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PE-GPT: a New Paradigm for Power Electronics Design

Fanfan Lin, *Member, IEEE*, Xinze Li, *Member, IEEE*, Weihao Lei, *Student Member, IEEE*,
Juan J. Rodriguez-Andina, *Fellow, IEEE*, Josep M. Guerrero, *Fellow, IEEE*, Changyun Wen, *Fellow, IEEE*, Xin Zhang, *Senior Member, IEEE*, Hao Ma, *Senior Member, IEEE*

Abstract— Large Language Models (LLMs) have shown exciting potential in powering the growth of many industries, yet their adoption in the power electronics (PE) sector is hindered by a lack of specialized PE technical expertise and challenges in processing PE-specific data. This study presents a pioneering approach to establish a multimodal LLM tailored for PE design applications, named PE-GPT. The methodology involves enhancing PE-GPT with retrieval augmented generation from a PE knowledge base, and proposes a hybrid framework that integrates an LLM agent with metaheuristic algorithms, Model Zoo, and Simulation Repository. This enhances its multimodal processing capabilities and enables integration into the existing design workflow. The PE-GPT methodology is demonstrated with two case studies: modulation design of the dual-active bridge (DAB) converter and circuit parameter design of the buck converter. PE-GPT demonstrates a 22.2% increase in correctness compared to human experts. Against other leading LLMs, PE-GPT shows a 35.6% improvement in correctness and a 15.4% enhancement in consistency, reducing hallucination. Hardware experiments validate PE-GPT's multimodal capabilities in optimizing a five-degree-of-freedom modulation strategy for the DAB converter. The generalizability of PE-GPT to other PE design applications and associated AI ethical considerations are also discussed. This research concludes by outlining inspiring future research directions, encouraging researchers to expand the boundaries of the PE industry and advance toward a more intelligent era.

Index Terms — Large language model, multimodal AI, power electronics design, power converter design, physics-informed AI.

I. INTRODUCTION

TO accelerate the world's transition to sustainable energy, power electronics (PE) devices play important roles. Unlike traditional fossil energy from which we can expect steady and predictable power, most of the sustainable energy sources exhibit the characteristic of intermittency, including solar and wind energy [1]. This intermittency, resulted from day-night cycle for solar energy and wind speed for wind energy, poses serious challenges for grid stability and reliability. To address this challenge, PE devices adjust the voltage and frequency of the generated power before it is fed into the grid. Furthermore, PE devices work in conjunction with energy storage systems like batteries in microgrids to store excess energy generated during peak generation hours and release it during low generation or high-demand hours [2].

PE design is an intricate and highly specialized process, necessitating extensive experience and domain knowledge. The

design usually covers the main circuit, switching device, magnetic component, control mechanism and modulation strategies, structural design, etc. To ensure optimal operating performance, the design process typically considers various performance metrics comprehensively. Crucially, as the grid evolves to be more dominated by PE devices, the scale and complexity of PE systems increase, leading to exponentially increasing work and difficulty in PE design [3].

Intriguingly, large language models (LLMs) such as ChatGPT (2022), GPT-4 (2023) [4], LLaMa2 (2023) [5], and Gemini (2024) [6] have garnered significant attention, as they show great potential for augmenting humans in certain role across many industries. Essentially, LLMs are deep neural networks pre-trained on large general corpora like Wikipedia or Common Crawl in an unsupervised manner. With billions of parameters, LLMs embody vast linguistic and factual knowledge, enabling a spectrum of language-related tasks, including understanding, translation, question-answering, and summarization [4]. Recent studies have delved into specialized applications of LLMs. In the healthcare sector, Lee et al. explored applications in medical note-taking and clinical consultation support [7]. Wang et al. introduced TransGPT [8], a multimodal LLM tailored to elucidate traffic phenomena, address traffic queries, and generate traffic reports, offering valuable insights for transportation professionals. In the realm of electric energy, LLMs are leveraged for tasks like insulation defect detection, load forecasting, wildfire recognition, and optimal power flow quantification from linguistic data stipulations [9].

However, amidst the excitement of these diverse applications, the PE industry faces specific challenges when incorporating LLMs for the PE design:

- **Challenge 1 - Limited PE Technical Expertise:** Trained on general corpora, LLMs lack domain expertise. Consequently, they may struggle to offer precise insights or outcomes, particularly in PE-design-related tasks.
- **Challenge 2 - Incapability to Process PE-Specific Unstructured Data:** PE design often involves unstructured data types like time-series operating waveforms which LLMs are not capable to handle. Furthermore, the specialized processing techniques required, such as Fourier transforms, and machine learning, are beyond the conventional capabilities of LLMs, limiting their potential contributions to PE design.

As a solution to these challenges, this paper proposes PE-GPT, a multimodal LLM tool tailored for PE design. **To address Challenge 1 mentioned above, PE-GPT is enhanced by retrieval augmented generation (RAG) built upon PE-specific knowledge base.** This enables the LLM to obtain

domain knowledge from the provided knowledge base before generating text responses. **To address the aforementioned Challenge 2, we propose a hybrid framework for PE-GPT, integrating an LLM agent, metaheuristic algorithms, a Model Zoo, and a Simulation Repository.** This hybrid framework supports three workflows: Design with Model Zoo, Simulation Verification, and Model Fine-Tuning. Firstly, through the metaheuristic algorithm and Model Zoo for function evaluation, PE-GPT optimizes design parameters and performs quantitative analysis. Secondly, PE-GPT can initiate simulation software and embed the design outcomes upon the user's request, facilitating simulation verification. Thirdly, it supports fine-tuning data-driven models within the Model Zoo to enhance accuracy. The proposed hybrid framework addresses the LLM's limitations in processing PE-specific quantitative data, equipping it with multimodality processing and PE design capabilities. For illustration and verification, this paper presents two design cases: modulation design for the dual-active-bridge (DAB) converter and circuit parameter design for the buck converter. In these cases, PE-GPT provides sequential text guidance to users, understands design requirements, performs optimized quantitative design, and conducts PE-specific reasoning and analysis.

In summary, the contributions of this research are listed below:

- We firstly propose PE-GPT, a multimodal LLM tailored for PE design, marking the beginning of a new paradigm for PE design.
- We introduce a hybrid framework, consisting of an LLM agent, metaheuristic algorithms, a Model Zoo, and a Simulation Repository. This framework supports three workflows, enhancing the flexibility and generalization of the LLM for various tasks in PE design and seamlessly integrating PE-GPT into existing design workflows.
- We present a PE knowledge-associated RAG technique, which addresses the limitations of LLMs in PE domain expertise.
- Building upon this initial version of PE-GPT, this research sheds light on the promising potential of LLM-empowered intelligent PE design. We also discuss potential future directions and relevant ethical considerations.

This paper is organized as follows: Section II covers preliminary knowledge about LLMs. Section III introduces the proposed PE-GPT methodology. Sections IV and V analyze design cases in detail. Section VI discusses the extension of PE-GPT to other PE design applications and relevant AI ethical concerns. Section VII validates the feasibility and effectiveness of PE-GPT. The conclusion and future directions are presented in the final section.

II. PRELIMINARIES: LARGE LANGUAGE MODELS

The rapid advancement of LLMs commenced with the introduction of the Transformer model in 2017 [10]. Its core innovation, the self-attention mechanism [11], is defined in (1) consisting of the query (Q), key (K), value (V) and dimensionality of the keys (d_k). Based on the similarity between Q and K , the weighted sum of the values is obtained as an attention score. This allows the Transformer to assess the relative significance of words in context, thereby enabling it to

capture long-term dependencies in language.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

Following that, Google introduced Bidirectional Encoder Representations from Transformers (BERT) in 2018 which overcame the preceding language models' constraints in unidirectional language modeling. In 2023, OpenAI trained GPT-4 on extensive Internet datasets, which has 1.76 trillion parameters, pushing the development of LLM to a new height. Although GPT-4 is capable of processing both text and image data formats, its direct application to technical tasks in the field of PE remains challenging.

To tailor LLMs for specific industry applications, generally there are three prevailing methods: Prompt Engineering, RAG and model fine-tuning [4].

- **Prompt Engineering** involves leveraging textual inputs to guide the LLM in generating the desired output. Chain of thoughts (CoT) is a prompt engineering technique which guides the model to answer multi-step questions through a logical sequence of reasoning steps.
- **RAG** equips the LLM with an external, vectorized knowledge base, thereby expanding the model's access to domain-specific, professional, or exclusive knowledge beyond its initial training data.
- **Model Fine-tuning** is a technique where the pre-trained weights of the LLM are retrained with new training data. This retraining process may involve specific layers of the model, with others remaining frozen. The computational efforts required for retraining can vary based on the complexity and size of the task-specific dataset.

Fig. 1 compares the three techniques against five criteria: accuracy of the response (less hallucination), simplicity of implementation, explainability of the technique, lightweight computation and flexibility to update external knowledge base. Considering the flexibility and simplicity, combinations of prompt engineering and RAG are applied to develop a tailored PE-GPT model.

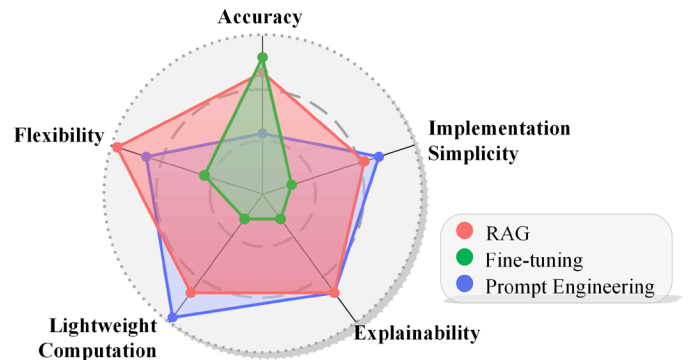


Fig. 1. Comparison of three LLM customization techniques.

III. PE-GPT METHODOLOGY

This section introduces the methodology behind the proposed multimodal PE-GPT from the following pivotal perspectives: the hybrid framework, the adaptation of a RAG technique for PE, and the integration of Model Zoo as well as the adopted physics-in-architecture neural network (PANN) inside Model Zoo.

The PE-GPT methodology is generally applicable to power

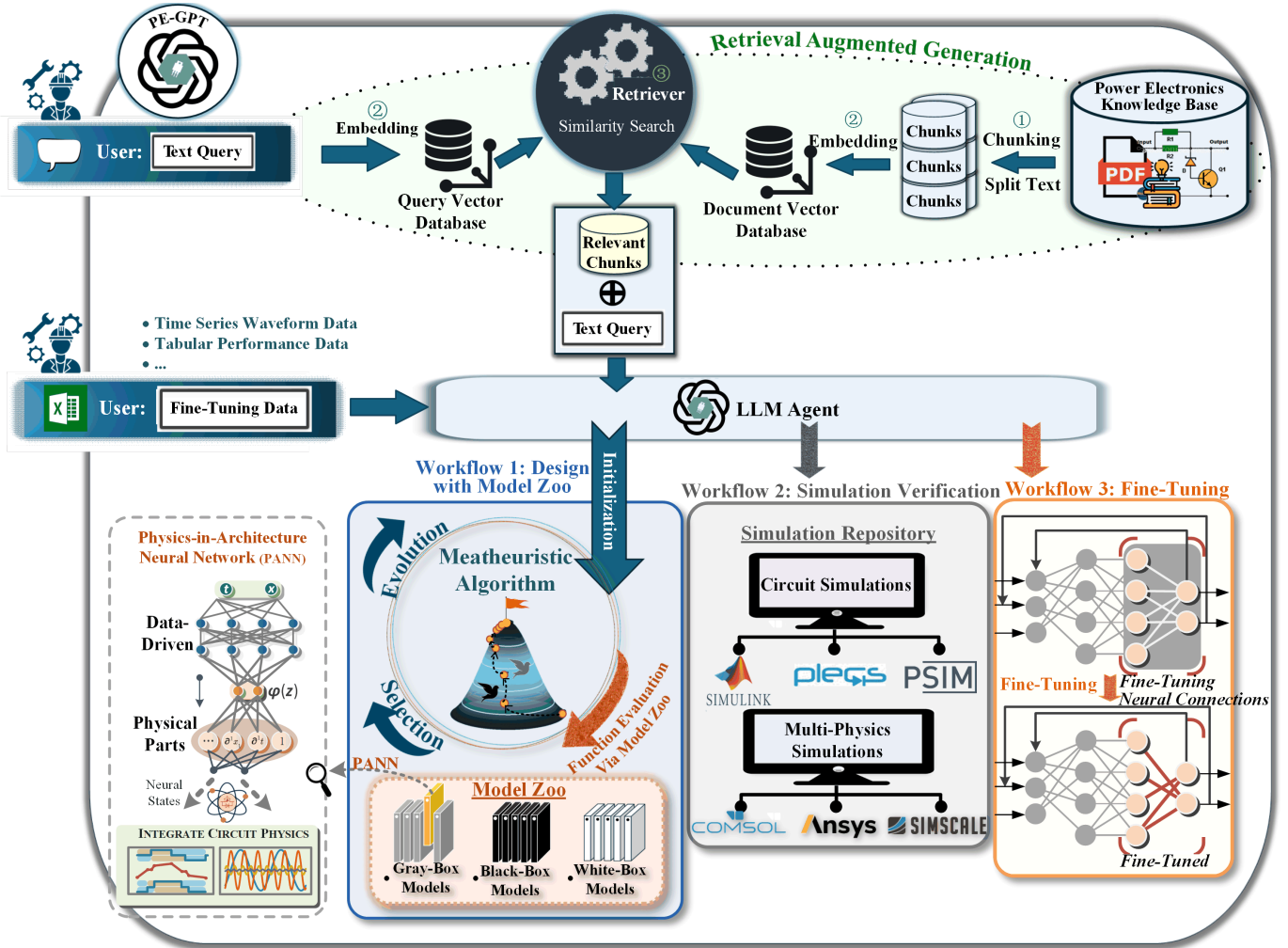


Fig. 2. The proposed hybrid framework of PE-GPT.

converters. For clarity, this section presents the methodology with a focus on the modulation design of the DAB converter. Generalization of the methodology and its applications to other cases are discussed afterwards.

A. Hybrid Framework of PE-GPT

Fig. 2 presents the proposed hybrid framework of multimodal PE-GPT. There are two types of acceptable input data from the user: textual queries and PE-specific fine-tuning data.

All textual queries first go through the RAG process, indicated by the green dotted section in Fig. 2, to enhance the domain expertise of the original LLM agent. To facilitate RAG, a specialized PE knowledge base is constructed beforehand based on the application-specific needs. For instance, if the PE-GPT is expected to handle modulation design tasks, relevant academic papers and technical documents on modulations can be intentionally collected for the knowledge base. Both the textual query and the knowledge base are stored in a vector database after vector embedding. Relevant information chunks are then retrieved based on the similarity of these embeddings, combined with the textual queries, and passed forward to the LLM agent.

When the LLM agent takes in the textual query processed by RAG or the PE-specific fine-tuning data such as time-series

waveforms, one of the following three workflows will be initiated.

- **Workflow 1: Design with Model Zoo.** With a design request, the LLM agent initiates Workflow 1. This process involves a metaheuristic algorithm that iterates through three steps until the optimal design parameters are found [12]: Function Evaluation via Model Zoo, Selection, and Evolution. Metaheuristic algorithms are advantageous in PE design tasks because they offer robust global optimization, adapt to complex problems effortlessly and handle multi-objective optimization. The Model Zoo, detailed in Section III-C, evaluates the performance of candidate design solutions, such as the DAB converter's time-series performance across different modulation parameters. It plays a crucial role in overcoming the limitations of the original LLM agent in processing PE-specific data.
- **Workflow 2: Simulation Verification.** As engineers and researchers often verify their PE designs using simulation tools, Workflow 2 offers an easy integration of design outcomes into existing simulations. The simulation repository includes relevant tools for PE design, such as Simulink, PLECS, and PSIM for circuit simulation, and COMSOL, ANSYS, and SIMSCALE for multi-physics simulation. Upon the user's request for simulation

verification, the appropriate simulation tool is initialized, and the design outcome is passed to the simulation model for one-click verification.

- **Workflow 3: Fine-Tuning.** The design outcome is greatly influenced by the model accuracy in Model Zoo. To address discrepancies between model outputs and practical results, PE-GPT offers a mechanism for further fine-tuning the data-driven models in Model Zoo. When the user provides fine-tuning data, such as time-series waveform data or tabular performance data, Workflow 3 is activated to fine-tune the neural connections within the data-driven models.

B. Retrieval Augmented Generation (RAG)

a) Why RAG

LLM agents such as GPT-4 and Llama have been pretrained on vast and general corpora. The pretraining equips them with rich general domain knowledge. However, it also inherently limits their depth in specific domain expertise.

The analysis in Section II explores three techniques: prompt engineering, RAG, and model fine-tuning. Among these, PE-GPT notably leverages RAG to tailor LLM for PE-specific applications. RAG effectively bridges the knowledge gap of LLMs through retrieving relevant excerpts from external knowledge bases. It notably enhances PE-GPT's response performance in two key ways:

- **Accuracy and Relevancy:** PE-specific applications demand a high degree of technical details. A knowledge base comprising technical documents, such as academic literatures, compensates for LLMs' limitations in domain-specific expertise, thereby enhancing the accuracy and relevancy of PE-GPT's outputs.
- **Customizability and Generalization:** In PE design, tasks can significantly diverge in technical specifics. For instance, PE-GPTs designed for converter modulation might require different expertise than those aimed at converter circuit design. Through access to varied knowledge bases, RAG ensures both customizability and generalization for diverse applications.

b) RAG Workflow

Fig. 2, outlined by the green dotted part, illustrates the comprehensive workflow of RAG, which includes three critical steps: chunking, embedding, and retrieval.

- 1) **Chunking:** As an initial preprocessing step, the existing knowledge database, comprising academic literature and industrial documents, is segmented into discrete, smaller units through a process known as "chunking."
- 2) **Embedding:** Both the chunks from the knowledge base and the text query are transformed into vector representations during the embedding process, with these vectors subsequently stored in a vector database. As formulated in (2), A denotes the embedded vector of the text query, and B_i is the vector representation of the i^{th} chunk.
- 3) **Retrieval:** The retriever calculates the similarity score $similarity_i$ between the query vector A and the vectorized chunks B_i , as given in (3). Based on the similarity search results, the most pertinent chunks are identified, retrieved, and integrated with the text query to formulate a

synthesized prompt. This enriched query then serves as the basis for the LLM agent to generate a PE-aware response.

$$A = \text{Embed}(query), B_i = \text{Embed}(chunk_i) \quad (2)$$

$$similarity_i = \frac{A \cdot B_i}{\|A\| \|B_i\|} \quad (3)$$

Within the RAG workflow, there are 2 important hyperparameters to tune to optimize the effectiveness and efficiency of RAG for the PE-specific knowledge base: one is chunk size that determines the maximum number of characters that a chunk contains, and another one is top-k that refers to the number of top results retrieved after similarity search.

C. Model Zoo and the Adopted PANN Model Inside

a) Model Zoo

As elaborated in PE-GPT Workflow 1, the role of the Model Zoo is function evaluation, upon which the metaheuristic algorithm iterates until the optimal design outcome is found.

Model Zoo consists of three types of models: white-box models, black-box models and gray-box models. Both black-box models and gray-box models are open for finetuning with new data from the user.

- **White-Box Models:** These are theoretically closed-form analytical formulas for the evaluated objective.
- **Black-Box Models:** These are pure AI-based data-driven models built on statistical information from the data [13].
- **Gray-Box Models:** These models combine partial theoretical structures with partial data-driven structures, such as Physics-Informed Neural Networks (PINNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [14].

The integration of Model Zoo in Workflow 1 facilitates adaptability to various PE design tasks. Given the limited scope of this research paper, we highlight the use of PANN, an emerging PINN method, as a detailed example in Model Zoo. In the long term, the diversity of models in the Model Zoo will require collective contributions from the entire PE community.

b) PANN Model

PANN, featuring a bespoke recurrent neural architecture designed to integrate circuit physics, plays pivotal roles in evaluating diverse performance metrics, such as current stress, soft switching conditions, circulating current, etc. Its lightweight and explainable advantages of PANN foster prompt and flexible design of PE devices [15].

Inspired by neural ordinary differential equations, PANN uses numerical differentiation algorithms to customize its recurrent architecture, effectively characterizing the general form of circuit physics, as shown in (4). $x(t)$ and $u(t)$ represent state and input variables, while $g(u(t); \theta)$ and $h(u(t); \theta)$ are their respective behavioral functions, and θ symbolizes the circuit parameters.

$$\frac{\partial}{\partial t} x(t) = g(u(t); \theta) x(t) + h(u(t); \theta) \quad (4)$$

For the typical topology of DAB converters, the customized architecture of PANN is shown in Fig. 3. It embeds the physics of inductor current i_L using an implicit Euler algorithm, as formulated in (5), where Δt_{k+1} is the time interval, i_L is the state

variable being modeled, v_p and v_s are input variables, and the parameters θ include L , R_L and n . PANN predicts the subsequent state $i_L(t_{k+1})$ based on the present state $i_L(t_k)$ and inputs $v_p(t_{k+1})$ and $v_s(t_{k+1})$, whose prediction process is recurrently implemented for a switching period T_s as necessitated by performance evaluation.

$$i_L(t_{k+1}) = \frac{L i_L(t_k) + (v_p(t_{k+1}) - n v_s(t_{k+1})) \Delta t_{k+1}}{L + R_L \Delta t_{k+1}} \quad (5)$$

The interaction between Model Zoo and other constituents of the PE-GPT suite is outlined. In Workflow 1, upon receiving a design request from the LLM agent, a metaheuristic algorithm is triggered. As evident in Fig. 3, candidate modulation parameters are delivered to the selected model in Model Zoo, namely PANN, for performance evaluation during each evolutionary iteration, consisting of three steps: First, inputs v_p and v_s are generated based on the domain knowledge inherent in the suggested modulation, where D_0, D_1, D_2 are phase shift angles, and ϕ_1, ϕ_2 indicate adjustable duty cycles; Second, the PANN model recurrently predicts the inductor current i_L ; Third, diverse performance metrics are assessed with v_p, v_s , and the predicted i_L in the time domain. For instance, current stress i_{pp} is evaluated by the difference between the maximum and minimum of i_L . Soft switching performance is assessed by judging the directions and values of inductor current at each switching instant. The assessed performances are used to compute objective function values which guide the metaheuristic algorithm in the evolving process.

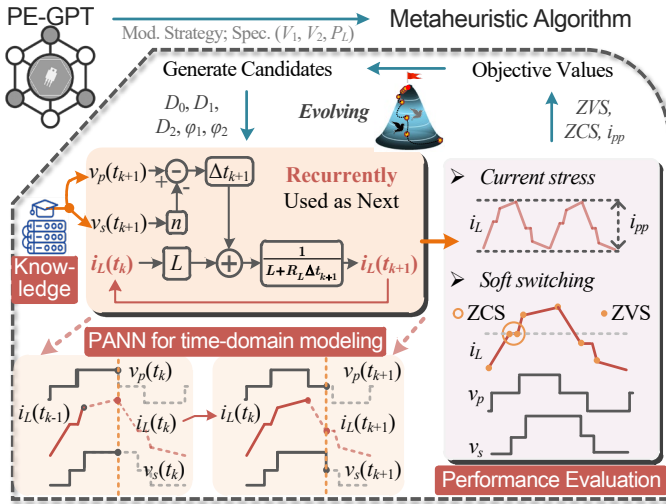


Fig. 3. PANN for the function evaluation of metaheuristic algorithm.

Other than textual requests from users, the proposed PE-GPT receives time-series data to fine-tune Model Zoo, exhibiting multimodal processing competency. The provided time-series data is divided into three datasets for the training of PANN, selection of hyperparameters, and test of generalization capability. Feeding the training data into the computational graph in Fig. 3, the mean-squared error MSE between the ground truth i_L^* and the predicted i_L in (6) is back-propagated to fine-tune circuit parameters θ , where N_T is the sequence length of the provided time-series data.

$$\min_{\theta} MSE(i_L^*, i_L; \theta) = \min_{\theta} \frac{1}{N_T} \sum_{k=1}^{N_T} (i_L^*(t_k) - i_L(t_k; \theta))^2 \quad (6)$$

D. Discussion on the Generalization of PE-GPT

a) RAG Enhances Generalization

RAG significantly enhances the generalization of PE-GPT by creating a flexible and customizable knowledge base. The flexibility allows users to tailor the knowledge base as per specific requirements or objectives, incorporating diverse types of text-based resources such as academic literature, industrial documents, customized case studies or other documents encapsulating domain expertise and experience. A regular update routine to the RAG will also be helpful for capturing up-to-date information.

b) Model Zoo Enhances Generalization

The integration of the Model Zoo in Workflow 1 enhances PE-GPT's generalization. Different design cases in Workflow 1 have various objective functions to evaluate when calling the metaheuristic algorithm. And Model Zoo is a repository of different models, providing flexibility in selecting the relevant model for function evaluation. Admittedly, building a comprehensive Model Zoo for PE-GPT is a long-term and collaborative commitment and the authors aim to inspire more researchers in the PE community to join this campaign.

Moreover, some gray-box models in the Model Zoo also enable stronger generalization capability. Taking the adopted PANN as an example, for the case of modulation parameter design, PANN is trained to learn and predict the time-series performance for different modulation parameter selections. Thanks to its "training free" domain transfer capability, a trained PANN model can be seamlessly transferred to various PE topology variants through physics-guided deformation of its neural architecture, while accommodating diverse operating conditions through the direct assignment of priori domain knowledge [15], [16].

IV. DESIGN CASE I: MODULATION DESIGN

A. Design Case I Background: the DAB Converter and Modulation Strategies

The DAB converter is taken as a design case to validate the proposed methodology of PE-GPT. The bidirectional isolated DC-DC converter is commonly adopted in the solid-state transformer, energy storage systems, electric vehicles, and more [17]. As depicted in Fig. 4, it is composed of two full bridges, a high-frequency transformer providing galvanic isolation, and a leakage inductor L .

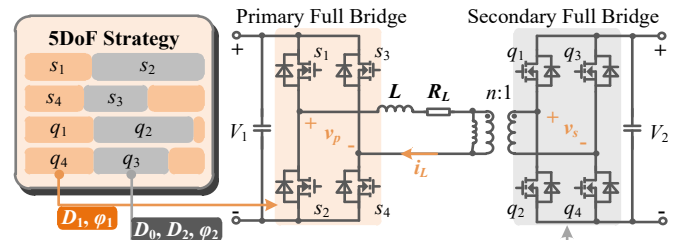


Fig. 4. The DAB converter and its 5DoF modulation scheme.

To regulate the power transfer, modulation scheme of a DAB converter determines how the switches of two full bridges are controlled. There are five common modulation schemes: single

phase shift (SPS), double phase shift (DPS), extended phase shift (EPS), triple phase shift (TPS) [18] and five DoF modulation schemes (5DoF) [19]. The adopted 5DoF scheme features an outer phase shift D_0 , two inner phase shifts D_1 , D_2 , and two duty cycles ϕ_1 , ϕ_2 , which is simplified to phase shift strategies if primary and secondary duty cycles are fixed at 50%.

For professionals to design modulation strategies and parameters, the paramount factors steering the design process encompass the complexity of modulation implementation and the critical performance metrics of the converter. These metrics include current stress, zero voltage switching range, zero current switching range, reactive power, efficiency, etc. [20].

B. Design Case I Specifications

TABLE I. DESIGN CASE I SPECIFICATIONS AND HARDWARE SETUPS

OPERATING CONDITIONS OF THE DESIGN CASE I			
Input voltage V_1	200 V	Output voltage V_2	[160 V, 240 V]
Rated power P_{rated}	1 kW	Switching frequency f_s	50 kHz
SETTINGS OF HARDWARE PROTOTYPE			
Semiconductors	Wolfspeed SiC C2M0080120D		
Transformer	Nanocrystalline ribbon 1K107B; Turn ratio $n = 1$; Leakage inductance $L = 64.6 \mu\text{H}$; $R_L = 1.9 \Omega$		
Oscilloscope	Lecroy HDO8058a	Controller	DS1202 platform
CONFIGURATIONS OF PE-GPT			
LLM	LLM model: GPT-4-0125; temperature = 0.1; RAG hyperparameters: chunk size = 512, top-k = 7; RAG knowledge base: Research articles about modulation design		
PANN	Train-validation-test partition: 5, 100, 100 samples; In-domain cases: 160 V; Out-of-domain cases: 200 V and 240 V; $N_T = 250$; Time interval $\Delta t_k = 80 \text{ ns}$; $\theta = \{L; R_L; n\}$		

The operating conditions for the design case are shown in Table I. The prototype built for data collection and hardware validation is shown in Fig. 5, where a DS1202 MicroLabBox is

used as the control platform, and a Lecroy HDO8058a oscilloscope captures the time-series waveforms at 25 MS/s.

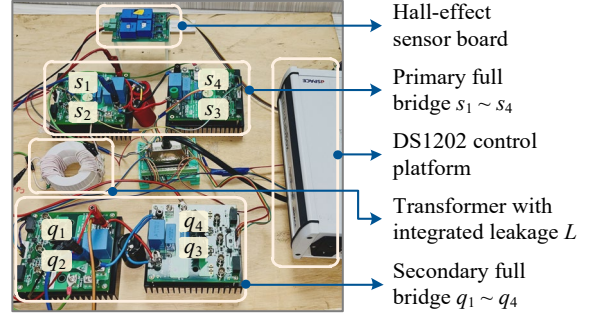


Fig. 5. Hardware prototype.

C. Design Case I Breakdown and Analysis on the Competencies of PE-GPT

A design case study is presented, illustrating an iterative design approach for developing the modulation strategy of the DAB converter. The performance requirements outlined in this case are current stress and soft switching. Table II provides an analysis of a specific dialogue excerpt between the user and PE-GPT, with the full interaction available for reference online¹. The capability of PE-GPT has been divided into three types: adaptive semantic understanding (ASU), PE-specific knowledge and reasoning (PE-KR), multimodal processing (MMP).

The case study covers both Workflow 1 and Workflow 3, and unfolds across four key conversational stages:

- 1) *Initial modulation strategy recommendations* (ID 1 and 2): PE-GPT initiates the process by suggesting a modulation strategy tailored to the operational requirements.
- 2) *Design of modulation parameters and performance analysis*

TABLE II. DESIGN CASE I DIALOGUE EXCERPT: MODULATION DESIGN (Video demo¹)

ID	User's Textual Input	PE-GPT's Response	Capability and Workflow (WF)
1	INITIALIZE DESIGN PROCESS: Hi, can you help me design the modulation strategy for my dual active bridge converter?	Of course, I'd be happy to assist (...) If there are any particular performance indicators or constraints you're aiming for, such as efficiency, thermal performance, control complexity, or ease of implementation, please let me know. Your detailed requirements will help me provide you with the most suitable modulation strategy.	➤ PE-KR
2	DEFINE DESIGN REQUIREMENTS Can you recommend a phase shift modulation for a lowest inductor current for the full operating range?	(...), I would recommend the Triple Phase Shift (TPS) modulation method. The TPS method is effective in reducing the current stress on the inductor by allowing independent control of the phase shifts between the primary and secondary sides of the converter, as well as between the active bridges. This can lead to a reduction in the RMS current, which in turn minimizes the current stress on the inductor. To further refine the recommendation and (...), could you please provide the following operating conditions (...)	➤ PE-KR
3	PROVIDE OPERATING CONDITIONS: The operating conditions are $V_1 = 200 \text{ V}$, $V_2 = 160 \text{ V}$, $P_{rated}=1000 \text{ W}$	Under the TPS modulation strategy, the optimal D_1 is (...), the number of switches that achieve zero-voltage turn-on is 8. (...) At rated power level ($P_{rated} = 1000 \text{ W}$), the peak-to-peak current is 19.05 A. Under light load conditions ($P_L = 300 \text{ W}$), (...) Under the SPS modulation strategy, the number of switches that achieve zero-voltage turn-on is (...). Under light load conditions ($P_L = 300 \text{ W}$), (...) The performance of current TPS modulation far exceeds that of conventional SPS.	➤ MMP ➤ PE-KR ○ WF1
4	PROVIDE FEEDBACK FOR ITERATIVE DESIGN But I think the soft switching range cannot satisfy my application in TPS.	If the soft-switching range provided by the TPS modulation strategy does not meet the requirements of your application, I recommend considering the Five-Degree-of-Freedom (5DoF) modulation scheme. The 5DoF modulation scheme is not a phase shift modulation method, but it offers superior performance in terms of soft-switching range. The 5DoF modulation scheme provides enhanced control over the converter by independently adjusting five different parameters: (...). This level of control allows for an expanded ZVS and ZCS ranges, which can significantly improve efficiency, especially under varying load conditions. (...)	➤ ASU ➤ PE-KR
5	CONFIRM MODULATION STRATEGY OK, let us go ahead with 5DoF in the same operating conditions.	Under the 5DoF modulation strategy, the optimal D_1 is (...), ϕ_1 is designed to be (...), the number of switches that achieve zero-voltage turn-on is (...). At rated power level ($P_{rated}=1000 \text{ W}$), the peak-to-peak current is 18.69 A. Under light load conditions ($P_L = 300 \text{ W}$), (...)	➤ MMP ○ WF1
6	ASK FOR MODEL FINE-TUNING Now I have some experimental data. Can you help improve the design accuracy?	Absolutely, I can assist you with improving the design accuracy using your experimental data. Please upload three CSV files containing the following waveforms. (...)	➤ MMP ○ WF3

■ **ASU**: Adaptive Semantic Understanding; **PE-KR**: PE-Specific Knowledge and Reasoning; **MMP**: Multimodal Processing; **WF1**: Design with Model Zoo; **WF3**: Fine-tuning.

(ID 3): PE-GPT proceeds to design modulation parameters through metaheuristic algorithm based on specified operational specifications and conducts a thorough performance analysis.

- 3) *Adaptation to user feedback and redesign* (ID 4 and 5): PE-GPT flexibly adjusts its approach in response to user feedback, iteratively refining the modulation strategy.
- 4) *Model fine-tuning* (ID 6): Lastly, PE-GPT enhances its function evaluation accuracy by incorporating the user's experimental data, which is Workflow 3 as denoted in Fig. 2.

The unique competencies of the proposed multimodal PE-GPT are analyzed as follows:

a) Adaptive Semantic Understanding (ASU)

Building upon the linguistic capability inherited from GPT-4, PE-GPT's capabilities are further enhanced through RAG technique. As demonstrated in Table II, PE-GPT effectively interprets and adapts to the user's specific requirements and feedback regarding operational performance.

b) PE-Specific Knowledge and Reasoning (PE-KR)

PE-GPT exhibits strong domain expertise by recommending optimal modulation strategies tailored to user requirements and providing thorough analyses. This capability showcases the model's advanced reasoning within the PE field.

c) Multimodal Processing (MMP)

Integration with PANN in Model Zoo allows PE-GPT to analyze the time-series performance of the design outcomes. Additionally, it can incorporate experimental time-series data provided by users to refine and enhance model accuracy.

D. Fine-Tuning of PANN Model

Multimodality is a convincing feature that distinguishes the proposed PE-GPT from the original GPT framework. Upon receiving time-series waveforms acquired from hardware experiments and the fine-tuning query from user's textual inputs, Workflow 3 will be initiated, and the PANN model will be fine-tuned to reduce the loss in (6), bridging the gap between the modeling of inductor current i_L and experimental measurements i_L^* .

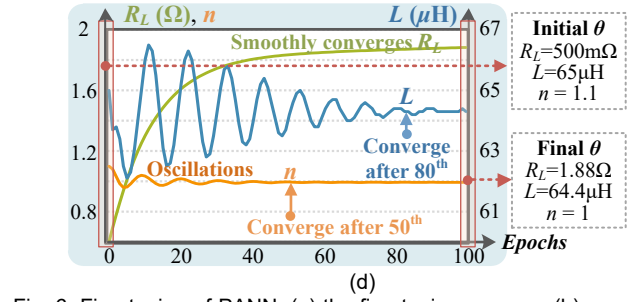
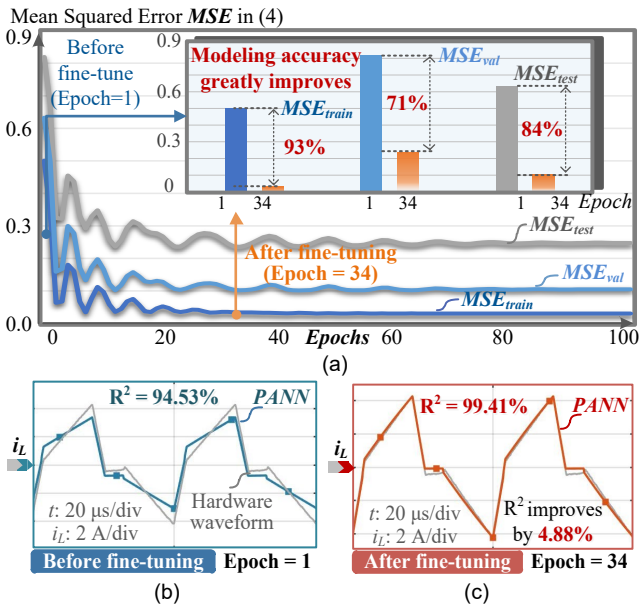


Fig. 6. Fine-tuning of PANN: (a) the fine-tuning process; (b) exemplary waveforms before fine-tuning; (c) waveforms after fine-tuning; (d) trajectory of parameter variations during fine-tuning.

The fine-tuning procedure is shown in Fig. 6 (a), which reduces the test mean square error (MSE_{test}) by 84%. Exemplary waveforms of the 5DoF modulation strategy are provided to justify the modeling accuracy, as shown in Fig. 6 (b) and (c), where $V_2 = 160$ V and $P_L = 300$ W. After the fine-tuning process, the coefficient of determination R^2 is refined by 4.88%. The trajectory of parameter variations during fine-tuning is disclosed in Fig. 6 (d), where under the learning rates of $5e^{-6}$ for L and $1e^{-1}$ for n and R_L , the estimations for L and n oscillate and gradually stabilize until convergence, whereas that for R_L smoothly converges.

Additionally, the time-domain modeling accuracy of various data-driven models is comparatively studied in Fig. 7. Long-short-term-memory (LSTM) net, temporal convolutional net (TCN), time-series transformer (TST), and PINN [21] are benchmarked. Trained on a purposefully biased and incomplete dataset with 5 time-series samples, PANN advances the latest TST and PINN models by 84% and 81.9% in in-domain cases. When extrapolating to out-of-domain cases, PANN outperforms the latest PINN by 37.3%. Notably, PANN demonstrates the highest robustness, with negligible accuracy variations over 10 algorithm repetitions.

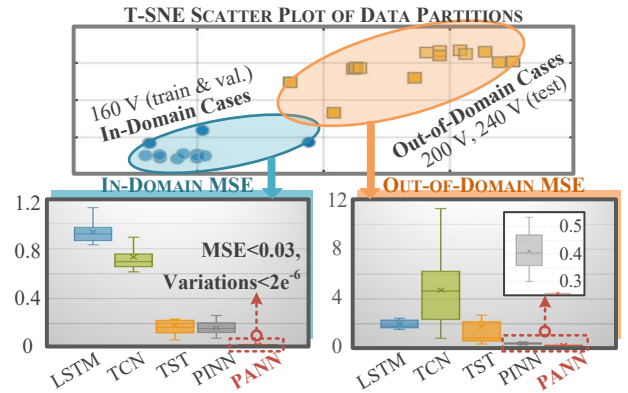


Fig. 7. MSEs of diverse data-driven models (repeated for 10 times) in in-domain (160 V) and out-of-domain (200 V and 240 V) cases.

E. Hyperparameters of RAG

In PE-GPT, hyperparameters of RAG need to be finely adjusted to efficaciously balance between the information precision and the query efficiency for the PE-specific domain knowledge. Performances of PE-GPT with respect to diverse chunk size and top-k are depicted in Fig. 8, including hit rate (HR), mean reciprocal rank (MRR), response speed (RS), faithfulness (FF), and relevancy (Rel). These five evaluators comprehensively describe diverse aspects of PE-GPT: HR

evaluates precision in retrieving related responses, MRR ranks the correct answers, RS measures the response generation speed, FF denotes the extent to truthfully reflect the PE knowledge base, and Rel reflects the relevancy between the response contexts and the user's queries.

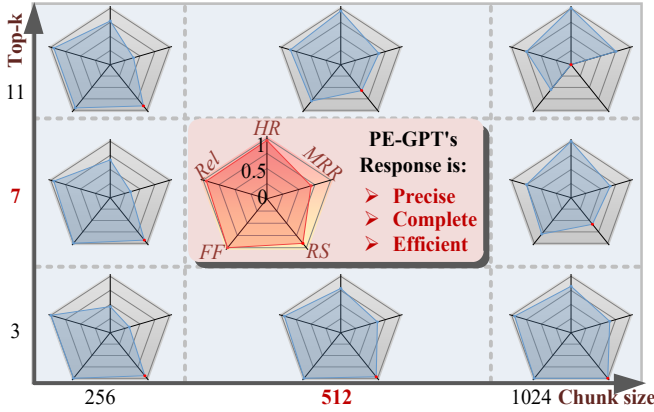


Fig. 8. Fine-tuning the hyperparameters of RAG (higher metrics indicating better performance), and RS and MRR are normalized to unit scale.

The finely tuned chunk size and top-k for RAG are 512 and 7, respectively, contributing to response completeness, balanced information granularity, and prompt retrieval. HR, FF, and Rel are close to 1, while a high MRR and fast response speed have been realized, demonstrating the optimal comprehensive performances. Other hyperparameter combinations either sacrifice their hit rate and MRR or compromise the response speed.

V. DESIGN CASE II: CIRCUIT PARAMETER DESIGN

A. Design Case II Specifications

Given the specifications in Table III, Design Case II presents a design process of circuit parameters for the buck converter using PE-GPT. It includes the design of the inductance L_f and

capacitance C_f of the output LC filter, with design requirements on ripple constraints and high power density.

TABLE III. DESIGN CASE II SPECIFICATIONS			
OPERATING CONDITIONS OF THE DESIGN CASE II			
Input voltage V_1	200 V	Output voltage V_2	[20 V, 180 V]
Rated power P_{rated}	1 kW	Switching frequency f_s	50 kHz
Current ripple i_{ripple}	20%	Voltage ripple v_{ripple}	0.5%
CONFIGURATIONS OF PE-GPT			
LLM	RAG knowledge base: Research articles about buck converter design		
PANN	$N_T = 250$; Time interval $\Delta t_k = 80$ ns; $\theta = \{L_f, C_f\}$.		

B. Design Case II Breakdown and Analysis

Design Case II covers both Workflow 1 and Workflow 2, and unfolds across three key conversational stages, as the dialogue excerpt presented in Table IV and available online²:

- 1) *Circuit Parameter Design* (ID 1-3): PE-GPT understands the user's request, guides the user to specify the design requirements and initializes Workflow 1 to find the optimal circuit parameters.
- 2) *Rationale Analysis* (ID 4-5): PE-GPT explains the rationale behind the recommended design with PE-specific knowledge.
- 3) *Simulation Verification* (ID 6): With the user's request to verify the design, PE-GPT initiates Workflow 2, starting PLECS for circuit simulation and passing the design parameters into the simulation.

Similar to Design Case I, PE-GPT exhibits unique competences in this case. It understands users' design requirements (*ASU*), automates the optimal design process (*MMP*) and provides professional rationale for the design outcome (*PE-KR*).

C. Design Outcomes Analysis

The L_f and C_f designed for the buck converter via PE-GPT are 482.7 μ H and 12.5 μ F, respectively. As shown in Fig. 9, i_L

TABLE IV. DESIGN CASE II DIALOGUE EXCERPT: CIRCUIT PARAMETER DESIGN (Video demo¹)

ID	User's Textual Input	PE-GPT's Response	Capability and Workflow (WF)
1	INITIALIZE DESIGN PROCESS: I want to design the output LC filter for a Buck converter. Can you help me?	Absolutely, I'd be glad to help with (...) To get started, could you share with me the specific design objectives and requirements for your converter? For example, are you focusing on minimizing ripple, maximizing efficiency, or optimizing for power density? Any details you provide will help me tailor my assistance to best meet your needs.	➤ PE-KR
2	DEFINE DESIGN REQUIREMENTS Yes, I have two design requirements. Firstly, the output voltage ripple and inductor current ripple should be limited. Secondly, high power density is expected.	Great, (...). To provide you with the best guidance, could you please share the following details: 1. The output voltage ripple constraint (%) 2. (...)	➤ ASU
3	PROVIDE OPERATING CONDITIONS: Voltage ripple constraint is 0.5%, and current ripple constraint is 20%. And operating conditions are as follows: switching frequency is 50 kHz; input voltage is 200V; output voltage is 80V; output power is 800W.	Well received. (...) The optimal inductance L is designed to be 482.7 μ H, and the optimal capacitance C is designed to be 12.51 μ F. The output voltage ripple and inductor current ripple are 0.398 V (0.50%) and 1.992 A (19.92%), respectively. The output waveform of the inductor current in steady state under this operating condition is shown in the following figure: (...)	➤ MMP ○ WF1
4	ASK FOR RATIONALE What is the rationale behind this design?	(...) Output Voltage Ripple Constraint: Minimizing the output voltage ripple is critical for stable load operation. A smaller output ripple requires an adequately sized capacitor, which directly influences the quality of the DC output. Inductor Current Ripple Constraint: Controlling the inductor current ripple is essential for efficient energy transfer and minimizing losses. It also impacts the inductor size—lower ripple percentages typically require larger inductors. (...)	➤ PE-KR
5	ASK FOR FURTHER ANALYSIS Can you analyze the harmonic components of the inductor current and the capacitor voltage?	The harmonics of inductor current are 10.0 A (DC), 0.8 A (1st), 0.123 A (2nd), 0.0549 A (3rd)... The harmonics of output voltage are 80.0 V (DC), 0.204 V (1st), 0.0157 V (2nd), 0.00466 V (3rd)...	➤ MMP
6	ASK FOR SIMULATION VERIFICATION The design sounds reasonable. Can we verify this design in PLECS?	Waiting... PLECS is starting up... The PLECS simulation is running... Complete! (...)	○ WF2

¹ [ASU](#): Adaptive Semantic Understanding; [PE-KR](#): PE-Specific Knowledge and Reasoning; [MMP](#): Multimodal Processing; [WF1](#): Design with Model Zoo; [WF2](#): Simulation Verification.

and v_o predicted by PANN closely align with the PLECS simulation results with MSE of only $2.9e^{-3}$ and $3.02e^{-4}$, respectively.

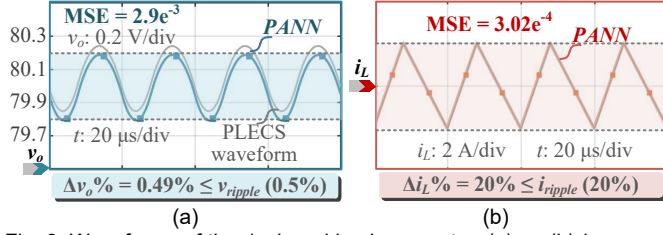


Fig. 9. Waveforms of the designed buck converter: (a) v_o ; (b) i_L .

Based on the design rationale analysis, larger inductor and capacitor values provide better ripple limitation performance but result in lower power density. The design outcome demonstrates that PE-GPT understands the trade-off between these design objectives. It presents a reasonable design that meets the ripple constraints without requiring an oversized filter for the buck converter.

VI. HARDWARE VALIDATION

Experiments have been conducted to verify the effectiveness of Design Case I in two aspects: PE domain comprehension, and the performance of the DAB modulation design case.

A. Validation for PE Domain Comprehension: Benchmark with Human Experts and State-of-the-Art (SOTA) LLMs

Apart from the linguistic capability justified in Section IV-C, 32 user requests targeting at various converter performances are meticulously prepared, acting as composite recommendation tasks to validate the capability to comprehend PE domain knowledge.

As benchmarks, we have invited 5 human experts with 1~10 years of experience to recommend suitable modulation strategies based on the requests individually, which is to verify the usefulness of PE-GPT for both newbies and experienced engineers. Additionally, SOTA LLMs, incorporating ChatGPT (2022), GPT-4 (2023) [4], Llama-2-13b (2023) [5], Gemini (2024) [6], Claude 3 Sonnet (2024) [19] are compared to verify the superior PE domain comprehension of PE-GPT. For LLMs, each request is repeated 10 times, and the average accuracy and consistency are computed. The reference answers are formulated by a group of domain experts.

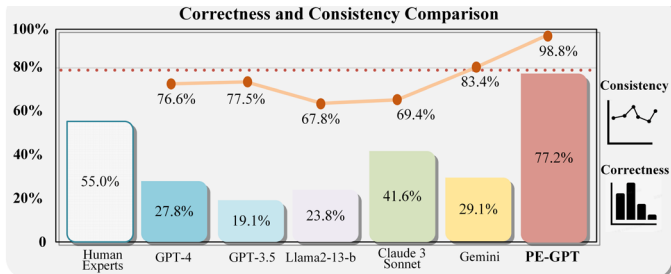


Fig. 10. Comparisons among human experts, SOTA LLMs, and PE-GPT.

As summarized in Fig. 10, the proposed PE-GPT attains an average correctness of 77.2%, which substantially outperforms experienced human experts by 22.2%. Besides, PE-GPT surpasses the best benchmarked LLM, Claude 3 Sonnet, by

35.6%. Moreover, although being derived from GPT-4, the PE-specific RAG of PE-GPT greatly enhances its recommendation accuracy by 49.4%. From the perspective of consistency, the benchmarked LLMs cannot generate outputs coherently, suffering from hallucination. In contrast, the proposed PE-GPT addresses LLM's hallucination by the PE-tailored RAG. Furthermore, as evident in Table II, PE-GPT has generated structured, rational, and comprehensive explanations to support its recommendation, manifesting great reasoning capability.

B. Validation for the 5DoF Design Case: Steady-State Waveforms and Performance Analysis

a) Steady-State Waveforms

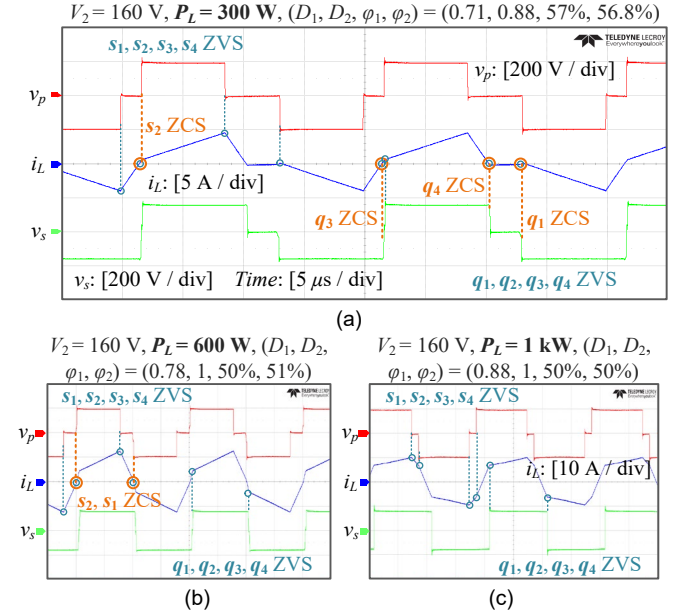


Fig. 11. v_p , v_s , and i_L when $V_2 = 160$ V and: (a) 300 W; (b) 600 W; (c) 1 kW.

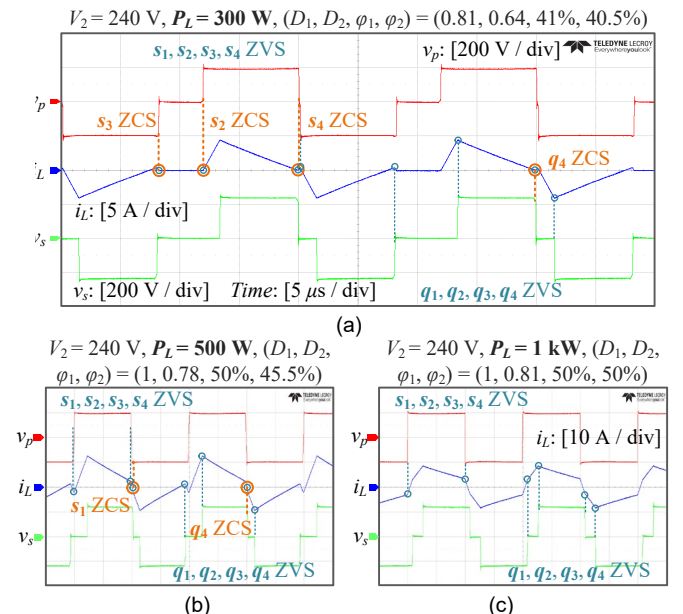


Fig. 12. v_p , v_s , and i_L when $V_2 = 240$ V and: (a) 300 W; (b) 500 W; (c) 1 kW.

The design cases of the 5DoF modulation strategy discussed in Section IV are verified in hardware experiments for the sake of demonstrating the multimodal capability of the proposed PE-

GPT. The 5DoF design cases are validated from two main dimensions: steady-state waveforms and performance analysis.

v_p , v_s , and i_L waveforms of voltage step-down scenarios ($V_2 = 160$ V) are shown in Fig. 11. For the soft-switching-optimized 5DoF strategy, all 8 switches have met zero voltage switching (ZVS). Meanwhile, when $P_L = 300$ W, s_2 , q_1 , q_3 , and q_4 have realized zero current switching (ZCS), and when $P_L = 600$ W, s_1 and s_2 have achieved ZCS. Under light-load conditions $P_L = 300$ W, the zero-voltage plateau of v_s is aggregated to its right side by applying a wider duty cycle to q_1 (56.8%).

Voltage step-up waveforms ($V_2 = 240$ V) are depicted in Fig. 12. Similarly, across the entire operating conditions, all-switch ZVS has been attained, while ZCS ranges are expanded for light and medium loads. Under $P_L = 300$ W, s_2 , s_3 , s_4 , and q_4 , and when $P_L = 500$ W, s_1 and q_4 have satisfied ZCS. By assigning a wider duty cycle to s_2 (59%), the zero-voltage plateau of v_p under $P_L = 300$ W is shifted to its left side, achieving wider ZCS ranges.

b) Detailed Performance Analysis

Diverse performances of the designed 5DoF strategy, including the current stress i_{pp} , efficiency η , and soft switching conditions, are evaluated and compared with current-stress-optimized TPS (CSO-TPS) and SPS. Performance comparison results are provided in Fig. 13 and Fig. 14.

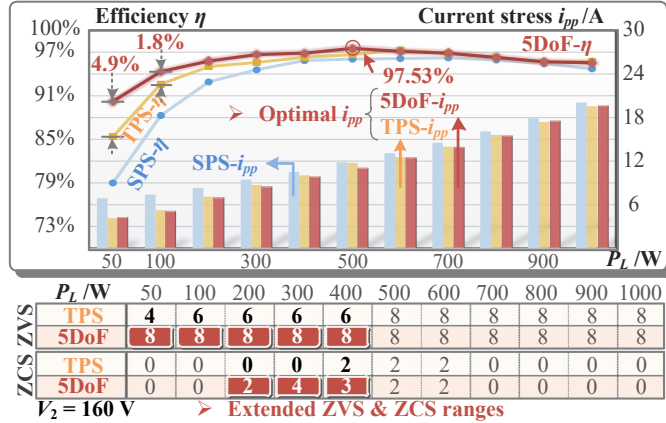


Fig. 13. i_{pp} , efficiency η , ZVS, and ZCS performances of the SPS, CSO-TPS, and the designed 5DoF strategy via PE-GPT under $V_2 = 160$ V.

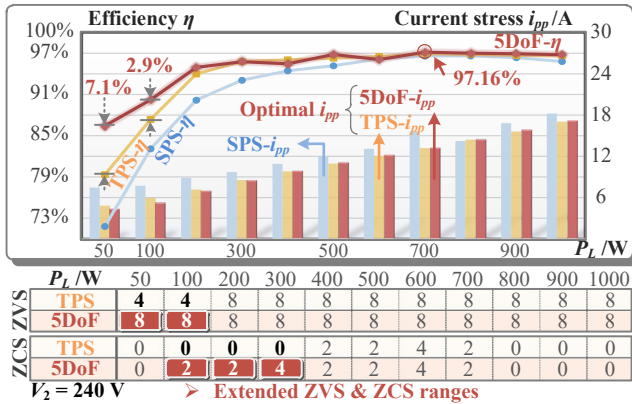


Fig. 14. i_{pp} , efficiency η , ZVS, and ZCS performances of the SPS, CSO-TPS, and the designed 5DoF strategy via PE-GPT under $V_2 = 240$ V.

Generally, efficiency η enhancements of the designed 5DoF are more considerable in light-load conditions $P_L \leq 500$ W,

while i_{pp} of 5DoF and TPS are comparable across all load levels. Under voltage step-down scenarios when V_2 is 160 V, the 5DoF design cases enhance efficiency of CSO-TPS by 4.9%, 1.8%, and 0.8% for 50 W, 100 W, and 200 W, respectively, by virtue of their optimized soft switching ranges. The CSO-TPS strategy compromises its ZVS and ZCS for the pursuit of low i_{pp} , with 4 switches realizing ZVS for 50 W, and 6 switches operating at ZVS under other light loads. In comparison, the 5DoF strategy attains all-switch ZVS and extends its ZCS ranges within [100 W, 600 W], as the 4-switch ZCS under 300 W and 2-switch ZCS under 600 W shown in Fig. 11. In terms of voltage step-up conditions when V_2 is 240 V, the efficiency of the designed 5DoF surpasses that of CSO-TPS by 7.1%, 2.9%, and 0.94% for 50 W, 100 W, and 200 W, respectively, and the ZCS ranges within [100 W, 300 W] are extended to 2, 2, 4 switches.

The analysis above has validated that the design output of PE-GPT delivers optimal performance in meeting the user's requirements in the design case.

VII. DISCUSSIONS

A. Extending Across the PE Design Workflow

The hybrid framework of PE-GPT enables flexibility and generalization beyond the DAB converter modulation design case and the buck converter circuit parameter design. It can be tailored for applications across the entire PE design workflow, as illustrated in Fig. 15.

The customization of PE-GPT extends across various stages separately or coordinately, including topology design, component selection, circuit parameter design, modulation and control design, thermal management, electromagnetic interference (EMI) and electromagnetic compatibility (EMC) considerations, prototyping (PCB and mechanical structure design, etc.) and documentation. Implementing the methodology outlined in Section III, the effective customization of PE-GPT necessitates the provision of knowledge base for RAG, and enriching of Model Zoo to forecast design objectives pertinent to the corresponding design cases.

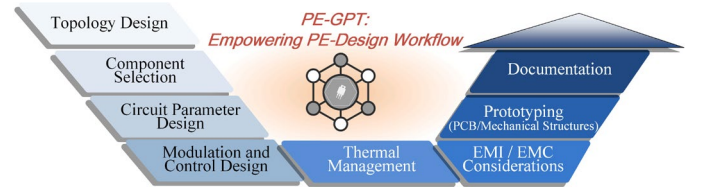


Fig. 15. Potential applications of PE-GPT in PE design workflow.

B. AI Ethics of PE-GPT

With the intention of “AI for Good”, it is crucial to understand the potential ethical risks of PE-GPT and some preventive measures stakeholders could take.

a) **Privacy and Security:** Privacy concern covers not only the confidentiality of uploaded data for model finetuning or proprietary information in RAG, but also the design outcome for the user-specified design cases. Cyber-attacks, such as data poisoning or manipulation of model parameters, pose significant threats by potentially skewing the PE-GPT's functionality. Therefore, privacy regulations, robust encryption techniques and continuous cybersecurity

monitoring and defense should be adopted.

- b) **Bias and Fairness:** Bias in model will generate design outputs which deviate from the true value. For example, if to design a magnetic component and the information of RAG over-represents a certain type of ferrite core, the model might unintentionally favor this core in the design. Fairness refers to the absence of favoritism towards any of the stakeholders [22]. For instance, an unfair PE-GPT might be exploited to repeatedly recommend switching devices from a single brand, disregarding other equally viable options. To mitigate bias and unfairness, diverse data, bias-aware algorithms and user-feedback mechanism and regular third-party audit are helpful.
- c) **Transparency and Accountability:** Transparency in how design decisions are made by PE-GPT will enhance trust and industry acceptance, especially in risk-averse applications like aerospace or electric aircraft [23]. And the accountability mechanism should be held in place in case mistakes or unintended consequences occur, ensuring that responsible stakeholder throughout the whole workflow, including data collection, algorithm design, PE design and production, are held accountable and corrective actions can be taken promptly.
- d) **Impact on Employment and Skills:** To the authors' intention, PE-GPT is aimed to assist PE engineers and researchers and accelerate the growth of the industry. PE-GPT frees the PE designers from the repetitive, standard or computational-heavy tasks so that the concept to production cycle could be boosted exponentially. It is predictable that some of the low-skilled engineering roles will be disrupted with this new transformation, whereas senior engineers will still be needed to evaluate designs and make final decisions [24]. In the long run, more job opportunities will emerge in the interdisciplinary sector of PE and AI. Consequently, upskilling and reskilling education programs are crucial in PE education to embrace the changes brought by AI.
- e) **Ethical Use:** It is important to define the intended and unintended uses of PE-GPT to ensure it operates safely within ethical and legal boundaries. Technologies like AI guardrails [25] and well-established government regulations and compliance measures are vital to addressing this concern.

VIII. CONCLUSION

This research introduces PE-GPT, the first multimodal large language model (LLM) specifically designed for power electronics (PE) design. What impedes the adoption of LLMs in the industry of power electronics mainly includes their limited technical expertise and incapability to process PE-specific data. **To address these challenges, PE-GPT is enhanced by retrieval augmented generation (RAG) with customized PE knowledge base, which empowers PE-GPT with PE-specific knowledge and reasoning. Moreover, we propose a hybrid framework that integrates an LLM agent, metaheuristic algorithms, a Model Zoo, and a Simulation Repository.** This framework supports three workflows based on the user's query: Design with Model Zoo, Simulation Verification, and Model Fine-Tuning. The Model Zoo enhances

the framework's multimodal processing capability with PE-specific quantitative data and improves its generalization. Simulation Verification allows users to seamlessly integrate design outcomes into their existing design workflows. Model Fine-Tuning improves model accuracy by refining the data-driven models within the Model Zoo.

As a validation of the proposed methodology of PE-GPT, two design cases are demonstrated: modulation design for the DAB converter and circuit parameter design for the buck converter. Through the iterative design process and model fine-tuning with users' data, PE-GPT demonstrates strong adaptive PE-specific reasoning and multimodal processing capability. It achieves 77.2% in correctness, outperforming experienced human experts by 22.2% and the second-best LLM by 35.6%. Moreover, PE-GPT attains 98.8% in output consistency, 15.4% better than the second-best LLM, delivering high quality and reliable design outputs. Separately, as validated by hardware experiments, the modulation parameter design outcome by PE-GPT guarantees optimal soft switching performance, as requested by the user. This design case validates the effectiveness of the proposed PE-GPT, which has great potential to be generalized into other applications in the domain of PE design.

Looking ahead to the promising era of LLM, several future research areas can help unleash the full potential of PE-GPT for the entire PE industry:

- a) Enhancing PE-GPT Expertise:** Explore diversified domain knowledge enhancement techniques, like advanced RAG or LLM finetuning, to integrate more comprehensive PE knowledge, while ensuring information correctness and rapid inference.
- b) Generalizing PE-GPT's Applications:** Improve PE-GPT's generalization capabilities by enhancing generation of single model, enriching the Model Zoo, combining models for complex design cases, or creating novel hybrid frameworks to integrate additional workflows.
- c) Integrating into the Existing Design Workflow:** Facilitate the integration of design outcomes into the existing PE design workflow by establishing interaction mechanisms between PE-GPT and simulation/Hardware-in-the-Loop systems, thereby enhancing user experience and real-world applicability.

The codes of PE-GPT will be progressively open-sourced on the [GitHub repository](#)¹, as the authors' commitment to advancing the PE industry into a more intelligent era.

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Fanfan Lin (Member, IEEE) received the bachelor's degree in Electrical Engineering, with a minor in English language and literature, from Harbin Institute of Technology, Harbin, China, in 2018. After that, she obtained the joint Ph.D. degree from Nanyang Technological University (NTU) Singapore, and the Technical University of Denmark, Kongens Lyngby, Denmark, in 2023, with the interdisciplinary research in power electronics and artificial intelligence (AI). Her research interests include power converter design with artificial intelligence, life cycle management, and responsible AI for electrical engineering. As an entrepreneur, she founded an AI start-up in Singapore (2022–2023) and was part of the Sequoia Capital (Southeast Asia) Spark Fellowship Program. She was honored as the sole recipient of the 2023 NTU Graduate College Innovation and Entrepreneurship Award. Dr. Lin won the Second Prize Paper Award from the IEEE Industry Applications Society in 2022.



Xinze Li (Member, IEEE) received his bachelor's degree in Electrical Engineering from Shandong University, China, 2018. He has been awarded the Ph.D. degree in Electrical and Electronic Engineering from Nanyang Technological University, Singapore, 2023. He joined the University of Arkansas, USA, as a research fellow in 2024.

His research interests include power converter design, modulation design, design process automation, light and explainable AI for power electronics with physics-informed systems, and the application of AI in power electronics. Dr. Li was honored as the sole recipient of the 2023 NTU Collaborative Research Award Winner. Dr. Li won the Second Prize Paper Award from the IEEE Industry Applications Society, and he was awarded the Outstanding Presentation Award at IEEE APEC 2023. He is currently serving as the Guest Editor for MDPI Mathematics.



Weihao Lei (Student Member, IEEE) received his bachelor's degree in Electrical Engineering and its Automation from Tianjin University, China, 2023. He is currently pursuing his master's degree at Zhejiang University. His research interests include dual active bridge converter, modulation design and application of AI in power electronics.



Juan J. Rodríguez-Andina (Fellow, IEEE) received the M.Sc. degree from the Technical University of Madrid, Madrid, Spain, in 1990, and the Ph.D. degree from the University of Vigo, Vigo, Spain, in 1996, both in electrical engineering. He is currently a Professor with the Department of Electronic Technology, University of Vigo, and also with the School of Electronic and Information Engineering, Ningbo University of Technology, Ningbo, China. From 2010 to 2011, he was on sabbatical leave as a Visiting Professor with the Advanced Diagnosis, Automation, and Control Laboratory, North Carolina State University, Raleigh, NC, USA. From 2015 to 2017, he delivered summer courses with Harbin Institute of Technology, Harbin, China. His research interests include the implementation of complex control and processing algorithms and intelligent sensors in embedded platforms. He has authored more than 180 journal and conference articles and holds several Spanish, European, and U.S. patents.

Prof. Rodríguez-Andina is a co-author of the articles awarded the 2023 IEEE Transactions on Industrial Electronics Outstanding Paper Award and the 2017 IEEE Industrial Electronics Magazine Best Paper Award. He received the 2020 Anthony Hornfeck Award from the IEEE Industrial Electronics Society. From 2016 to 2021, he was the Vice President for Conference Activities of the IEEE Industrial Electronics Society. He served as the Editor-in-Chief for IEEE INDUSTRIAL ELECTRONICS MAGAZINE, from 2013 to 2015, and as an Associate Editor for IEEE Transactions on Industrial Electronics, from 2008 to 2018, and IEEE Transactions on Industrial Informatics, from 2011 to 2022. He is currently serving as a Co-Editor-in-Chief for IEEE Transactions on Industrial Electronics and as an Associate Editor for IEEE Open Journal of the Industrial Electronics Society.



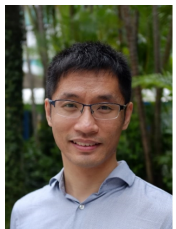
Josep M. Guerrero (Fellow, IEEE) received the B.Sc. degree in telecom engineering, M.Sc. degree in electronics engineering, and PhD degree from the Technical University of Catalonia, Barcelona. Since 2011, he has been a Full Professor with AAU Energy, Aalborg University, Denmark. In 2020, he initiated neuroscience studies and research. As a result, in 2022 he received the M.Sc. degree in Psychobiology and Cognitive Neuroscience from the Institute of Neuroscience (INc) at the Autonomous University of Barcelona. In 2023, he received the M.Sc. degree in Sleep: Physiology and Medicine at the University of Murcia, Spain. In 2023, he joined the

Technical University of Catalonia as an ICREA Research Professor. He has published more than 1,000 journal papers in the fields of microgrids and renewable energy systems, which are cited more than 100,000 times. During nine consecutive years, from 2014 to 2022, he was awarded by Clarivate Analytics as Highly Cited Researcher.



Changyun Wen (Fellow, IEEE) received the B.Eng. degree from Xi'an Jiaotong University, China, in 1983 and the Ph.D. degree from the University of Newcastle, Australia in 1990. From August 1989 to August 1991, he was a Postdoctoral Fellow at University of Adelaide, Australia. Since August 1991, he has been with Nanyang Technological University, Singapore, where he is currently a Full Professor. His main research activities are in the areas of control systems and applications, cyber-physical systems, smart grids, complex systems and networks.

Prof Wen is a Fellow of IEEE and Fellow of the Academy of Engineering, Singapore. He was a member of IEEE Fellow Committee from January 2011 to December 2013 and a Distinguished Lecturer of IEEE Control Systems Society from 2010 to 2013. Currently he is the co-Editor-in-Chief of IEEE Transactions on Industrial Electronics, Associate Editor of Automatica (from Feb 2006) and Executive Editor-in-Chief of Journal of Control and Decision. He also served as an Associate Editor of IEEE Transactions on Automatic Control from 2000 to 2002, IEEE Transactions on Industrial Electronics from 2013 to 2020 and IEEE Control Systems Magazine from 2009 to 2019. He has been actively involved in organizing international conferences playing the roles of General Chair (including the General Chair of IECON 2020 and IECON 2023), TPC Chair (e.g. the TPC Chair of Chinese Control and Decision Conference since 2008) etc.



Xin Zhang (Senior Member, IEEE) received the Ph.D. degree in electronic and electrical engineering from Nanjing University of Aeronautics and Astronautics, China, in 2014, and the Ph.D. degree in automatic control and systems engineering from the University of Sheffield, U.K., in 2016.

From February 2017 to December 2020, he was an Assistant Professor in power engineering with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. Currently, he is a Professor with Zhejiang University, Hangzhou, China. His research interests include power electronics, power systems, and advanced control theory, together with its applications in various sectors.



Hao Ma (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees from the Zhejiang University, Hangzhou, China, in 1991, 1994, and 1997, respectively, all in electrical engineering.

Since 1997, he has been a Lecturer, an Associate Professor, and a Professor with Zhejiang University. From September 2007 to September 2008, he was a Delta Visiting Scholar with North Carolina State University. He is the Vice Dean of the ZJUUIUC Institute. He has authored two books and has authored or co-authored over 200 technical papers. His research interests include advanced control in power electronics, wireless power transfer, fault diagnosis of power electronic circuits and systems, and application of power electronics. Dr. Ma is currently the Vice President of China Power Supply Society. He was the AdCom Member of the IEEE Industrial Electronics Society, the Technical Program Chair of the IEEE ISIE 2012, IEEE PEAC 2014, IEEE PEAC 2018, and IEEE PEAS 2021.