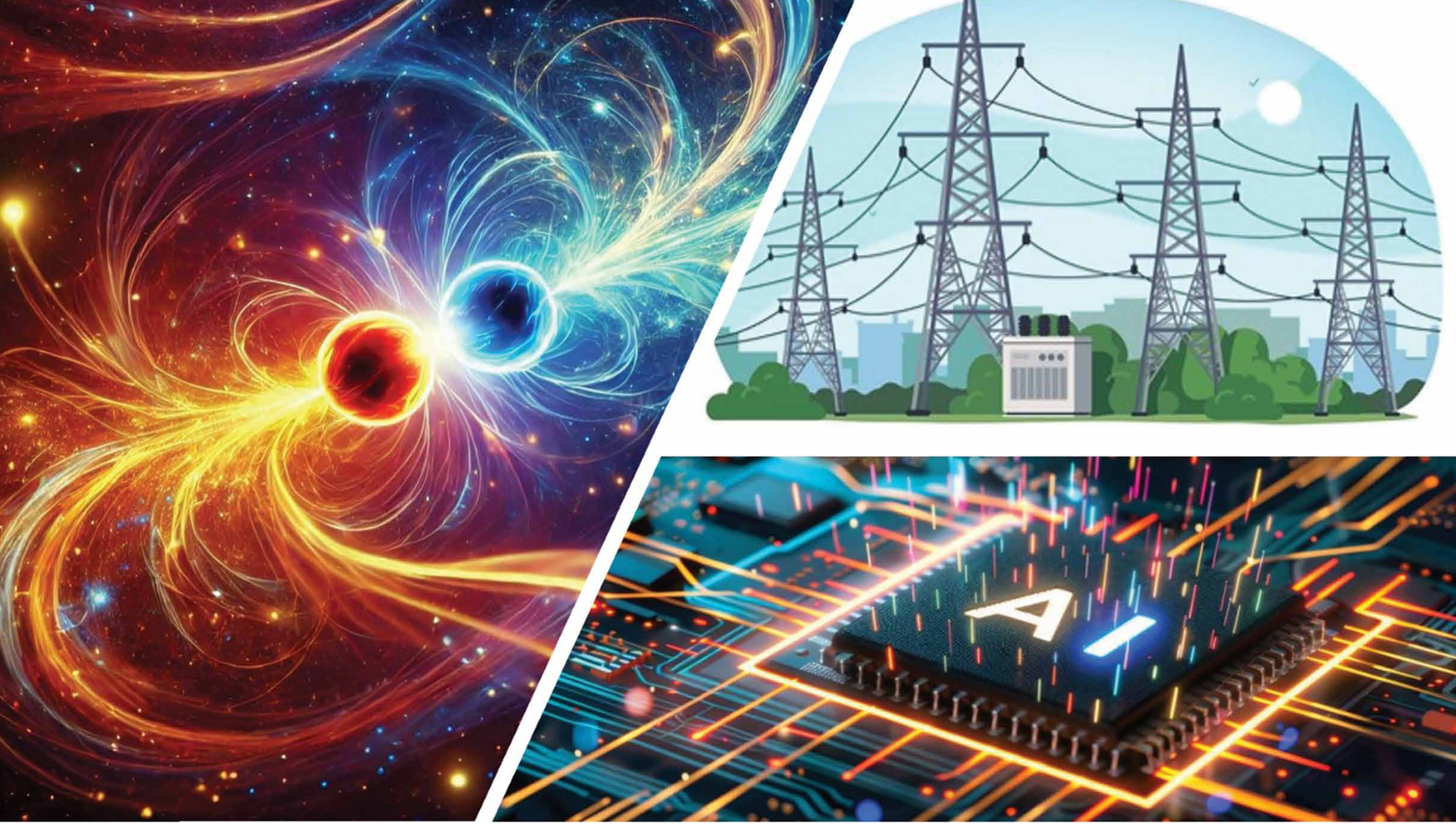

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Power for AI and AI for Power: The Infinite Entanglement Between Artificial Intelligence and Power Electronics Systems

by Minjie Chen, Han Cui, Frede Blaabjerg, Leo Lorenz, Rolf Hellinger, Tom Gray, Olga Fink, and Kevin Hermanns

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Power electronics embeds intelligence into energy systems. Modern artificial intelligence (AI) systems place massive demand on electrical power, and in return, introduce new opportunities in improving energy systems design and implementation [1], [2], [3]. Power electronics systems demand extreme performance and sophisticated functions. Innovations are needed from new and better semiconductors, novel passive components and devices, and more complex system modeling and control. Modern machine learning tools such as transformer architectures can learn highly complex physical characteristics and control strategies of future power electronics systems, given sufficient training data and computational power. Generative AI systems, such as GPT-3 and more advanced versions, are rapidly developing. Structured, cognitive understanding of abstracted human intelligence is in demand. Power electronics, as sensors and actuators for all types of energy systems, need to embrace AI to address large-scale societal challenges such as industrial decarbonization, transportation, and climate change.

Cognitive power electronics Turing test is just around the corner ...

Limited by cost effectiveness and application needs, the physical and functional complexity of classical power electronics systems is traditionally low compared to other electronic systems. Recently, power electronics has been playing critical and high-value roles in renewable energy systems, automation, transportation, electrification, and high-performance computing. Recent advancements in devices, circuits, control, and integration techniques have made it possible to implement more complex and smarter power conversion systems. This shift allows for greater intelligence to be integrated in design, manufacturing, control, and maintenance. Moving away from the conventional focus on simplicity and cost-effectiveness, these systems can incorporate advanced embedded functions and embrace state-of-the-art AI, enhancing their energy efficiency, compactness, capability, reliability, security, and performance.

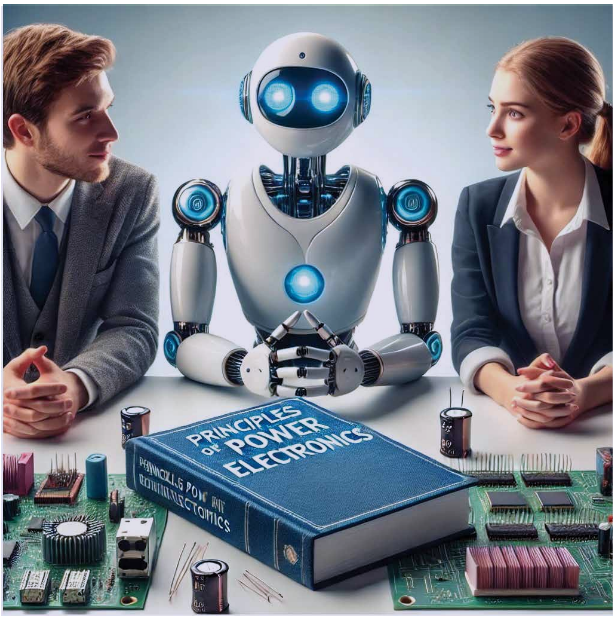

FIG 1 A Chat-GPT generated image describing human-machine interaction of power electronics.

At the 12th IEEE Power Electronics Society (PELS) Future of Electronic Power Processing and Conversion (FEPPCON XII) near the beautiful Lake Geneva in Switzerland, invited speakers and participants presented viewpoints and discussed ideas in the session "Power for AI and AI for Power." The three invited speakers were Dr. Rolf Hellinger of Siemens, Germany, Dr. Tom Gray of NVIDIA, USA, and Prof. Olga Fink, EPFL, Switzerland. The session was jointly hosted by Prof. Minjie Chen of Princeton University, USA and Mr. Kevin Hermanns of PE-Systems, Germany, on behalf of IEEE PELS Technical Committee on Design Methodologies (TC10). The session was jointly organized by the organizing committee, including Prof. Han Cui of Tianjin University, China, Prof. Frede Blaabjerg of Aalborg University, Denmark, and Dr. Leo Lorenz of European Center of Power Electronics (ECPE).

Prof. Minjie Chen of Princeton University opened the session with a brief discussion on the entanglement between AI and power electronics (PE) (Figure 1). He questioned if we should rethink AI as a tool for PE, or PE as a tool for AI. The answer may be both—power electronics is sensors and actuators for future AI. He then commented on the necessity of exploring structured, artificial, abstracted machine understanding of power electronics to enable AI to communicate with human designers with logic thinking, and ultimately enable strong AI in power electronics [4], [5], [6], [7]. PELS has the capability and is responsible for converting traditional power electronics problems into data driven problems and collaborating with domain experts to advance strong AI in power electronics.

In the first presentation, Hellinger and Bischoff [8] of Siemens delivered an insightful presentation on digitalization and AI in power electronics, and specifically elaborated on Siemens's 4S approach—Sustainability, Scalability, Smartness and Speed (Figure 2). Digitalization and AI are vertically integrated in the full technology stack of Siemens's portfolio, ranging from power semiconductors to software defined functionality, and horizontally integrated in the fully life cycle of industrial development, spanning across proof-of-concept to product phase out. AI is a way to overcome the bottleneck in skilled worker shortage, and the role of engineers will be shifted to more valuable tasks such as creative decision making. Specifically, Siemens is applying AI in power electronics for (1) predictive maintenance; (2) parameter optimization; and (3) industrial co-pilot and

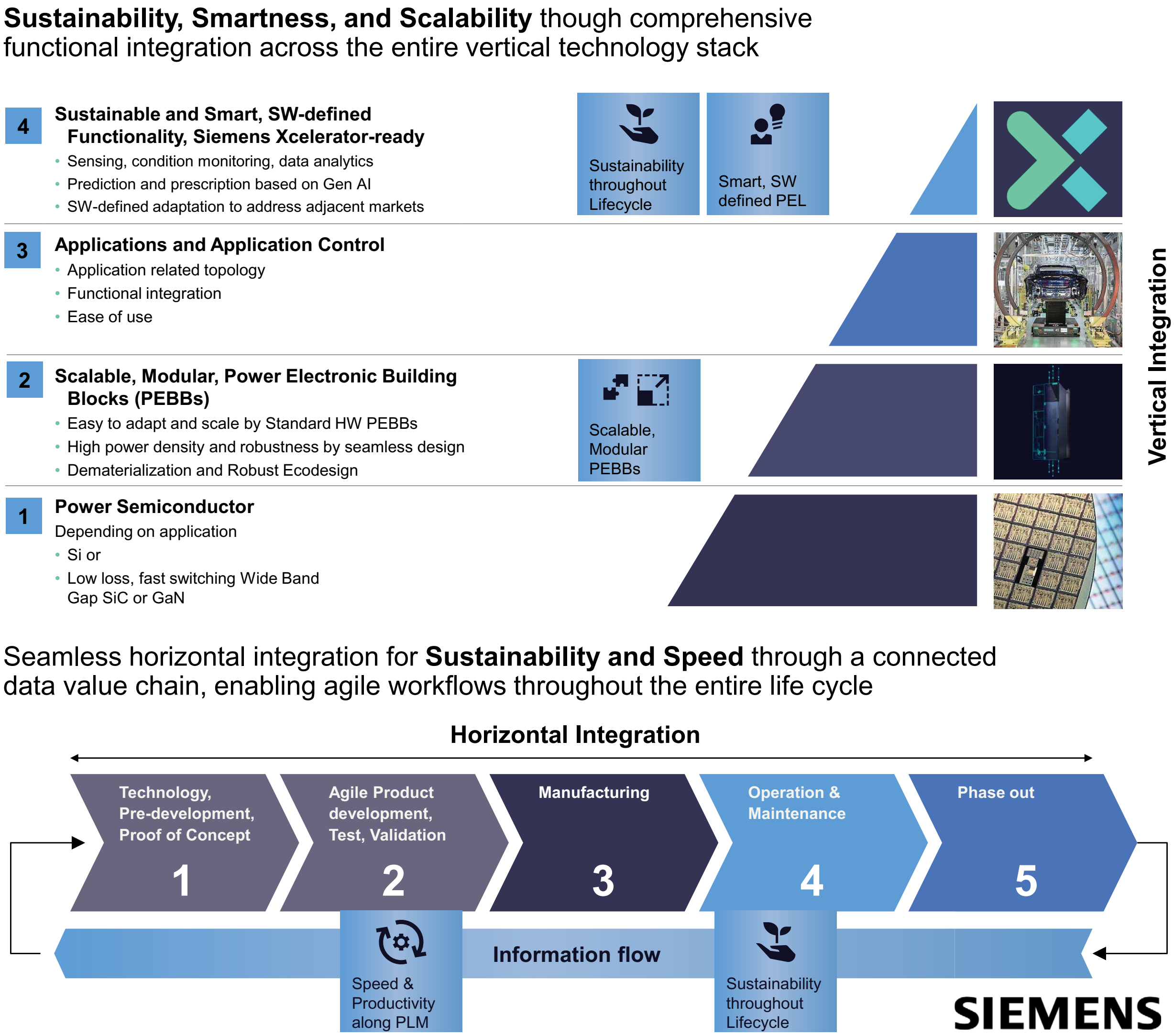

FIG 2 Siemens's 4S approach for vertical and horizontal integration of digitalization and AI.

Generative AI. Finally, Hellinger et al. [9] pointed out that while industry is rapidly embracing AI in design automation, data privacy, cybersecurity and model explainability are still concerns.

In the second presentation, Dr. Tom Gray of NVIDIA broadly discussed the synergy between AI and power conversion (Figure 3). On Power for AI, Dr. Gray first emphasized that the main motivation for higher power density in computing systems is driven by the need for reduced communication power, and modern computers are limited by power delivery at all levels, from die, module, rack, to datacenters. With the rack power level exceeding 100 kW, the future power delivery for high performance computing demands (1) higher voltage distribution; (2) vertical power delivery; (3) distributed, fine grained power domains in microprocessors; and (4) dynamic load management. On AI for Power, Dr. Gray stressed that we should focus our attention on leveraging the unique capability of modern AI on (1) pattern recognition and prediction; and (2) content generation based on patterns. To elaborate on this opinion, he provided a few example projects that NVIDIA is conducting, including (1) power management based on telemetry patterns, and (2) design assistance/automation tools [10], [11], [12]. Finally, Dr. Gray emphasized that it is never too early

AI is a way to overcome the shortage in skilled workers. The role of engineers will be shifted to creative decision making.

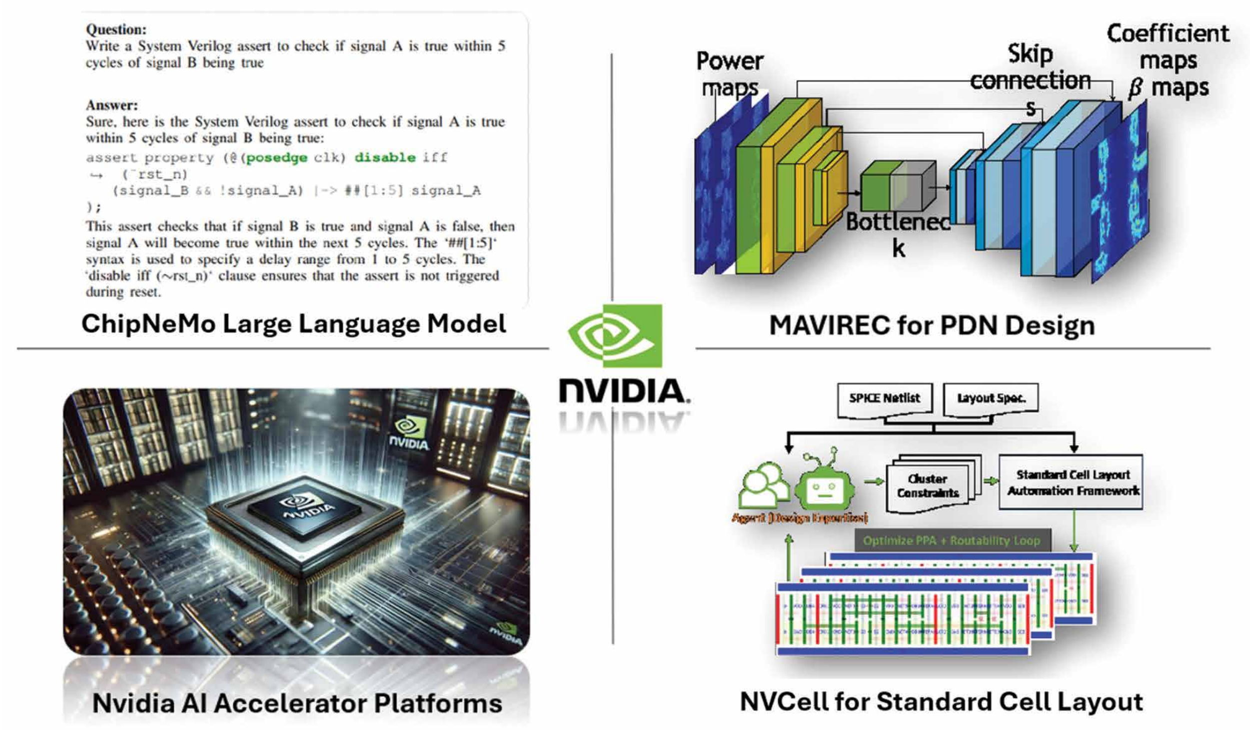

FIG 3 NVIDIA's closed-loop approach for power management and AI, spanning from ChipNeMo for design [10], MAVIREC neural network for PDN modeling [11], NVCell for standard cell layout [12], to AI accelerator hardware platforms such as Blackwell.

or too late to embrace AI. AI is ready to have major impact on the design process of circuits and systems; and as the AI tools and methods get more mature, it may be able to tackle more challenging problems in specific application domains.

It is never too early or too late to embrace AI.

In the last presentation, Prof. Olga Fink of EPFL shared her research on the application of hybrid physics-based and deep learning models to predictive maintenance and prescriptive operation (Figure 4). Fink et al. [13] first highlighted the challenges of applying modern AI techniques to a traditional engineering field, including limited data availability (in terms of size and quality), limited data representativeness (the degree to which a sample of data accurately reflects the characteristics of a larger population), interpretability of model outputs (and model explainability), and limited generalizability of learning. Hybrid physics and deep learning models have the potential of overcoming these limitations by embedding already known physical principles to deep learning models to relax the above-mentioned constraints. Examples include a modified transformer architecture—Dynaformer—for predicting the remaining state-of-charge of batteries [14] and optimal operation for urban air mobility using deep reinforcement learning [15]. Prof. Fink then presented how to downscale models while improving generalization and extrapolation by introducing physics based inductive bias in graph neural networks. The physics-based graph neural network can better generalize the dynamics of a physical system with less training data. Similar concepts can be applied to model complex power electronics systems.

Other topics that the panel covered in the discussions include but are not limited to: 1) more energy efficient computing mechanisms such as quantum computing and neuromorphic computing, and the power electronics opportunities; 2) water and other environmental concerns of future computing; 3) advanced cooling technologies; 4) the risks of AI designing machines without human in the loop; 5) the extrapolation capability of AI in power electronics; 6) the importance of making industrial AI product adaptive to rapid changes in both tools and application environments; 7) scalable and sustainable AI.

A successful integration of AI in an engineering domain requires three key elements: Data, Computing Power, and Algorithms. To embrace AI in power electronics, it is PELS's responsibility to prepare data, ensure data quality, and develop data-driven algorithms with high impact. Power electronics also will play continuous roles in supporting the development of computing power in terms of compact and robust power delivery and providing the necessary functions for energy efficient computing. Finally, there are unique opportunities to merge physical insights into general purpose machine learning algorithms to greatly reduce the data burden and computing requirements.

It is promising to connect data-driven methods with physical insights, motivating physics-based machine learning and abstractive thinking. As shown in Figure 5 and elaborated in [16] and [17], using the synergy between magnetics and AI as an example, AI and physical insights can broaden the scope of power electronics in two folds through: 1) bottom-up physics-based models; and 2) top-down data-driven models. While bottom-up physics insights can deeply explain the fundamental principles behind the data, top-down behavior models such as unsupervised machine learning and reinforcement learning also hold great potential. While data-driven models hold true practical potential, physics-based models may offer safety guarantees and needed explainability. They can be applied to develop advanced algorithms to control sophisticated power electronics systems. One could also image a complete digital twin model of power electronics systems with data-driven or physics-informed models capturing sophisticated behaviors of passive components, with the capability of adaptively controlling itself with reinforcement learning. All these advances will facilitate the realization of a successful "Turing-Test" [4], [5] in power electronics, when AI demonstrates similar capability levels as human experts.

A few notable open-source AI and machine learning projects in power electronics are listed in the Appendix. The communities behind these active projects are the foundation of PELS machine learning and AI task forces.

In summary, the "Power for AI and AI for Power" panel generated lots of excitement in FEPPCON XII. These discussions will have a continuous impact on the future development of power electronics. The opportunities and challenges of embracing AI in power electronics, as identified in FEPPCON XII, include:

1) When applying AI tools to power electronics, identifying areas in power electronics where modern AI tools can do well, such as pattern recognition, curve-fitting, time

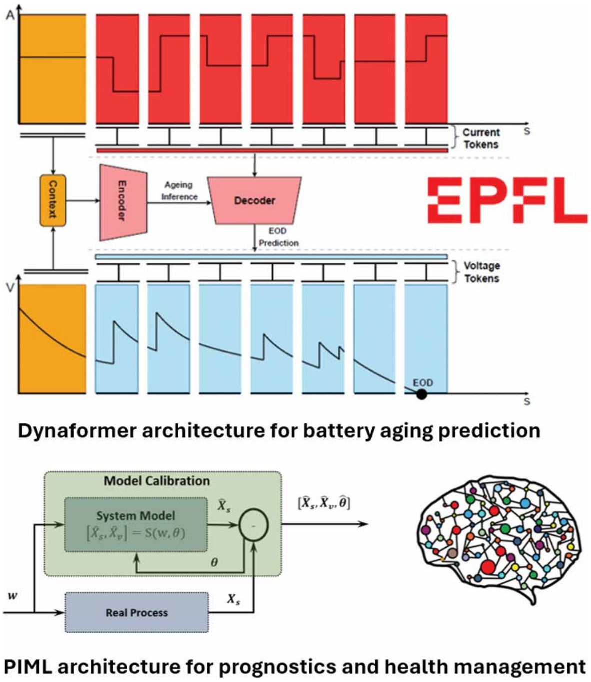

FIG 4 Dynaformer architecture for battery aging prediction [14] and a physics-informed machine learning (PIML) architecture proposed for prognostics and health management applications [15].

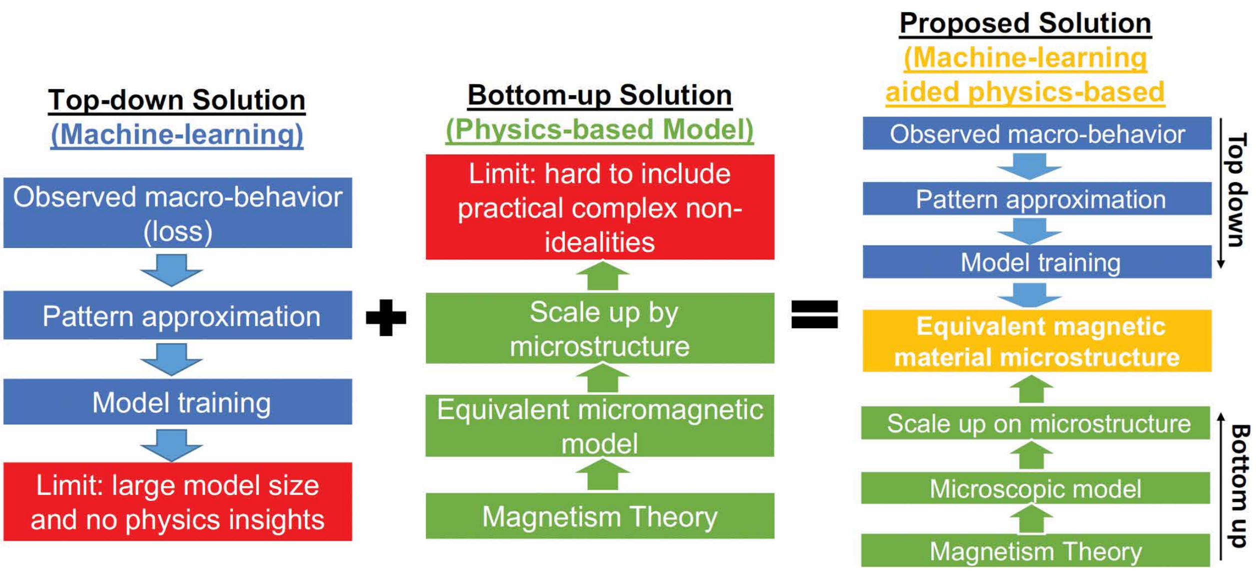

FIG 5 Top-down and bottom-up approaches for broadening the scope of power electronics with AI and machine learning, with the synergy between magnetics and AI as an example [16], [17].

sequence regression, image processing, reinforcement learning, and transfer learning. Notable research topics include materials and component modeling [16], [17], [18], thermal modeling [19], grid-edge power converter control [20], computing load modeling [21], power electronics system's reliability and maintenance [22], and power module design [23].

2) When developing strong AI in power electronics, focusing on bridging the data and algorithm gaps between domain knowledge and general-purpose AI. It is PELS's responsibility to prepare and certify large-scale, high-quality data, encourage open-source and data sharing, and to enhance AI with physical insights. Notable research topics include power electronics schematic recognition [4], [5], [6], power electronics large-language model [7], [9], and power electronics topology synthesis and analysis [24], [25].
3) When considering the threats and risks of AI in power electronics, following the on-going discussion in the general-purpose AI community and adapt the most recent rules and considerations to power electronics. Power electronics is the backbone technology for future energy systems and demands special considerations in cyber-security, safety, and technology explainability.
4) When meeting the power need of future computing systems, preparing for what is needed soon, and forecasting what may be needed in the long term. The demand of human society for more computing and more intelligence in energy systems is infinite. The power electronics community needs to stay engaged while forward-looking with the future evolution of energy efficient computer systems.
5) When addressing the future education needs of power electronics and AI, creating an inclusive and welcoming environment to motivate interdisciplinary researchers and students to address power electronics problems.
6) When bridging the gap between academia and industry, challenges exist in standardization, protection of intellectual property, and transparency. Closely follow the open-source vs. closed-source debates in general-purpose AI community, and customize the rules and common practices in power electronics.

Key remaining questions for the interdisciplinary areas of power electronics and AI include:

1) Modeling—Regression models for materials and components. Leveraging modern AI's capability of performing multi-dimensional curve-fitting.
2) Design—Cognitive AI agent in power electronics. Computer vision for schematic recognition; teaching large-language models to understand power electronics; developing powerful AI tools that can accelerate the design process.
3) Control—Data-driven framework and reinforcement learning models. Control of power electronics without explicit physical models. Enhancing power electronics control based on the rapid advance in robotics and cognitive decision making.
4) Maintenance—Predictive models for thermal, maintenance, and reliability. Applying modern AI's pattern recognition, classification, regression, and forecasting capabilities for evaluating the operating and health states of power electronics.
5) Sustainability—Ensuring sustainability throughout the entire product lifecycle. Embrace AI from the selection and extraction of raw materials to a robust eco-design for repair, refurbish, reuse, remanufacturing, disassembly, and recycling as well as achieving high energy efficiency during operation.

Appendix

Notable Open-Source AI and ML Projects in Power Electronics

[1] Aalborg University – Artificial Intelligence for Next-Generation Power Electronics: https://vbn.aau.dk/en/projects/artificial-intelligence-for-next-generation-power-electronics
[2] ETH Zurich – AI-mag: Tool for Designing Magnetics with Artificial Neural Network: https://ai-mag.github.io/
[3] OpenMagnetics – A Platform for Sharing Knowledge about Magnetic Components: https://github.com/OpenMagnetics/
[4] Paderborn University – Awesome Open-Source Power Electronics Tools: https://github.com/OpenMagnetics/
[5] Paderborn University – OMG: An OpenAI Gym Environment for Microgrids: https://github.com/upb-lea/openmodelica-microgrid-gym
[6] Paderborn University – GEM: An Open-Source Gym Environment for Electric Motors: https://github.com/upb-lea/gym-electric-motor
[7] Princeton University – MagNet Project for Data Driven Modeling of Power Magnetics: https://github.com/minjiechen/magnetchallenge
[8] Princeton University – PowerVision: Power Electronics Schematic Recognition: https://github.com/minjiechen/PowerVision
[9] Texas A&M University – Power Electronics Meets Gen AI Module 1&2: https://www.linkedin.com/pulse/power-electronics-meets-genai-module-1-development-circuit-9fibc/?trackingId=SQ%2F3yJW6RjuzQsC36wCibg%3D%3D
[10] University of Arkansa - PowerSynth 2: Power Modules Design Automation Tool: https://github.com/e3da/PowerSynth2-gui
[11] University of Houston – PedApp: AI Tool for Automated Circuit Simulation: https://github.com/Varat7v2/PEDApp-AI-Tool-for-Automated-Circuit-Simulation
[12] University of Sydney – MagNet Engine: GUI Tool for Magnetics Core Loss Modeling: https://github.com/moetomg/magnet-engine/

[13] Zhejiang University – PE-GPT: a New Paradigm for Power Electronics Design: https://github.com/XinzeLee/PE-GPT

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