tiny data challenge"		"special material challenge"		"temperature challenge"		"waveform challenge"		"f and B challenge"	
		Material A	Material A	Material B	Material B	Material C	Material C	Material D	Material D	Material E	Material E
Team Name	Team #	% Error	# Size	% Error	# Size	% Error	# Size	% Error	# Size	% Error	# Size
ASU	#1	9.6	1576	5.6	1576	8.5	1576	55.3	1576	13.5	1576
Bristol	#2	8.5	90653	2.0	90653	4.5	90653	15.9	16449	8.0	16449
CU-Boulder	#3	40.5	11012900	7.8	11012900	25.2	11012900	44.1	11012900	36.3	11012900
Fuzhou	#4	4.9	8914	2.2	8914	2.9	8914	20.7	8914	9.0	8914
HDU	#5	16.0	2396048	3.7	2396048	6.8	2396048	201.4	2396048	19.3	2396048
IISc	#6	4.6	25923	2.8	25923	6.8	25923	39.5	25923	9.3	25923
KU Leuven	#7	72.4	118785	58.0	118785	66.1	118785	71.3	118785	53.7	118785
Manchester	#8	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Mondragon	#9	21.3	60	7.9	60	14.4	60	93.9	60	21.5	60
NJUPT	#10	45.9	9728	6.9	29600	26.4	21428	59.4	1740	68.4	8052
NTU	#11	99.8	28564	88.7	28564	93.7	28564	99.3	28564	97.8	28564
NTUT	#12	19.9	86728	7.4	86728	7.7	86728	65.9	86728	85.1	86728
Paderborn	#13	4.8	1755	2.2	1755	3.4	1755	22.2	1755	6.6	1755
PoliTO	#14	32.1	610	33.4	760	27.7	748	47.1	700	28.5	610
SAL	#15	351.2	329537	138.7	329537	439.5	329537	810.1	329537	152.8	329537
SEU-MC	#16	38.8	81	6.9	56	21.0	61	50.5	23	28.2	53
SEU-WX	#17	26.1	139938	12.9	139938	15.6	139938	79.1	139938	19.1	139938
Sydney	#18	10.0	1084	3.7	1084	5.0	1084	30.7	1084	19.9	1084
Tribhuvan	#19	24.5	1033729	8.0	1033729	8.9	1033729	67.9	276225	118.7	1033729
Tsinghua	#20	13.1	116061	6.4	116061	9.3	116061	29.9	116061	25.7	116061
TUDelft	#21	7.2	1419	1.9	2197	3.5	2197	29.6	1419	9.1	2454
UTK	#22	15.6	23000	4.3	23000	9.3	23896	79.2	32546	98.0	25990
XJTU	#23	12.4	17342	3.8	17342	10.7	17342	30.0	17342	14.1	17342
ZJUI	#24	15.5	4285	6.1	4285	10.1	4285	67.9	4285	77.0	4285

Material-Specific Ranking

Team Name	Material A		Material B		Material C		Material D		Material E		Overall Ranking	
	Accuracy	Size	Accuracy	Size	Accuracy	Size	Accuracy	Size	Accuracy	Size	Accuracy	Size
ASU	6	6	10	5	9	5	12	6	6	5	7	5
Bristol	5	16	2	16	4	16	1	11	2	11	3	15
CU-Boulder	19	23	16	23	18	23	9	23	15	23	15	23
Fuzhou	3	9	4	9	1	9	2	10	3	10	2	9
HDU	12	22	7	22	6	22	22	22	9	22	10	22
IISc	1	13	5	12	7	13	8	13	5	13	5	13
KU Leuven	21	18	21	18	21	18	17	18	16	18	21	18
Manchester	24	24	24	24	24	24	24	24	24	24	24	24
Mondragon	14	1	17	2	15	1	20	2	11	2	15	2
NJUPT	20	10	14	14	19	11	13	7	17	9	20	10
NTU	22	14	22	13	22	14	21	14	20	15	22	14
NTUT	13	15	15	15	8	15	14	16	19	16	12	16
Paderborn	2	7	3	6	2	6	3	8	1	6	1	6
PoliTO	17	3	20	3	20	3	10	3	14	3	18	3
SAL	23	20	23	20	23	20	23	21	23	20	23	20
SEU-MC	18	2	13	1	17	2	11	1	13	1	14	1
SEU-WX	16	19	19	19	16	19	18	19	8	19	15	19
Sydney	7	4	6	4	5	4	7	4	10	4	6	4
Tribhuvan	15	21	18	21	10	21	16	20	22	21	18	21
Tsinghua	9	17	12	17	12	17	5 (undergrad)	17	12	17	9	17
TUDelft	4	5	1	7	3	7	4	5	4	7	4	7
UTK	11	12	9	11	11	12	19	15	21	14	13	12
XJTU	8	11	8	10	14	10	6	12	7	12	7	11
ZJUI	10	8	11	8	13	8	15	9	18	8	11	8

Estimated Competition Ranking

- **Note: Winning models may NOT be good, Good models may NOT be winning**



- **Performance Track : Paderborn 1st (10000$) Fuzhou 2nd, Bristol 3rd**
- **Innovation Track: Sydney 1st (, TU Delft 2nd, Mondragon 3rd**
- **Honorable Mention ($1000): ASU, IISC, XJTU, ZJUI, UTK, Tsinghua, SEU-MC, PoliTO, SEU-WX**
- **Software Engineering: Sydney**

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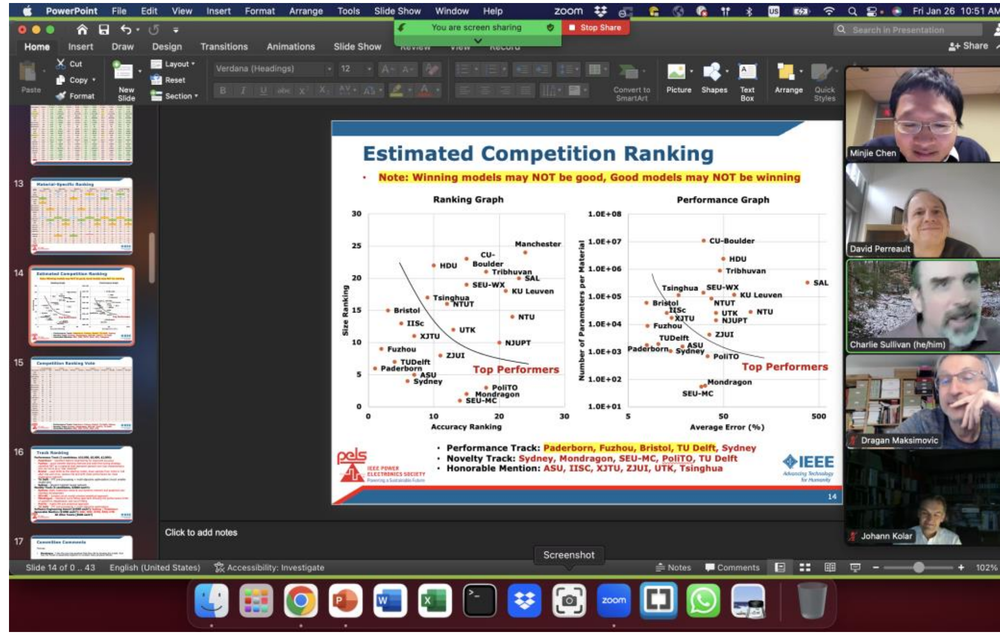
Final Competition Results

- **Performance Track :**
  - Paderborn 1st (10000$)
  - Fuzhou 2nd ($5000),
  - Bristol 3rd ($3000)
  - = $18000
- **Innovation Track:**
  - Sydney 1st (10000$),
  - TU Delft 2nd ($5000),
  - Mondragon 3rd ($3000)
  - = $18000
- **Honorable Mention ($1000):**
  - ASU, IISC, XJTU, ZJUI, UTK,
  - Tsinghua, SEU-MC, PoliTO, SEU-WX
  - = $9000
- **Software Engineering:** Sydney = $5000



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Track Ranking

Performance Track (3 candidates, $10,000, $5,000, $2,000):

- **Paderborn** – excellent feature engineering for improved accuracy
- **Fuzhou** – good transfer learning exercise and solid fine-tuning strategy, identified N87 as a material that represent general core loss characteristics and can serve as a "star material"
- **Bristol** – used 3C90 as the starting model, down-sample from 1024 to 128 after trail and error, random flip and shift (best performance for most challenging material)
- **TU Delft** – FFT pre-processing + multi-objective optimization (much smaller model size)
- **Sydney** – physics inspired neural network

Novelty Track (5 candidates, $3000 each?):

- **Sydney:** static hysteresis network and dynamic network and graphical user interface development
- **SEU-MC** – lumped circuit model oriented analytical approach
- **Mondragon** – intensive curve fitting approach showing the performance limits of waveform classification and curve fitting
- **PoliTO** – hybrid NN and analytical approach
- **TU Delft** – FFT pre-processing + multi-objective optimization

Software Engineering Award ($2500 each?): Sydney / Paderborn

Honorable Mention ($1000 each?): ASU, IISC, XJTU, ZJUI, UTK

All other Teams ($500 each?)

Committee Comments

Thomas:

- **Mondragon** - I like the core loss analysis that they did to develop the model. And how the model is assembled together to consider many physical effects.

- **NJUPT** - Loss map based approach with loss separation. The performances are not great, the code is quite convoluted but the idea is interesting.

- **SEU-MC** - Model is extremely interesting and also applicable a circuit simulation model. Curve fitting approach with the proposed circuit (not clear how the curve fitting is done and the different ranges are assembled). Non-sinusoidal data handling with FFT, which is an approximation. I would say the predicted losses over different frequencies has discontinuities.

- **SEU-WX** - Cool approach trying to mix micromagnetic modeling (LLG equation) with ML. Model size and performance are not great but the underlying idea is really good.

- **Sydney** - Probably my favorite submission. Good performance with a reasonable model size. Great physics inspired neural network. Clear code. I would include them in the performance track.

- **ZJUI** - Physics inspired network using the iGSE to constrain the NN (as a penalty in the loss function).

Committee Comments

Haoran / Shukai

- Performance Track:
  - **#1 Paderborn** – physics-inspired feature engineering and well-designed CNN-based neural network training
  - **#2 Fuzhou** – sequence-to-scalar transformer neural network model with transfer learning technique and effective training tricks for better accuracy
  - **#3 Bristol** – effective data augmentation, LSTM-based neural network with specific algorithm selecting the pre-trained model for transfer learning
  - **#4 TU Delft** – FFT+FNN method, where neural network is well designed and trained with Optuna optimization
- Novelty Track:
  - **#1 SEU-MC** – vector magnetic circuit theory-based analytical model with careful curve-fitting
  - **#2 Mondragon** – analytical model combining the segmentation of hysteresis loss and eddy loss, curve-fitting in iGSE, assumption of CWH, and relaxation effect in i2GSE
  - **#3 Sydney** – magnetization mechanism-inspired neural network method, combining the hysteresis characteristics and the neural network structure
- Honorable Mention: **PoliTO, IISC, ZJUI, ASU, XJTU**

- **Appendix: Team Highlights**

What has worked?
What has NOT worked?
Most interesting discoveries?
Paths toward a standard model?
How can we do better?
Next challenge?

ASU – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
7th	5th	18.53	1576	B+	

Summary:

- Downsampling from 1024 to 24 points with 2% loss in accuracy
- Standard feedforward neural network model to combine B, T, f
- Transfer learning from the 10 materials to the 5 new materials
- Decent model performance and model size
- A systematic machine learning practice

1) Input to model (29x1)
   a) First 24 points sample of "B" (24x1)
   b) Temperature (4 temperature) one-hot encoding (4x1)
   c) Frequency (1x1)
2) Model: Feed Forward Neural Network with
   a) Layer 1 : 29x29, Layer 2: 29x15, Layer 3: 15x15, Layer 4: 15x1
3) Output: 1x1 core loss

Material	A	B	C	D	E
Model size	1576	1576	1576	1576	1576
Training data size	2432	7400	5357	580	2013
Estimate 95th perc. Err.	7.9%	5.3%	8.2%	19.3%	10.2%
Sine 95th perc. Err.	18%	8%	20%	26%	21%
Tri 95th perc. Err.	6%	5%	7%	17%	10%
Trap 95th perc. Err.	6%	5%	7%	28%	9%

TABLE I

MODEL SIZE FOR EACH MATERIAL AND ESTIMATES OF 95TH BY WAVE TYPE

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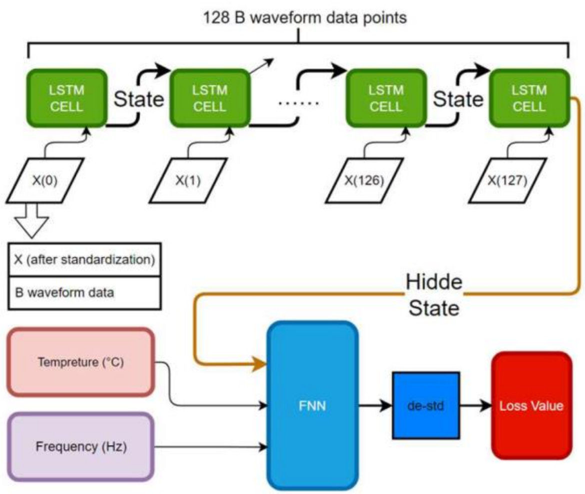
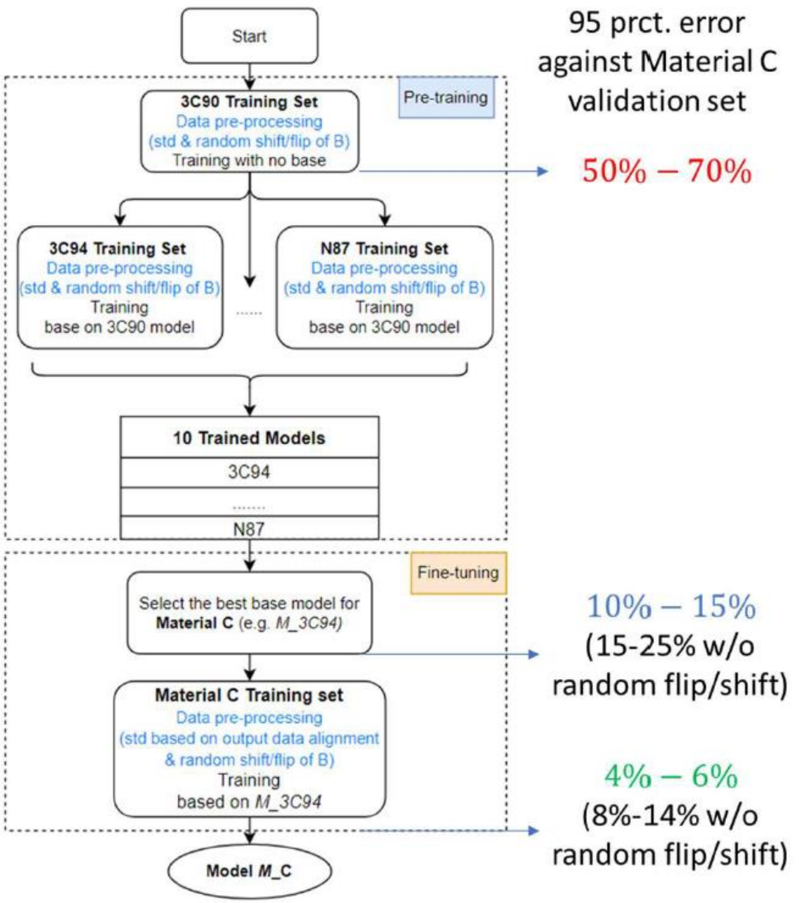
Bristol – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
3rd	15th	7.77	60971.4	A-	

Summary:
- LSTM + FNN Model
- Transfer Learning
- Data Augmentation
- Thorough NN Verification
- Good transfer learning and data augmentation exploration

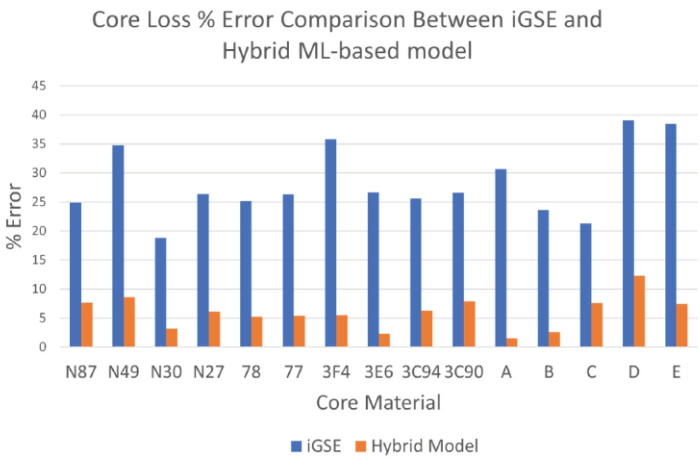


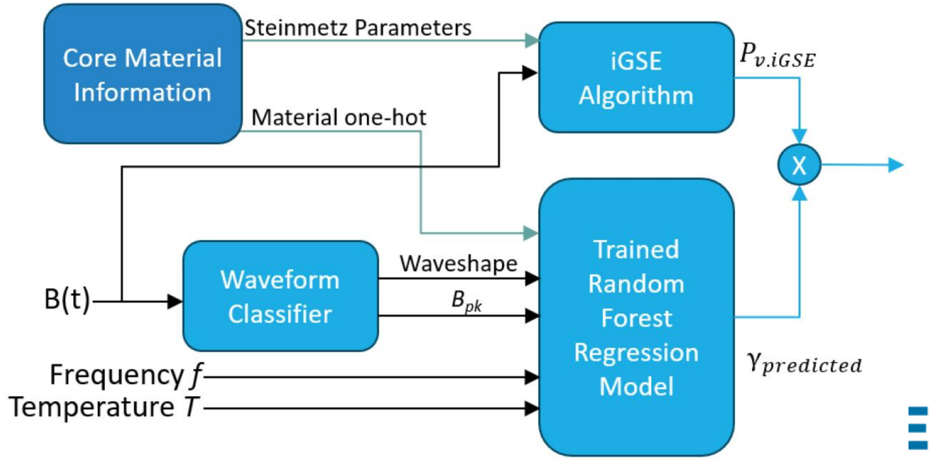


CU Boulder – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
15th	23rd	30.77	11012900	A-	

Summary:
- Hybrid Model
- Waveform Classification
- Random Forest Regression (Simple Computing, Massive Memory)
- Used machine learning to fit a correction factor
- Good error distribution analysis and comparison with iGSE
- Large model size not favoring competition, good differentiation





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Fuzhou U. – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
2nd	9th	7.94	8914	A-	

Summary:

- Transformer-Projector Model
- Transfer Learning – Fine Tuning Strategy
- Deep understanding about magnetics modeling and novel insights

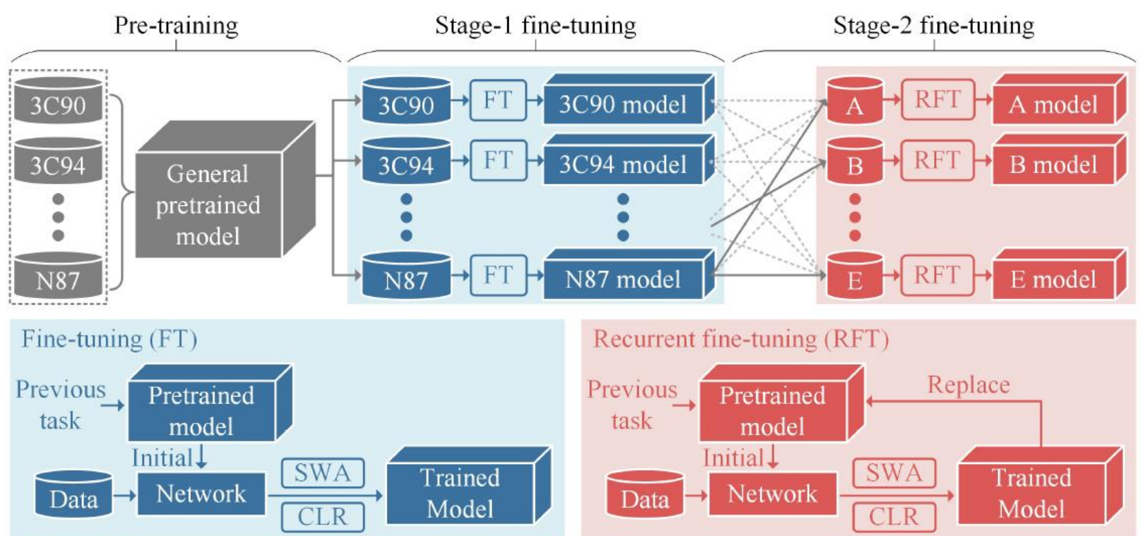
TABLE III
RESULTS OF RECURRENT FINE-TUNING. (TRAIN:VAL=9:1)

	A	B	C	D	E
Scratch	4.90	2.28	3.61	14.45	7.61
Fine-tuning	4.05	2.17	2.93	**7.58**	4.74
Fine-tuning (long)	4.21	2.13	2.93	**7.58**	**4.15**
Recurrent fine-tuning	**3.76**	**2.04**	**2.76**	7.79	4.29

TABLE I
PARAMETERS COUNTING OF THE NETWORK.

Layer	Input size	Output size	Parameters[a]
Projector B			
Linear (Tanh[b])	(1024,1)	(1024,24)	48
Linear	(1024,24)	(1024,24)	600
Transformer Encoder			
MHSA	(1024,24)	(1024,24)	2400
FFN	(1024,24)	(1024,24)	1984
LN	-	-	96
Projector Fusion			
Linear (Tanh)	(1024,26)	(1024,40)	1080
Linear (Tanh)	(1024,40)	(1024,40)	1640
Linear	(1024,40)	(1024,1)	41
Regression Head			
Linear	1024	1	1025

[a] Total parameters: 8914.
[b] The activation function of this Linear layer is Tanh.



Hangzhou Dianzi U. – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
10th	22nd	49.44	2396048	B+	

Summary:

- Vision Transformer model
- A ViT-based modeling method improved over Transformer-based methods.
- Pure NN approach with large NN models and parameters

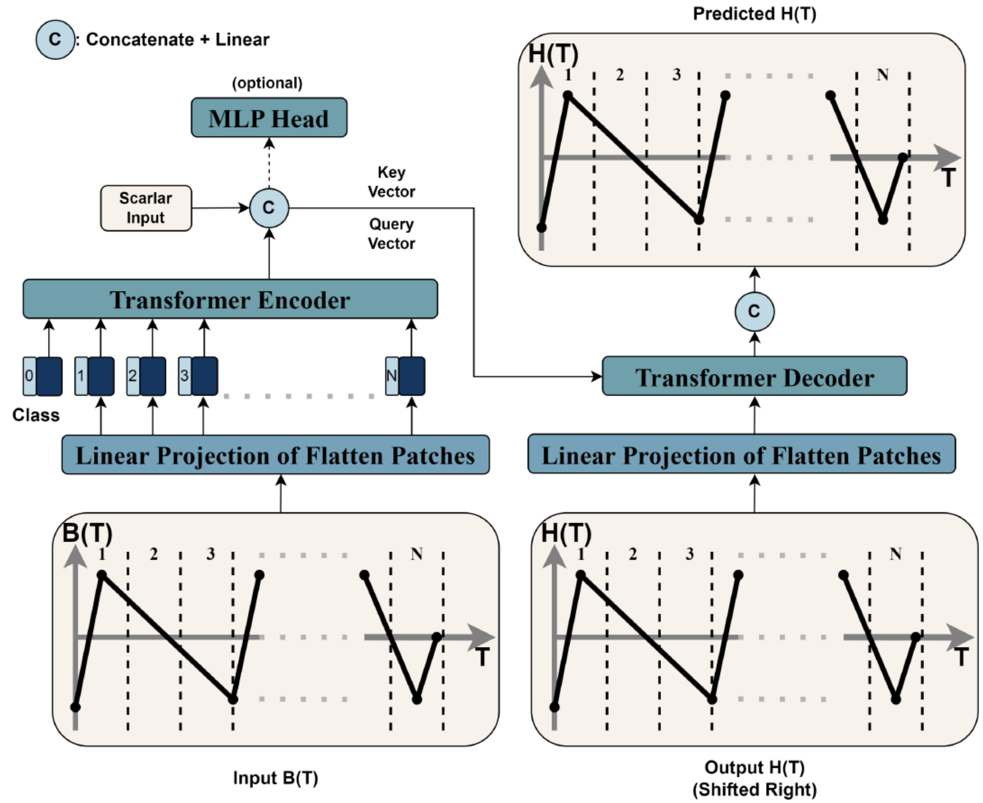


TABLE II
THE NUMBERS OF PARAMETERS IN THE MODEL

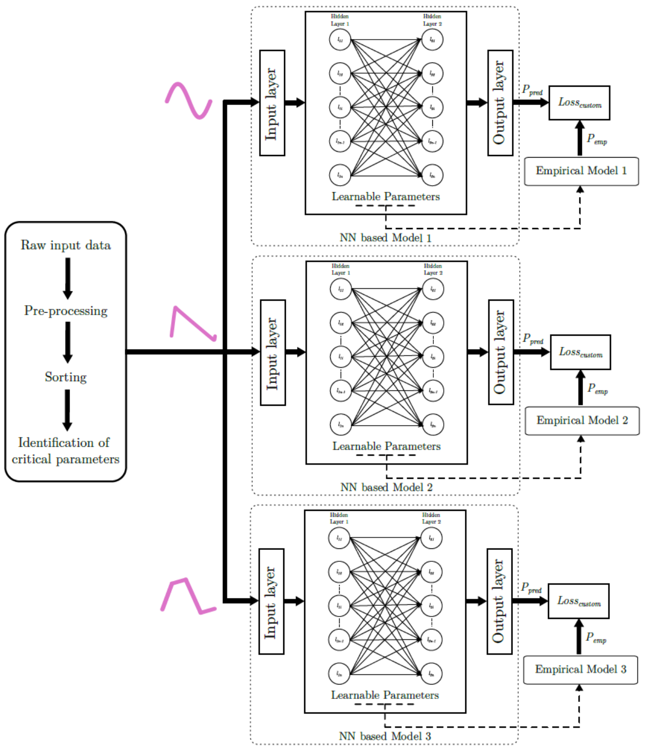
Model	Number of Parameters
Simple	2,396,048
Full(With MLP Head)	2,528,913

IISc – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
5th	13th	12.59	25923	B+	

Summary:

- Waveform classification
- Separate parameters for separate excitation
- Customized training loss function
- Redefine the training loss to make sure the prediction follows the data to improve generality.
- Modifying factor to fix the difference between CWH model and data fitting.
- Bounding NN with analytical models
- Large model size, good accuracy



$$Loss_{custom} = \lambda \times MSE(P_{pred}, P_{act}) + MSE(P_{pred}, P_{emp})$$

TABLE II
MODEL SIZE AND PARAMETERS FOR EACH EXCITATION AND MATERIALS

Model	Sinusoidal	Triangular	Trapezoidal
Size	One input layer: (7,16) Two hidden layers: (16,256), (256,16) One output layer: (16,1)	One input layer: (8,16) Two hidden layers: (16,256),(256,16) One output layer:(16,1)	One input layer: (12,16) Two hidden layers: (16,256), (256,16) One input layer: (16,1)
Parameters	8609	8625	8689

KU Leuven – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
21st	18th	64.29	118785	A	

Summary:

- Generative Adversarial Network (GANET)-based model.
- A NN fights with a generative adversarial network until the discriminator cannot find the difference between the two.
- Advanced NN model exploration. Large model, ok accuracy.

TABLE I: Hyperparameters and Setups of cGANET-based Model

Hyperparameter	Value
Epochs	2000
Batch Size	32
Activation	ReLu
Performance	Relative Error
Learning Rate	Scheduler
Optimizer	Adam
Generator Parameters	118785 (464.00 KB)
Discriminator Parameters	99585 (389.00 KB)

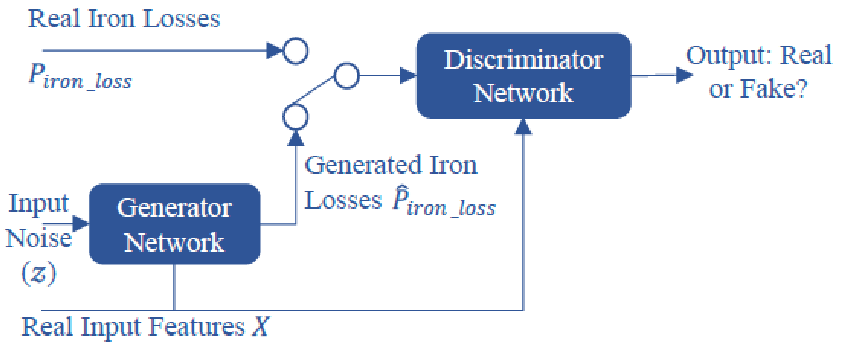


Fig. 2: Block Diagram of cGANET

Manchester – Analytical Model

- Tried to develop a model based on B, H, dB and dH
- Direct data interpolation method.
- Potential to lead to a dynamic transient model!
- Using the current T, B, H and dH/dt to predict dB/dH
- Key Assumption: B-H hysteresis can be piecewise constructed.

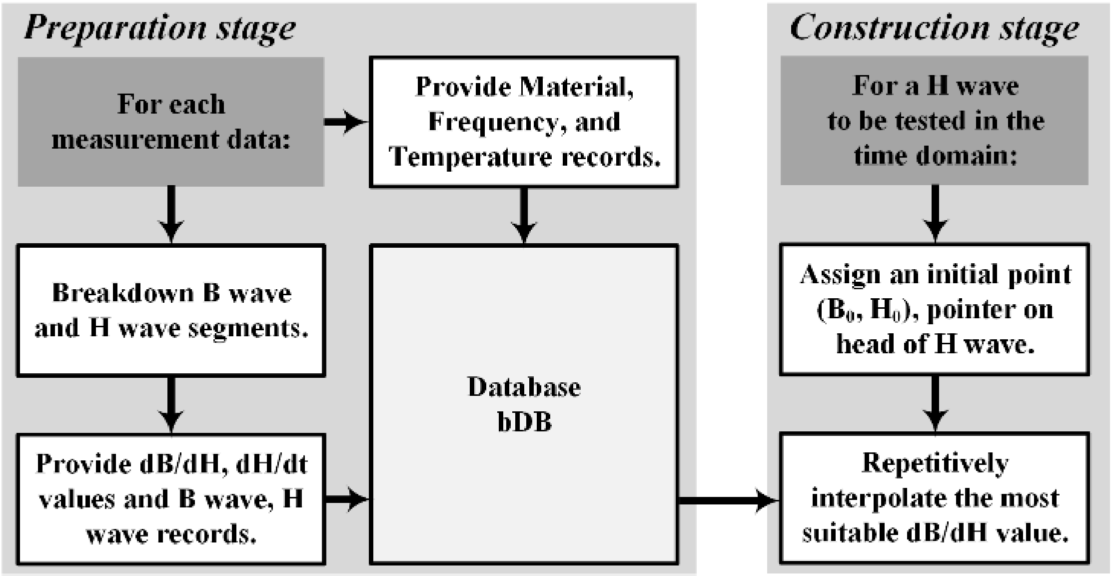


Fig. 2 The flow chart of the data interpolation method.

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Mondragon – Analytical Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
15th	2nd	31.81	60	A	

Summary:

- Pure Analytical Curve Fitting Approach
- 60 Parameters per material
- Do not capture the temperature effect
- Automated parameter fitting process

$$P_{\text{loss}} = \frac{1}{\mathrm{T}} \int_0^T \left[k_1 \left| \frac{dB}{dt} \right|^{a_1} \Delta B^{b_1} + k_2 \left| \frac{dB}{dt} \right|^{a_2} \Delta B^{b_2} \right]$$

$$P_{\text{loss}} = \sum D \left[\exp\left(k_1' + a_1 \ln \left| \frac{dB}{dt} \right| + b_1 \ln \Delta B \right) + \exp\left(k_2' + a_2 \ln \left| \frac{dB}{dt} \right| + b_2 \ln \Delta B \right) \right]$$

$$P_{\text{loss}} = \sum \left[D \left(\exp\left(k_1' + a_1 \ln \left| \frac{dB}{dt} \right| + b_1 \ln \Delta B \right) + \exp\left(k_2' + a_2 \ln \left| \frac{dB}{dt} \right| + b_2 \ln \Delta B \right) \right) \right. \\ \left. + f \exp\left(k_{rel}' + a_{rel} \ln t_{rel} + b_{rel} \ln \Delta B \right) \right]$$

TABLE II: FITTING RESULTS FOR THE FINAL 5 MATERIALS

Mat	Temp	k_1'	a_1	b_1	k_2'	a_2	b_2	k_{rel}'	a_{rel}	b_{rel}	E_{95th}
				$p00$	$p10$	$p01$	$p20$	$p11$	$p02$		
Material E	25°C	2.3859	1.1314	1.9734	-29.1130	3.2238	-0.5807	11.6155	0.6969	2.2377	
				19.6599	-1.8043	2.6016	0.1299	0.0197	-0.1340		
	50°C	1.4351	1.2128	2.1435	-32.3441	3.4352	-0.7411	7.7280	0.3912	2.4369	
				18.0486	-1.4739	3.2517	0.1125	-0.0639	-0.3650		
	70°C	1.7758	1.1882	2.1923	-32.5128	3.4874	-0.4860	11.4230	0.6770	2.3816	
				14.3141	-0.8358	3.6948	0.0829	-0.1775	-0.9002		
	90°C	1.9566	1.1807	2.1885	-33.1304	3.5205	-0.5941	11.2878	0.6594	2.3600	
				36.9005	-5.1469	2.2420	0.2855	-0.0357	-0.1442		
	All	60 parameters, 4x(9+6)									23.60%
Material D	25°C	3.5849	1.0122	1.7976	-19.0609	2.5856	-0.0737	0	0	0	
				11.3004	-0.4019	3.0320	0.0670	-0.0746	-0.1627		
	50°C	1.2973	1.1999	1.8173	-27.8189	3.1403	-0.8648	13.3134	0.9304	1.0925	
				15.3094	-1.6607	0.9518	0.1511	0.2150	0.1075		
	70°C	2.0268	1.1467	2.0771	-27.8331	3.1534	-0.7978	-0.2020	-0.3647	3.3655	
				-12.6105	4.3570	14.2491	-0.1631	-1.0063	-0.5620		
	90°C	-1.9950	1.4827	2.1022	-28.7020	3.1720	-0.9693	56.7664	3.7447	5.2287	
				31.3326	-3.5993	6.4942	0.2038	-0.2248	0.0109		
	All	60 parameters, 4x(9+6)									22.87%
Material C	25°C	-0.8090	1.2789	1.3626	-18.9273	2.6114	-0.3846	5.5581	0.3012	2.5923	
				26.7373	-3.3736	4.1984	0.2043	-0.1506	-0.0248		
	50°C	-0.7740	1.2812	1.5520	-18.1526	2.5238	-0.4213	6.4205	0.3511	2.7855	
				41.6026	-6.0729	4.7102	0.3290	-0.1567	0.0543		
	70°C	-0.4455	1.2615	1.8683	-18.0382	2.5584	-0.3343	5.5969	0.2720	3.0418	
				31.1284	-4.0782	7.5609	0.2357	-0.3864	0.0504		
	90°C	-1.8676	1.3913	1.8703	-18.4802	2.5937	-0.3934	0.9339	14.0935	4.8501	
				31.4340	-4.2160	7.2207	0.2471	-0.3361	0.1190		
	All	60 parameters, 4x(9+6)									14.60%
Material B	25°C	-0.6082	1.2897	1.8224	-12.5537	2.1550	-0.1191	5.6830	0.2541	2.9877	
				4.5861	0.3641	5.0111	0.0509	-0.1958	0.0717		
	50°C	-0.0972	1.2595	1.8690	-11.8026	2.1140	-0.0925	3.6906	0.0925	3.0152	
				0.9186	1.0051	4.8621	0.0243	-0.1831	0.0804		
	70°C	1.1251	1.1786	2.0075	-10.7112	2.0489	-0.0328	4.3712	0.1330	2.8837	
				-2.6573	1.7074	5.0152	-0.0087	-0.2046	0.0653		
	90°C	-0.1711	1.2885	1.7722	-9.7093	1.9818	-0.0017	4.3702	0.1647	2.5736	
				-9.0400	2.8436	4.9328	-0.0588	-0.2100	0.0434		
	All	60 parameters, 4x(9+6)									8.074%
Material A	25°C	4.7442	0.8548	1.4052	-18.7122	2.7643	-0.2571	2.4296	0.0808	2.4503	
				6.9005	-5.1469	2.2420	0.2855	-0.0357	-0.1442		
	50°C	3.1228	0.9707	1.3666	-19.5150	2.8185	-0.3063	5.0173	0.2651	2.8145	
				45.3397	-6.7173	3.1549	0.3577	-0.1022	-0.1063		
	70°C	-2.4755	1.4555	1.0968	-21.0851	2.9037	-0.5311	-5.9455	162.8406	36.2542	
				36.9005	-5.1469	2.2420	0.2855	-0.0357	-0.1442		
	90°C	-6.8894	1.8204	1.2179	-18.4851	2.7187	-0.3902	-3.2823	106.0626	24.0666	
				35.5932	-5.4185	3.7661	0.3210	-0.0771	0.0755		
	All	60 parameters, 4x(9+6)									18.24%

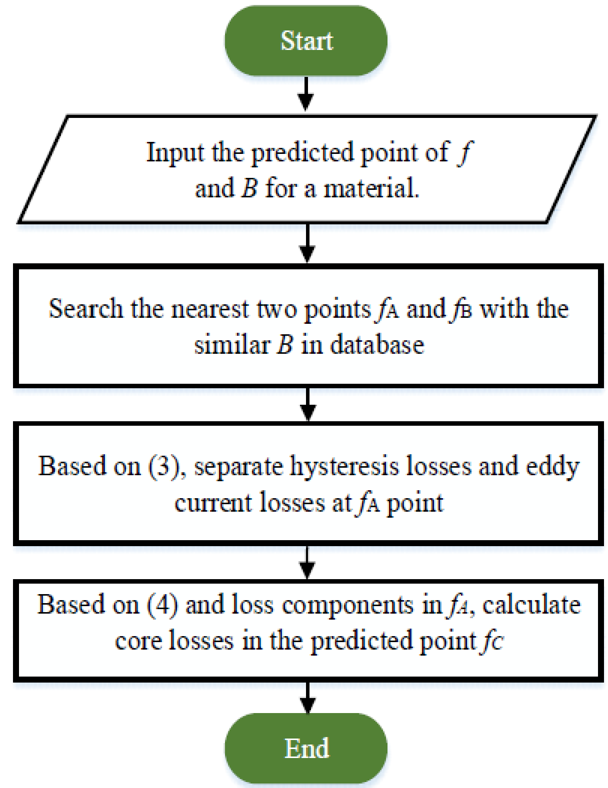
NJUPT – Analytical Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
20th	10th	41.40	14109.6	A-	

Summary:

- Pure Analytical Curve Fitting Approach
- Very few parameters for each material
- Need waveform classification
- Curve fitting for different duty ratios
- Can't be generalized for other waveforms

D_1	D_2	D_3	D_4	V_{D1}^*	V_{D2}^*	V_{D3}^*	V_{D4}^*
0.1	0.4	0.1	0.4	1	0	-1	0
0.2	0.3	0.2	0.3	1	0	-1	0
0.3	0.3	0.1	0.3	0.667	-0.167	-1	-0.167
0.3	0.2	0.3	0.2	1	0	-1	0
0.4	0.2	0.2	0.2	0.667	-0.167	-1	-0.167
0.4	0.1	0.4	0.1	1	0	-1	0
0.5	0.2	0.1	0.2	0.429	-0.286	-1	-0.286
0.5	0.1	0.3	0.1	0.667	-0.167	-1	-0.167
0.6	0.1	0.2	0.1	0.429	-0.286	-1	-0.286
0.7	0.1	0.1	0.1	0.25	-0.375	-1	-0.375



NTU – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
22nd	14th	95.88	28564	B	

Summary:

- CNN+Transformer
- Comparative study for five models
- B(t) is treated as a one-dimensional (1-D) image for ViT.
- Modeling performance is not superior
- Large model size and high error
- Perhaps bugs in coding

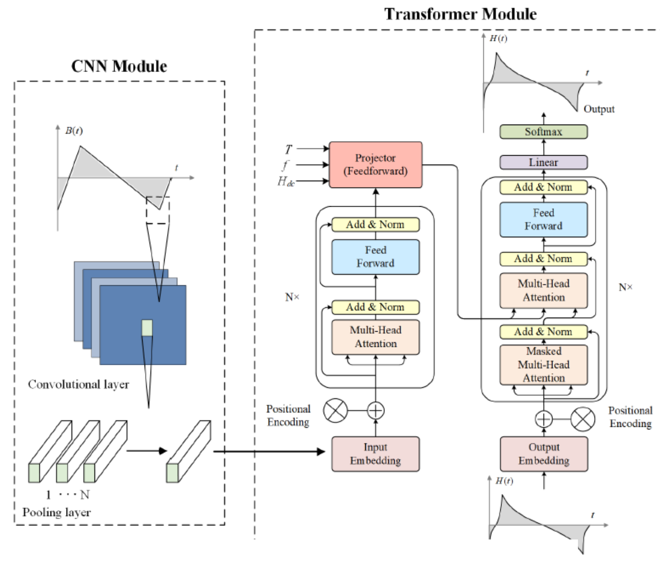


TABLE I
COMPARISON OF DIFFERENT MODELS WITH BASELINE

Name	Model	Parameters	CNN In	Transformer In	Decoder Layer	Average Error	95-Prct Error	Running Time
Baseline	Transformer	28481	NA	128*1	1	3.05%	9.64%	129mins
Model 1	Transformer	28481	NA	256*1	1	2.47%	8.38%	304mins
Model 2	CNN+Transformer	28564	256	128*2	1	2.4%	7.94%	152mins
Model 3	CNN+Transformer	28564	512	128*2	1	2.07%	6.97%	152mins
Model 4	CNN+Transformer	62788	512	128*2	4	1.45%	4.72%	502mins

NTUT – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
12th	16th	37.18	86728	A-	

Summary:

- Neural network model
- Treat f and T equally as B
- No down-sampling
- Similarity comparison

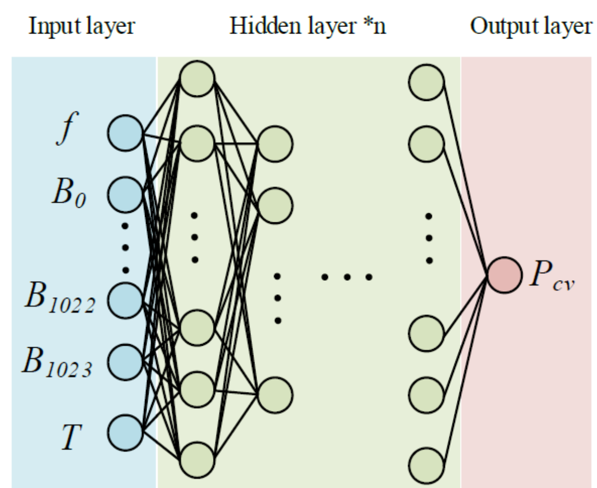


Fig. 1 A schematic diagram of the FNN architecture.

Table.6 The number of similar BH curve among different materials.

Material	3C90	3C94	3E6	3F4	77
A	75	132	294	1	341
B	93	223	1934	0	792
C	263	386	152	12	728
D	47	11	0	28	3
E	11	1	0	152	5
Material	**78**	**N27**	**N30**	**N49**	**N87**
A	256	181	348	5	98
B	528	259	2241	5	217
C	808	620	446	60	444
D	21	37	9	216	26
E	17	30	2	462	6

TABLE 9 Number of Parameters for Each Material

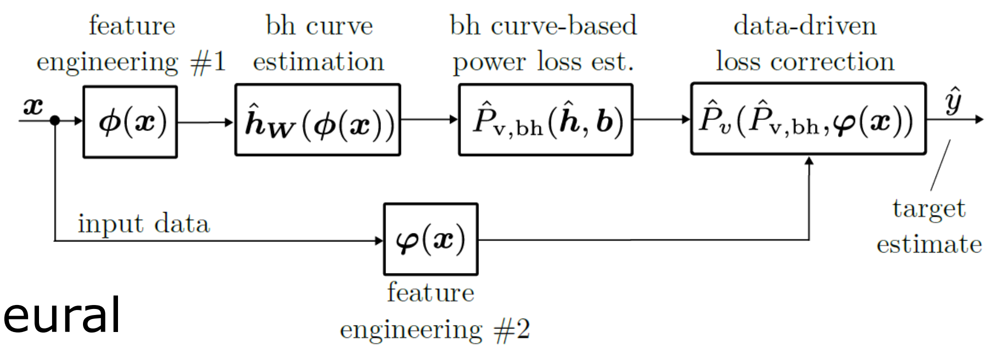
Material	*A*	*B*	*C*	*D*	*E*
Number of Parameters	*86728*	*86728*	*86728*	*86728*	*86728*

Paderborn – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
1st	6th	7.84	1755	A	

Summary:

- Interesting feature extraction
- Predict B-H curve
- Reverse feature feedback
- Similarity comparison
- Novel and carefully selected neural network architecture
- A good balance for model size/performance



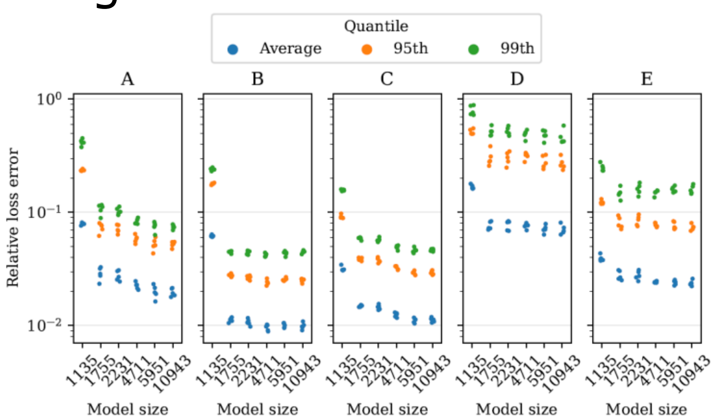


TABLE II
FINAL MODEL DELIVERY OVERVIEW

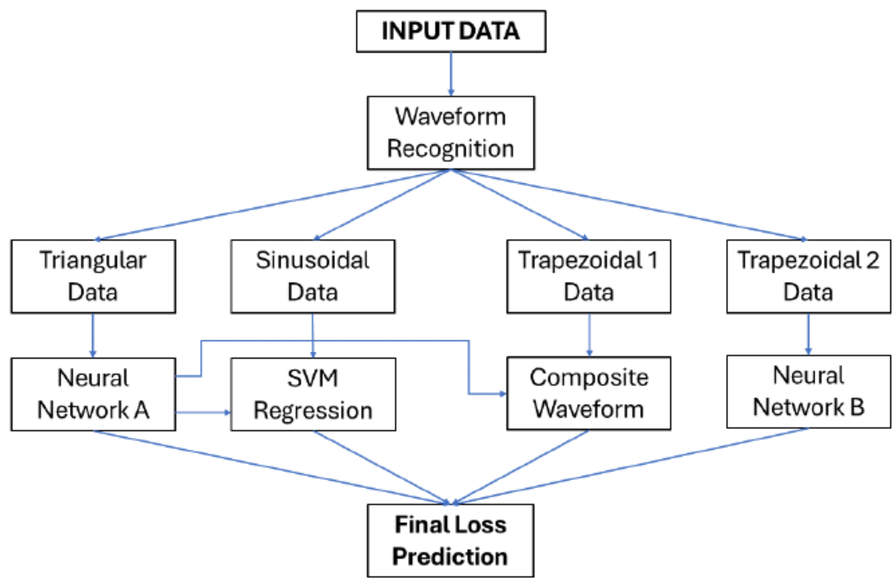
Material	Parameters	Training data	Model size	Relative error Average	Relative error 95-th quantile
A	1755	2432	43.13 kB	2.34 %	6.20 %
B	1755	7400	43.13 kB	1.10 %	2.68 %
C	1755	5357	43.13 kB	1.46 %	3.70 %
D	1755	580	43.13 kB	7.03 %	25.76 %
E	1755	2013	43.13 kB	2.51 %	7.10 %

PoliTO – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
18th	3rd	33.78	685.6	A	

Summary:

- Split input data into different groups and use them to train different part of the models.
- Waveform recognition
- Hybrid NN and Analytical
- Low parameter size
- A bit unclear design logic



	Mean (%)	95 perc (%)	Max (%)
Triangular	0.87	2.19	5.80
Sinusoidal	1.04	2.32	12.11
Trapezoidal CWH	22.6	36.42	40.02
Trapezoidal NN	1.32	3.48	21.02

TABLE V
MEAN VALUE, 95TH PERCENTILE, AND MAX VALUE OF THE RELATIVE ERROR ON THE LOSS PREDICTION FOR MATERIAL B (TRAINING SET)

TABLE II
NUMBER OF PARAMETERS OF THE SVR FOR EACH MATERIAL

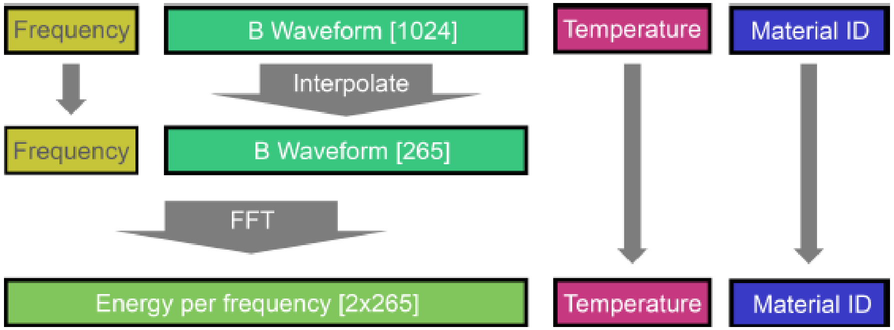
	A	B	C	D	E
N. parameters	138	288	276	228	138

SAL – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
23rd	20th	378.43	329537	B	

Summary:

- FFT + NN approach
- First process with FFT and then merge/fusion other information
- Perhaps a bug in coding which degraded the performance



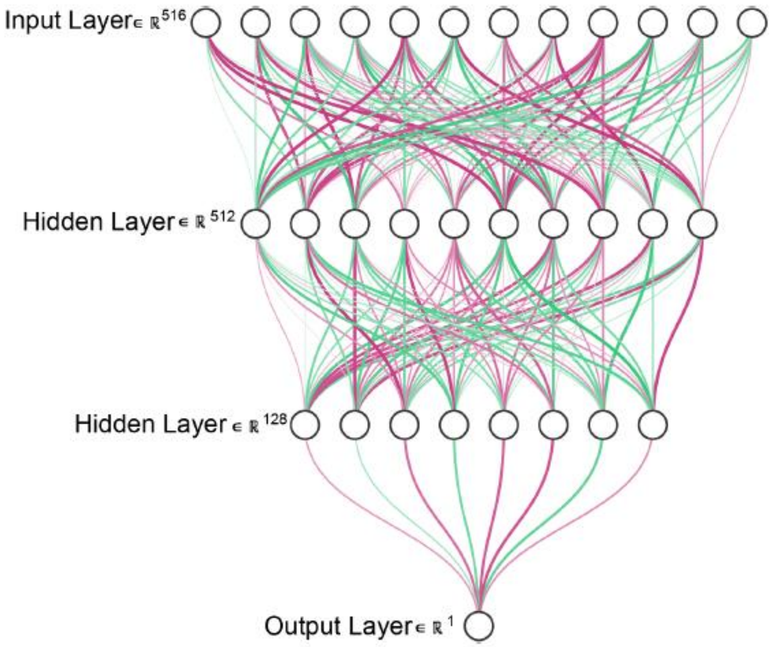


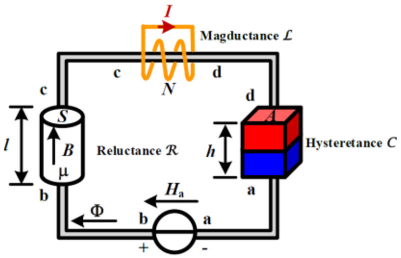
Fig. 4. The image visualizes the optimized neural network architecture with multiple input layers progressively reducing in size, from 516 nodes in the first layer to 512 in the second, and finally 128 nodes in the third layer, before converging to a single output node.

SEU-MC – Analytical Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
14th	1st	29.08	54.8	B	

Summary:

- Analytical + Curve Fitting
- Very low number of parameters but decent results
- Interesting R/L/C loss separation
- Not fully automated, human tuning needed



$$k_e = a_1 B_{peak}^{\ 3} + b_1 B_{peak}^{\ 2} + c_1 B_{peak} + d_1$$

$$k_h = a_2 B_{peak}^{\ 3} + b_2 B_{peak}^{\ 2} + c_2 B_{peak} + d_2$$

$$X_{\mathcal{L}_n} = \frac{k_e f_n^{\ 2}}{\omega_n \|\dot{\Phi}\|^2} = \frac{k_e f_n}{2\pi \|\dot{\Phi}\|^2}$$

$$X_C = \frac{k_h f_n}{\omega_n \|\dot{\Phi}\|^2} = \frac{k_h}{2\pi \|\dot{\Phi}\|^2}$$

$$P = \sum_{n=1,2,3\ldots}^{\infty} \sum_{m=1,3,5\ldots}^{\infty} (P_{\mathcal{L}} + P_C) = \sum_{n=1,2,3\ldots}^{\infty} \sum_{m=1,3,5\ldots}^{\infty} \left(\omega^2 \mathcal{L}_{mn} \|\dot{\Phi}_{mn}\|^2 + \frac{\|\dot{\Phi}_{mn}\|^2}{C_{mn}}\right) \qquad (12)$$

TABLE I

THE NUMBERS OF PARAMETERS FOR EACH OF THE MATERIAL

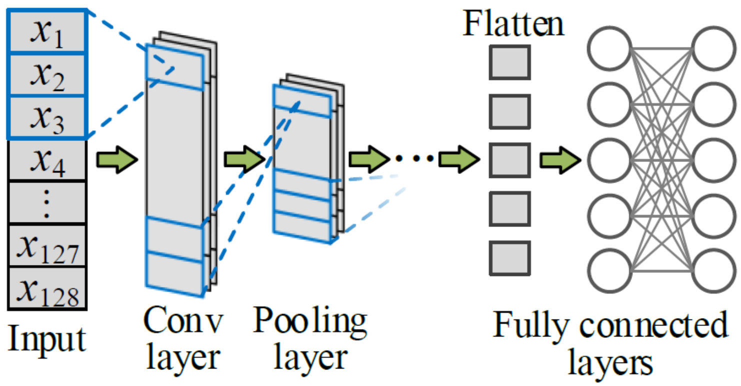
Material	A	B	C	D	E
Numbers of parameters	81	56	61	23	53
Model size (Byte)	5125	4421	4542	3255	4404

SEU-WX – NN Method

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
15th	19th	30.58	139938	B	

Summary:

- Full NN Approach
- Large Model Size
- Exploration of the NN model can be more systematic



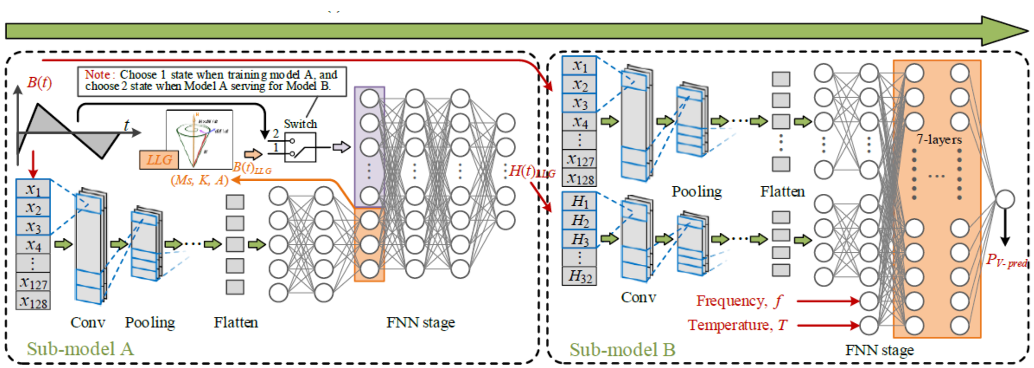


Fig. 4. The framework the proposed PI-MFF-CN method.

F. The Numbers of Parameters of Model

Material	A	B	C	D	E
Number of Parameters	139938	139938	139938	139938	139938
Model size / KB	(176+385)	(176+385)	(176+385)	(176+385)	(176+385)

Sydney – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
6th	4th	13.86	1084	A	

Summary:

- Predict B-H Loop
- Static hysteresis component + dynamic hysteresis component
- A component independent of frequency and a fixing component depending on f
- Outstanding software engineering

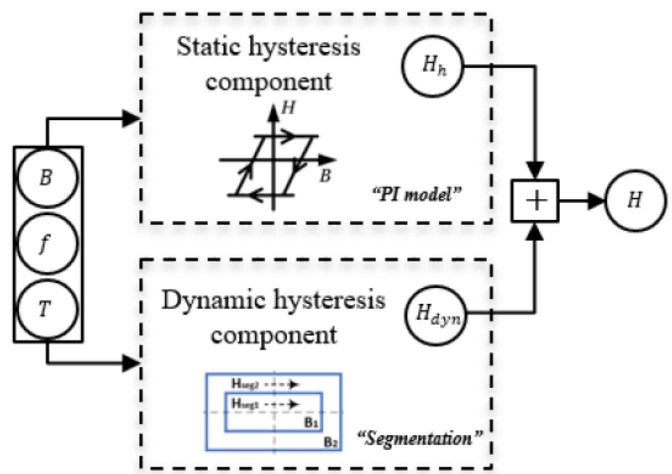


Fig. 4. Physical core loss model schematic diagram.

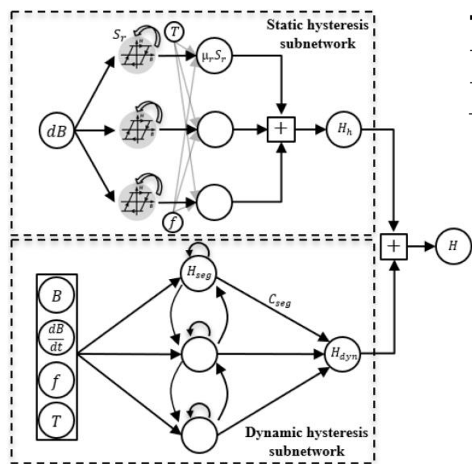


Fig. 5. Magnetization mechanism-inspired neural network.

Material	A	B	C	D	E
Num. of θ	1084	1084	1084	1084	1084
File size	7kb	7kb	7kb	7kb	7kb

$$\begin{cases} x(t) = {}^1w\,{}^1v(t) \\ h(t) = {}^2w\,{}^2v(t) + {}^hwH_{seg}(t-1) \\ H_{seg}(t) = f_h[h(t)] \\ H_{dyn}(t) = C_{seg}H_{seg}(t) + b \\ H_h(t) = \sum f_h[x(t)] \\ H(t) = H_h(t) + H_{dyn}(t) \end{cases}$$

Tribhuvan – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
18th	21st	45.60	882228.2	B	

Summary:

- FFT + LSTM + FNN
- Predict B-H Loop
- Only process the first 32 harmonics

TABLE IV
MODEL TOTAL PARAMETERS

Material	Model Layer	Total Params	File Size
A	LSTM+ Dense	1033729	3.94 MB
B	LSTM+ Dense	1033729	3.94 MB
C	LSTM+ Dense	1033729	3.94 MB
D	LSTM+ Dense (C to G)	276225	1.09 MB
E	LSTM+ Dense	1033729	3.94 MB

TABLE III
DENSE LAYER INFORMATION

Layer	Type	Neurons	Connected to
A	Dense	1024	LSTM Out
B	Dense	512	A
C	Dense	256	B
D	Dense	128	C
E	Dense	64	D
F	Dense	32	E
G	Dense	16	F
Output	Dense	1	G

Tsinghua – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
9th	17th	16.87	116061	B	

Summary:

- Transformer Type Model
- Simple MLP Structure
- Compared LSTM

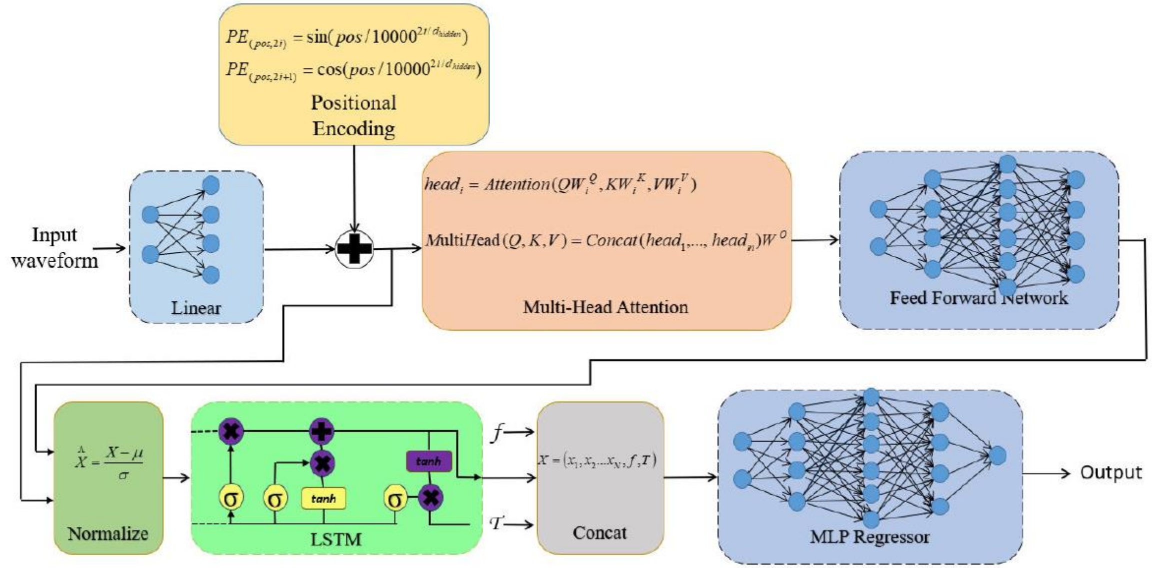


TABLE I Number of parameters in models for different materials

Materials	A	B	C	D	E
Parameter-number	116061	116061	116061	116061	116061

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TUDelft – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
4th	7th	10.28	1937.2	A	

Summary:

- NN Approach
- Multi-Objective Optimization
- Cross-material transfer learning for new materials

Table 5
Ten Existing Materials Optimized MOO Models Transfer Learning Results

material (number of parameters)	Self-training result		Transfer learning results								
			Material A		Material B		Material C		Material D		
	Average error	95% error	Average error	95% error	Average error	95% error	Average error	95% error	Average error	95% error	Aver err
N27(1419)	0.75	1.97	2	6.7	0.75	1.89	1.39	3.93	3.16	10	2.
N30(2197)	0.41	1.1	2.08	7.85	0.7	1.65	1.1	3.24	3.7	10	2.2
N49(1132)	1.9	5.78	2.688	8.9	0.79	2.2	1.37	3.9	5.11	19	2.4
3F4(2117)	1.45	3.8	2.58	7.8	0.84	2.17	1.23	3.4	5.2	15.7	2.6
3E6(1295)	0.455	1.19	2.25	6.3	0.74	1.98	1.23	3.62	4.26	10.65	2.7
3C90(2705)	0.83	2.35	2.23	8.1	0.76	1.97	1.2	3.78	3.86	10.9	2.3
3C94(3021)	0.75	2	3.1	10.4	0.75	2.02	1.37	4.2	5.9	22.4	2.6
N87(1525)	0.74	2	2.54	7.67	0.73	1.9	1.19	4	4.6	14.9	2.7
77 (2454)	0.77	2.1	2.2	6.37	0.92	2.48	1.21	3.54	4.77	14	2.
78(2285)	0.72	1.89	2.19	7.1	0.69	1.9	1.21	3.72	5.23	15.38	2.6

Table 6
Comparison of the Best Transfer Learned Results and Regular Trained Results for the Five New Materials

New Material	Self-training result			Transfer learning result			
	Number of parameters	Average error	95% error	Number of parameters	Average error	95% error	Base model
A	1662	2.18	6.73	1419	2	6.7	N27
B	552	0.9	2.2	2197	0.7	1.65	N30
C	935	1.65	4.4	2197	1.1	3.24	N30
D	1857	6.3	21.8	1419	3.16	10	N27
E	1551	2.47	7	2454	2.2	6.4	77

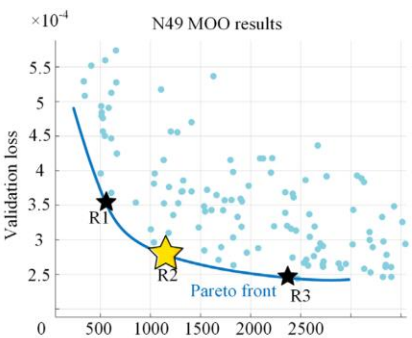
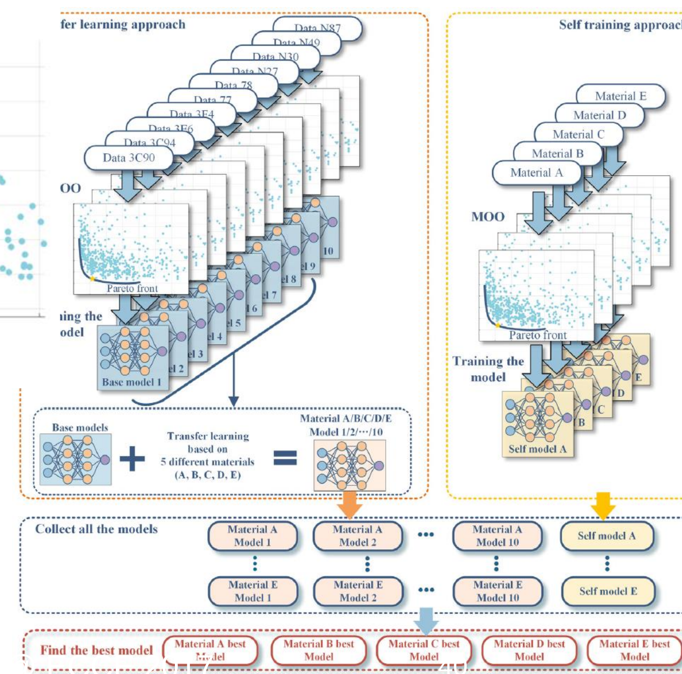


Fig. 3 MOO Result Example

Table 7
Number of Parameters for New Materials

Material	A	B	C	D	E
Number of parameters	1419	2197	2197	1419	2454



UTK – Hybrid

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
13th	12th	41.28	25686.4	A	

Summary:

- metadata-conditioned U-Net
- Integrating Gated Recurrent Units (GRUs) into a U-net architecture for sequence-to-sequence (seq2seq) generation represents a significant adaptation from its traditional applications. Both the encoder and decoder components of the U-Net are constructed using GRU layers.
- Knowledge Distillation
- Pure computer science approach

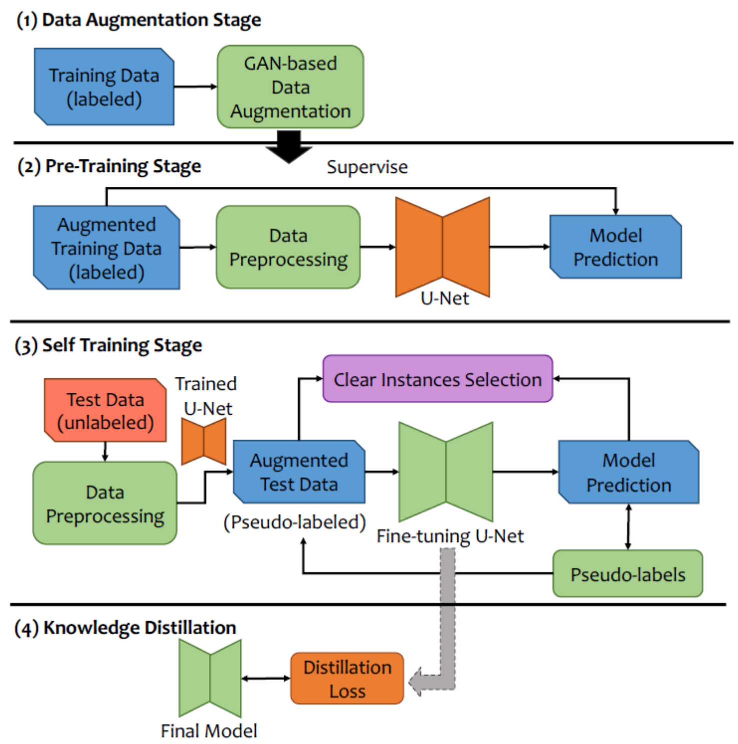


Fig. 1. Framework Overview.

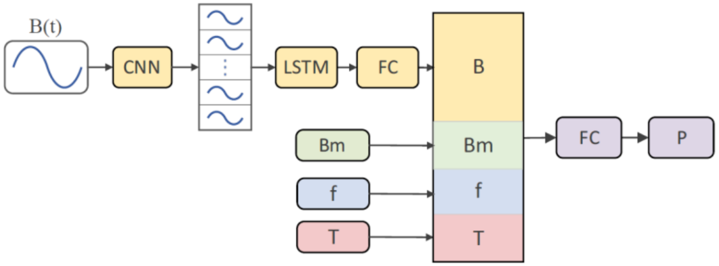
TABLE I
NUMBER OF MODEL PARAMETERS

Material	A	B	C	D	E
Number of Parameters	23,000	23,000	23,896	32,546	25,990

XJTU – NN Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
7th	11th	14.21	17342	A	

Summary:
- The total number of parameters in the model is 7154.



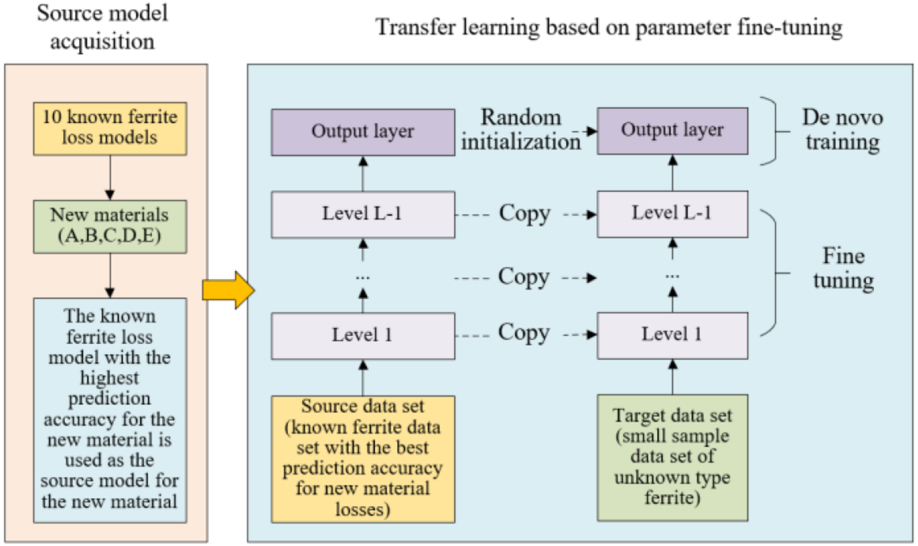
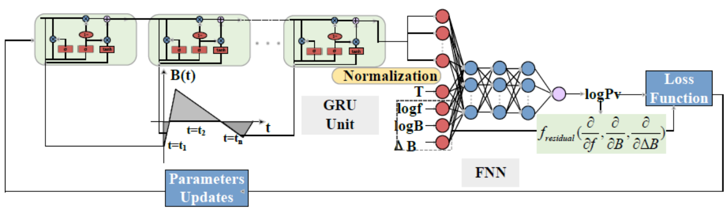


Fig. 4 Prediction of ferrite loss of unknown type based on parametric fine-tuning TL

ZJUI – Hybrid Model

Performance Rank	Model Size Rank	Average Error [%]	Parameter Size (#)	Novelty Grade	Software Engineering
11th	8th	35.32	4285	A	

Summary:
- Sophisticated physics informed machine learning.
- Hybrid GSE and NN.



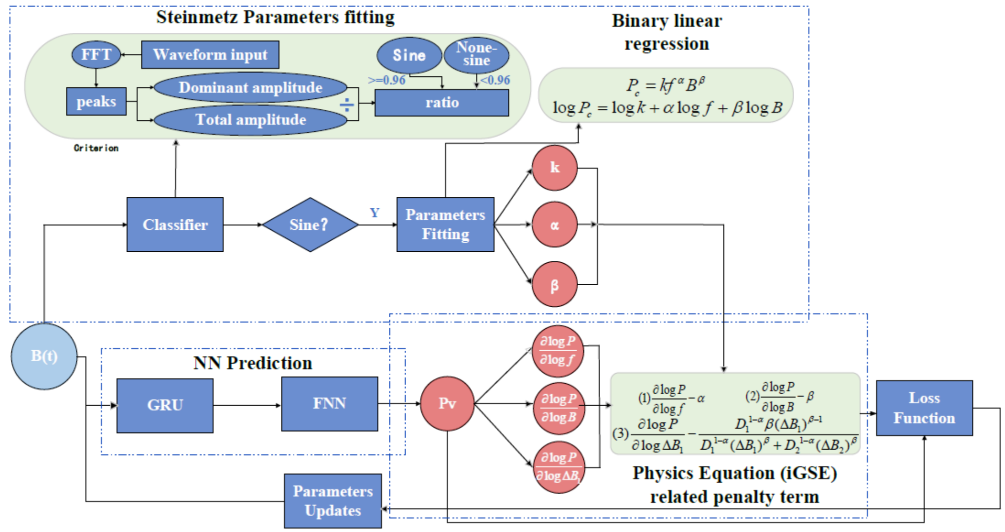


TABLE I
COMPARISONS WITH THE PROPOSED PINN MODEL AND OTHER EXISTING MODELS

Model	Model Size	Applicable Range	Test Condition		Error (%)
			Waveform Shape	Temperature	
Sequence-scalar[4]	5569	Handle only one temperature	tri.,	25°C	Avg:2.09% Max:14.35%
Sequence-sequence[4]	28481	Handle all waveforms and all temperature	Sine, tri., trape.	25°C,50°C, 70°C,90°C,	Avg: 4.2% Max: 30%
Proposed PINN model	4285	Handle all waveforms and all temperature	Sine, tri., trape.	25°C,50°C, 70°C,90°C,	Avg:1.36% Max:17.8%