

Revolutionizing power electronics design through large language models: Applications and future directions

Khalifa Aliyu Ibrahim^a,^{*} Patrick Chi-Kwong Luk^a, Zhenhua Luo^a, Seng Yim Ng^b, Lee Harrison^b

^a Centre for Energy Engineering, Cranfield University, MK43 0AL, United Kingdom

^b Energy Research Lab, Cranfield Technology Park, Unit 28/29 Innovation Centre, MK43 0AL, United Kingdom

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ABSTRACT

The design of electronic circuits is critical for a wide range of applications, from the electrification of transportation to the Internet of Things (IoT). It demands substantial resources, is time-intensive, and can be highly intricate. Current design methods often lead to inefficiencies, prolonged design cycles, and susceptibility to human error. Advancements in artificial intelligence (AI) play a crucial role in power electronics design by increasing efficiency, promoting automation, and enhancing sustainability of electrical systems. Research has demonstrated the applications of AI in power electronics to enhance system performance, optimization, and control strategy using machine learning, fuzzy logic, expert systems, and metaheuristic methods. However, a review that includes the recent AI advancements and potential of large language models (LLMs) like generative pre-train transformers (GPT) has not been reported. This paper presents an overview of applications of AI in power electronics (PE) including the potential of LLMs. The influence of LLMs-AI on the design process of PE and future research directions is also highlighted. The development of advanced AI algorithms such as pre-train transformers, real-time implementations, interdisciplinary collaboration, and data-driven approaches are also discussed. The proposed LLMs-AI is used to design parameters of high-frequency wireless power transfer (HFWPT) using MATLAB as a first case study, and high-frequency alternating current (HFAC) inverter using PSIM as a second case study. The proposed LLM-AI driven design is verified based on a similar design reported in the literature and Wilcoxon signed-rank test was conducted to further validate the result. Results show that the LLM-AI driven design based on the OpenAI foundation model has the potential to streamline the design process of power electronics. These findings provide a good reference on the feasibility of LLMs-AI on power electronic design.

1. Introduction

The demand for efficient power electronics (PE) is increasing due to rapid developments in data science, the Internet of Things (IoT), renewable energy, automobiles, sensor technology, edge computing, household appliances and big data analytics [1–3]. PE faces challenges such as thermal management, electromagnetic interference due to high frequency operation, scalability, and integration with renewable energy systems. Additionally, fault detection, recycling, compliance with international standards and sustainability in manufacturing remain critical issues. Addressing these challenges requires advanced tools like and methodologies

^{*} Corresponding author.

E-mail addresses: khalifa-aliyu.ibrahim@cranfield.ac.uk (K.A. Ibrahim), p.c.k.luk@cranfield.ac.uk (P.C.-K. Luk).

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to enhance efficiency and innovation. Consequently, design innovation in PE is required for efficient sustainable power systems and to meet future demands. Traditional design methodologies are time-consuming [4] and prone to mistakes [5]. Design automation and integration of artificial intelligence can overcome this challenge [6,7]. Artificial intelligence (AI) is one of the most rapidly changing fields of research in this 21st century. AI has been applied to several areas of study ranging from automobile [8], health care [9], business and finance [10], computer vision and robotics, education [11–13] engineering [14], and other industries as summaries in Fig. 1. Another specific area in which AI is applied is power electronics which includes, designs of power modules [15], intellectualization of controllers [16,17], implementation of maximum power point tracking controls for renewable energy systems [18–21], anomaly detection on inverters [22], prediction of the remaining useful life of converters [23,24], and other electronic devices. Nevertheless, AI applied to PE is characterized by challenges due to the diverse nature of design characteristics [25]. The challenges reported are complexity [15,26] and stages in the design process, high speed of tuning requirement in control, and high sensitivity in condition monitoring for ageing detection therefore presenting a challenge in the implementation of AI in PE. The recent advances in large language models AI can now be implemented to address design stage complexity. The adaption of this advancement would improve design to increase accuracy and reduce design time. Large language models (LLMs) have the potential to improve PE design workflow, automate repetitive tasks, and make decisions at a higher level of intelligence. The use of LLMs in PE design presents both significant opportunities and considerable challenges. While LLMs have the potential to streamline processes like design computation, modelling, and software development, they are heavily dependent on large datasets for training and fine-tuning, which may not always be available or of sufficient quality in PE contexts. Furthermore, the computational intensity of LLMs, coupled with high costs for implementation, maintenance, and ethical considerations poses a significant challenge for widely adoption. By addressing these challenges, LLMs could unlock transformative advancements in PE, enabling more efficient, effective, and ethical design processes. These will open new potentials in power electronics and advance the technology to achieve future demand and sustainability.

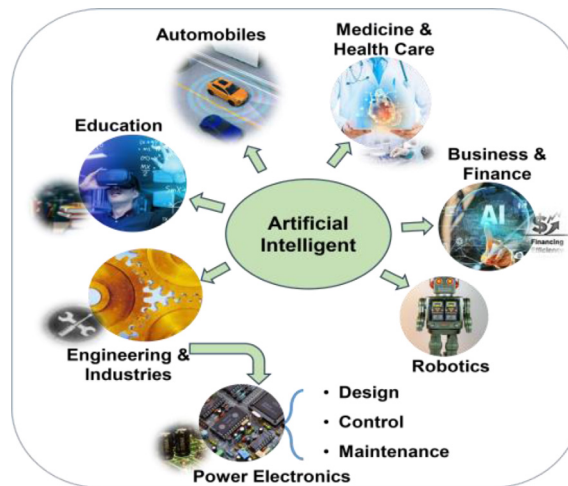


Fig. 1. Applications of artificial intelligence.

There has been research on the applications of AI in power electronics (PE) around design optimization, control and maintenance as reported in [6,27]. Various AI methods such as genetic algorithms [28,29], artificial neural networks [30,31], particle swarm optimization, and stochastic optimization [32] have been reported. However, AI applications are often applied at a specific stage of the PE design process stage. Similarly, reviews related to AI in power electronics do not include the recent advancement of AI such as large language models (LLMs). For example, recent reviews as reported in [6,25,33–36] discuss various methods including expert systems, neural networks, genetic algorithms, fuzzy logic, metaheuristic methods, and machine learning, but did not include recent developments in LLM such as generative pretrain transformers (GPT). Therefore, there is a need to provide an overview of AI applications in power electronics and include the feasibility of LLMs to advance PE research and applications. To our knowledge, we are the first to present an LLM-driven design for a power electronics system. This paper aims to fill this gap to benefit the research community by classifying the applications of AI in power electronics at design, maintenance, and control establishing the feasibility and the impacts that LLMs can bring to PE design. PE design equipped with LLM capabilities reduced design time and complexity while guaranteeing the accuracy and reliability of PE systems within the design process. This paper adopted narrative literature review with elements of comparative analysis to assesses the current methodologies, presents the existing gaps, and proposes future research directions on the feasibility of AI applications to power electronics design. The contributions of this paper

can be summarized as follows.

- (i) Provided a good foundation in the implementation of LLM AI on power electronics design to streamline the design process for beginners, improve researchers' and engineers' productivity.
- (ii) Investigated the feasibility of LLMs AI applications to PE design using high-frequency wireless power transfer (HFWPT) as an example.
- (iii) Proposed a LLMs-AI driven framework for PE design.
- (iv) Highlighted the potential impact of AI, challenges, and future research direction in AI applications to PE including LLMs.

The paper begins with a review of current AI applications to PE and proceeds with LLMs AI considering the power electronics design process. The rest of the paper is organized as follows: Section 2 discusses milestones, types, and methods of AI applied to PE including a research outlook landscape. Sections 3 to 4 present LLMs with integration to PE and the current design approach in PE proposing an AI-based framework. Section 5 provided the first case study of LLM implementation for the design of PE focusing on wireless power transfer with validation against reference paper. Section 6 discusses the second case study of high frequency AC inverter design and validation against results reported in the reference paper. Section 7 gives an outlook on future AI applications for PE, and Section 8 concludes the paper.

2. Function of artificial intelligence in power electronics

AI techniques applied to power electronics can be categorized into design, control, and maintenance. These applications involve optimization [37], classification [38], regression, and exploration of data structures [6]. Optimization is about finding solutions that maximize or minimize objective functions, whereas classification implies placing input data items into distinct classes. Classification is applied in maintenance ranging from anomaly detection to fault diagnostics as reported in [39,40]. Regression presents a statistical methodology that predicts continuous values of target variables, based on their relation to the input factors [41,42]. In a control system application, an intelligent controller can use regression analysis to build mathematical models of dependencies between the input signals and control variables as reported in [41]. Substantial reviews on AI applications to power electronics have been reported by [6,14,25,35]. Fig. 2 shows the research trend in AI applications to power electronics from the year 2000 to November 2024 based on Scopus data base. The substantial rise in the number of publications means the area is developing rapidly, gaining more attention from researchers. The complete workbook search strings, compile data with link to the Scopus search can be found in the supplementary section.

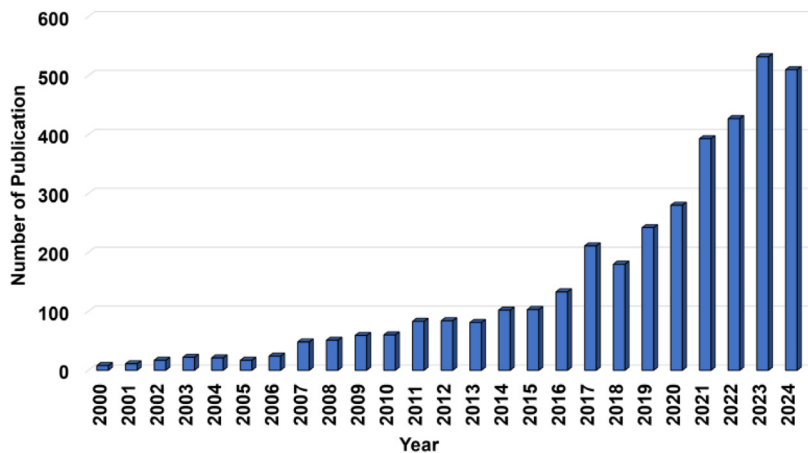


Fig. 2. Research output trend based on number of publications research.

Fig. 3 shows a landscape of AI applications to power electronics. This map represents an analysis across countries based on the number of publications, and funding sources behind those publications. 22% of the publications have defined the funding sources, while 78% are undefined. The first 14 countries representing the defined 22% are analysed. The table lists the countries with their respective number of publications corresponding to the funding percentage of that country represented in the pie chart. India is at the top, with 711 publications with 1% of the funding as shown in the pie chart. China has 632 with the largest funding sponsorship of 42%, followed by the United States had 360 publications with colour corresponding to 17% of the funding. Europe has 15% of the funding investment, while South Korea has 10%. Other countries, from Germany and Canada, have 3% each, while Japan and Taiwan have 2% each. United Kingdom, Italy and Qatar have 1% each of funding. This represents a global outlook of the funding landscape and publications in AI applications to PE among different countries. The applications of AI can be classified into design, control, and maintenance as discussed in the following subsections.

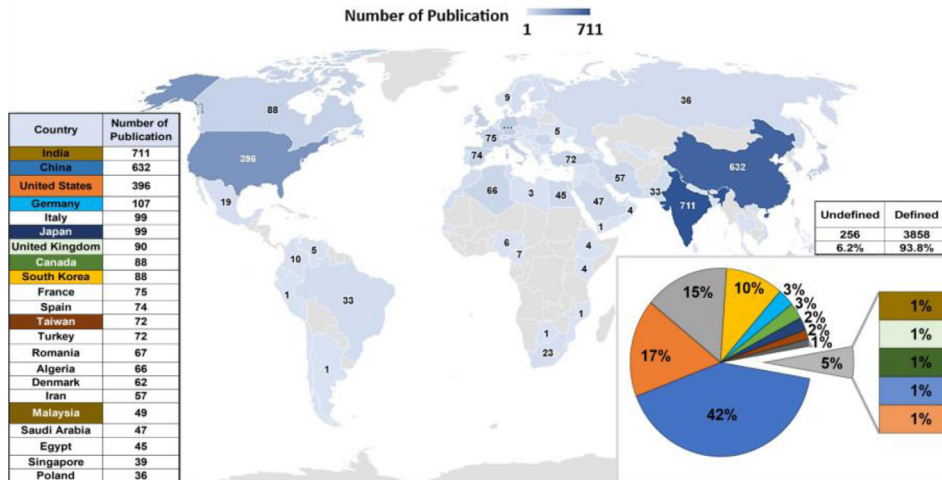


Fig. 3. Global AI research on PE outlook and funding sponsorship.

2.0.1. Design

The use of AI methods in modelling and optimization is essential in finding the optimum set of parameters for which to obtain the best performance with a given constraint in PE design. In [43], a heatsink design of a three-phase inverter has been optimized using a genetic algorithm (GA) combined with a finite-element analysis technique, realizing a striking reduction in size compared with conventional designs. Research by [44] reported that multi-objective optimization of a solar power-based microgrid system uses a genetic algorithm to maximize power distribution. Research by [45] employed particle swarm optimization (PSO) to optimize component values of electronic circuits to enhance performance. Other optimization techniques, like Ant Colony Optimization (ACO) [46–48], Artificial Bee Colony (ABC), differential evolution [48–50], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [51,52], and hybrid AI algorithms [53] have also been applied to different power electronics optimization problems to prove their capabilities and effectiveness.

In [54], two feed-forward (FF) NN models map was used to automate design parameters and improve the design reliability of power electronics systems. Their research reported a speed-up in the iterative design process. Data-driven design and automation of design in power electronics have the potential to reduce iterative design time [55,56]. Another article studies the applications of a nonlinear autoregressive network with exogenous inputs for thermal modelling of power electronics computational effort to reduce without the loss of accuracy [57]. In [58] the role of AI-driven optimization techniques, in enhancing the efficiency, reliability, and robustness of renewable energy-based microgrid systems is investigated. It highlights the potential of AI and parallel computing to address uncertainties and improve design of renewable microgrid. However, none of the research studies the feasibility of the applications of AI in the complete design process of power electronics and optimized the design cycles due to the lack of advanced algorithms to oversee the complexity of the PE design process. With the recent development of advanced LLM algorithms, it is possible to investigate the feasibility of improving the design process. Table 1 gives a summary of optimization algorithms used in PE with their strengths and weaknesses.

2.0.2. Control

The applications of AI techniques in the control of power electronics are classified into fuzzy logic control, neural network control, and reinforcement learning control. Various optimization tasks such as PID tuning, maximum power point tracking (MPPT) methods, most of which use fuzzy logic, and metaheuristic methods like GA-ACO for obtaining optimal solutions have been reported. A self-enhanced optimal control of converters has been proposed by [78]. In addition, regression is applied to control as a nonlinear input–output mapping application of AI techniques like fuzzy logic [79–81], neural networks [82], and reinforcement learning [83–85].

The applications of fuzzy logic controllers have been made in control tasks of power electronics, such as speed control [79,86] and MPPT [87]. It expresses a control strategy by using fuzzy sets and rules under expert knowledge. Control of the generator speed of a variable-speed wind generation system to maximize the extracted wind power output is implemented in a fuzzy logic controller through the adaptive approach [87]. Research by [88] employed neural network tools for approximating nonlinear functions showing 15% improvements. In addition, a hybrid approach, such as recurrent fuzzy neural network (RFNN), is used in dynamic control tasks due to their ability to treat time-series data as reported in [89]. The reinforcement learning control is applied to dynamic task optimization through learned strategies used to control interactions taken with the environment. Research by [18] controllers for MPPT in renewable energy systems based on RL adapt to changing conditions without the use of any predefined dataset, hence greatly improving the system's autonomy and efficiency. The various applications of AI in control depend on the task requirement in terms of dynamic performance, robustness, generalization, and convergence speed.

Table 1
Optimizations AI algorithm applied in PE.

Optimization algorithm	Applications in PE	Strengths	Weaknesses	Ref.
GA	Optimization of component parameters, design of magnetic components	Global optimization capability, good for complex multi-objective problems	Can be computationally expensive, and may converge to local optima if not tuned	[43,44,59–62]
PSO	Parameter optimization for power converters, Magnetic component design, Efficiency maximization, control optimization	Simple implementation, fast convergence, effective for continuous optimization problems	Prone to premature convergence, can struggle with discrete or combinatorial problems	[28,63–66]
ABC	Optimization of power electronics circuits, design of high-frequency magnetic components, loss reduction strategies	Good for dynamic optimization, flexible and robust, fast convergence behaviour	Can be less stable in convergence, and performance can degrade with large problem sizes.	[50,67,68]
ACO	Path optimization for power flow, design and optimization of magnetic components, component placement in circuits	Effective for pathfinding and routing, good at handling discrete problems, can adapt to dynamic changes	Slower convergence requires careful parameter tuning	[46,69]
Differential Evolution (DE)	Optimization of DC inductors, geometric parameters & quality factor	Simple and flexible, good convergence, manages non-linearities	Premature convergence, limited local search capability	[70,71]
NSGA-II	Multi-objective optimization, filter parameters design, magnetic design, multi-objective optimization	Pareto front exploration, adaptability to changes, improved design quality	High computational costs, premature convergence, limited applicability	[25,72]
ANN-GA	Geometric parameters, hybrid optimization, multi-objective optimization, design parameter synthesis of passive components	Time and cost minimization, improved accuracy, improved design quality	Data dependency, limited generalization, complexity	[30,73–75]
ANN-PSO	Hybrid optimization, magnetic design, passive components parameter optimization	Cycle time reduction, improved accuracy.	Data dependency, limited training scenarios, implementation complexity	[74,76,77]

2.0.3. Maintenance

Maintenance is a set of preventive activities that includes condition monitoring, anomaly detection, fault diagnosis, and remaining useful life (RUL) prediction according to the IEEE standard [90]. The maintenance activities included offline training, condition monitoring, and decision-making to improve electronic systems' reliability and safety [91]. In [92,93], parameter identification, data preprocessing, and component degradations to extract insightful knowledge for prognostic health management (PHM) applications have been reported. Research by [94] reported a model-free method based on AI algorithms which set up the relationship between the available signals and the parameter of interest; on the other hand, model-based methods use the system dynamics and models to optimize the identification of parameters. Abnormality detection and fault diagnosis are also part of maintenance problems in guaranteeing the reliability [95] and safety of the power electronic system [96]. AI techniques identify abnormal patterns and classify faults using historical data or real-time monitoring [97]. Predictive maintenance tries to project the RUL of components to allow initiative-action taking in maintenance. AI techniques such as supervised and reinforcement learning can also use model degradation behaviour of components and predict their RUL.

2.1. Types of AI techniques in power electronics

This section discussed types of AI and applications in power electronics. A review paper by [6] reported that the most applied AI method in PE is ML and reported that AI methods in power electronics can be divided into expert systems, fuzzy logic, metaheuristic methods, and machine learning. The sections below discuss each method.

2.1.1. Expert system

Expert systems create a catalogue of Boolean logic, which includes specialized information using IF-THEN rules [98], and it works by following human reasoning. ES is one of the earliest AI methods for applications in PE which uses a database with the expert's knowledge embedded in Boolean logic [99]. This technique mimics the human brain's reasoning, implemented by a set of IF-THEN rules. According to [6], the use of this technique has reduced and has 0.9% usage compared to other techniques due to limitations in universality and adaptability relative to more progressive AI methods.

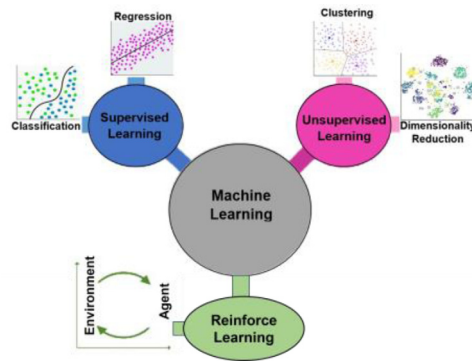


Fig. 4. Classification of machine learning.

2.1.2. Fuzzy logic

The fuzzy logic technique refers to extended Boolean logic designed to process system uncertainty and measurements [100]. This approach is based on fuzzy sets and membership functions, creating a fuzzy space for the input signals, and supplying nonlinear mapping between starts and stops. The methods of fuzzy logic are fuzzification, rule inference, knowledge base, and defuzzification [101–103]. This method is efficient in system uncertainties-related tasks [104]. However, it required expert experience in designing the membership functions and fuzzy rules. Fuzzy logic efficiently models uncertainties and imprecise measurements using fuzzy sets and membership functions in the solution of otherwise-fussy optimization problems. Research by [105], employed neuro-fuzzy logic system to design the navigation of a mobile robot which clearly shows the applicability of the technique to uncertain model.

2.1.3. Metaheuristic methods

Metaheuristic techniques are methods of optimization inspired by biological evolution or natural phenomena that are turned into optimization algorithms [106]. This method includes [32], ant colony algorithms [47] which mimic how ants effectively search for food, particle swarm optimization [45], differential evolutions [48], etc. It can be trajectory-based methods, such as Tabu Search and Simulated Annealing, and population-based methods. It is suitable for finding solutions for complex optimization tasks [107]. Table 1 summarizes the metaheuristic optimization methods. The Metaheuristics technique is suitable for global optimization and one of the most widely used optimization methods in the field of power electronics.

2.1.4. Machine learning

Machine learning means the automated learning of principles and trends from data, or interactions with an environment by a computer. It is classified into supervised (SL), unsupervised learning (UL), and reinforcement learning as illustrated in Fig. 4. Regression uses an algorithm that predicts specific attributes of an object using available data and other attributes [41]. On the other hand, classification is a common task in fault diagnosis [39]. It involves assigning an object to a specific class with input–output variables. It is used as a classification algorithm to determine two or more classes from a data set. Tasks in supervised learning include regression and classification in Fig. 4. This approach involves preparing data for further work with each object having a label that distinguishes it from other objects as illustrated in Fig. 8. Fault diagnosis in power electronics is mostly realized by employing supervised learning methods. The trained models that classify the types of faults with adequate accuracy require labelled data.

Supervised learning (SL) uses an input–output pair provided during training so that general functional relations can be established [37]. Working on power electronics in fault diagnosis and remaining useful life (RUL) prediction applies this kind of approach. Supervised learning could further divide based on connectionism-based schemes like neural networks, and probabilistic graphic schemes, into memory-based approaches like kernel methods [6]. Fig. 5 provides a summary of SL based on methods including their variants.

Fig. 6 shows an example of SL and UL of ML applied to electronic topologies to illustrate differences in training approach. These models can identify the features, which are extracted from the schematics. Unsupervised learning solves the clustering and data compression problem. [108] reported NN-based model can learn the relation of operating conditions to degradation patterns and applied to predict the RUL of IGBTs. As illustrated in Fig. 6, there are no predefined output labels, and applied in detecting certain patterns in the data, reducing the dimensionality of the data before further processing. This type of learning allows the model to learn independently by deriving patterns and making conclusions based on unlabelled data. Tasks in UL include clustering and dimensionality reduction. Unsupervised learning-based anomaly detection approaches do not consider any labelled data [22]. Such approaches to anomaly detection may lead to the identification of data patterns, which in turn may indicate faults. In [109], k-means algorithm and fitting a Gaussian mixture model to detect anomalies in power electronic systems by grouping similar data points. These techniques are useful in detecting abnormal behaviour, which in most cases may lead to a fault. Clustering is an unsupervised machine learning method that divides a data set into groups or clusters based on similar features and characteristics.

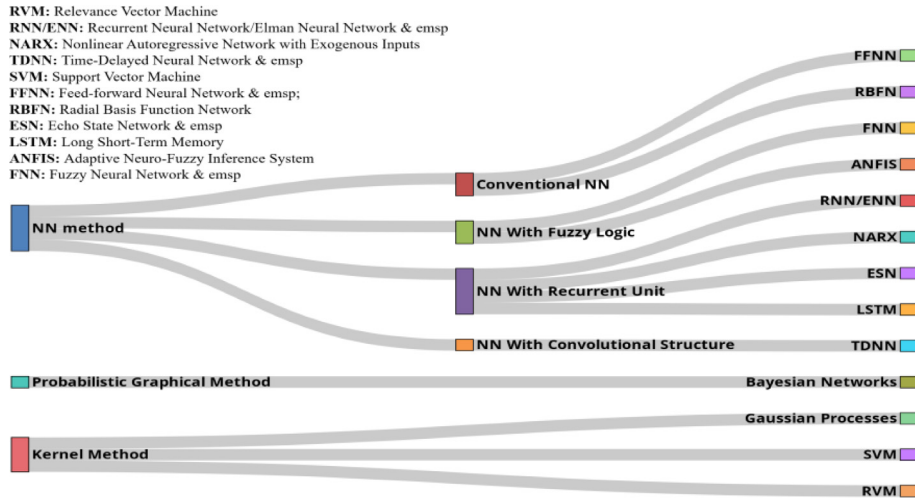


Fig. 5. Types of supervised learning machine learning methods with their variants.

It helps understand the internal structure of a data set and allows for more efficient work. Ensemble methods are another type of machine learning algorithm that is used to increase prediction accuracy. These methods are based on the Condorcet Jury theorem, which states that if a jury has independent opinions and the probability of making the right decision is more than 50%, the probability of making the right decision will approach 100% as the number of jurors increases. There are various perspectives on ensemble methods, including majority voting averaging and weighted averaging. The ensemble method is further divided into bagging, boosting and random forest.

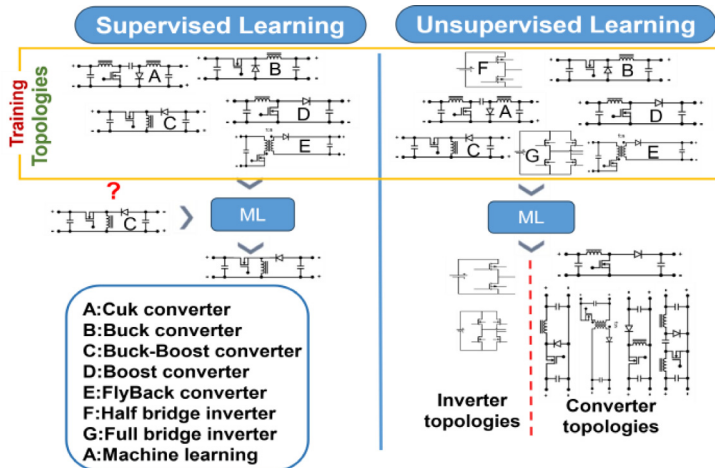


Fig. 6. Supervised and unsupervised learning of PE topologies.

Reinforcement learning (RL) employs a learned control strategy formulated by reward maximization through interaction with the environment. This approach is suitable for dynamic optimization tasks like MPPT in renewable energy systems [18]. A research by [83] proposed a PL-based controller. Their results show an advantage over complicated nonlinear processes. The learning from interactions with the environment is a factor taken into consideration by the RL models as they update the prediction in view based on new data and system states. In [85], applying a developed model using the RL methods for RUL prediction has been reported. The results show that RL-assisted control is more adaptive to changing operating conditions and degradation patterns, hence more accurate and timely predictions for maintenance planning. Table 2 shows a summary of AI techniques applied with PE based on applications, functioning layer, advantages, and disadvantages, while a summary of ML algorithms applied to PE with their applications, advantages, and limitations, including the prospect of LLMs AI is provided in Table 3. The following section discusses the design of PE and the prospect of LLMs AI.

Table 2

Summary of AI techniques applied to PE based on functioning layer, advantages, and disadvantages.

AI technique	Applications	Functioning layer/Method	Advantages	Disadvantages
Expert systems	Design maintenance	Regression	Speeding up the design process aids GA in component selection	Limitation of understanding decision basis, dependency on expert knowledge
Fuzzy logic	Design control maintenance	Classification, Regression, and can be Takagi–Sugeno–Kang-type or Mamdani method.	Suitable for system uncertainties applications, utilizes expert knowledge, multi-criteria optimization	The complexity of the design process, challenging knowledge acquisition
Metaheuristic methods	Design control maintenance	Optimization tasks can be trajectory-based or population-based methods.	Efficient and scalable, less expert experience needed	Intensive computational burden, no guarantee for global optimum
Machine learning	Design control maintenance	Classification, Regression, data structure exploration Optimization, and can be supervised unsupervised or reinforced learning.	No training dataset is required, learns from system interaction, reduces the computational burden, improves analytics accuracy, and establishes mapping with functional relationships between inputs and outputs.	High computational cost, requires significant resources, limited knowledge base, limited applications, and knowledge base, requires large, labelled datasets, generalization can be challenging, limited knowledge.

Table 3

ML applied to PE and the prospect of LLMs.

ML algorithm	Applications	Advantages	Limitations
RL	Dynamic optimization	No training dataset is required, learns from system interactions	High computational cost, requires significant resources, limited knowledge base
UL	Data preprocessing, Learn independently	Reduces computational burden, improves analytics accuracy	Limited applications and knowledge base, primarily used as preprocessing
SL	Predictive modelling, Interpolation	Establishes mapping and functional relationships between inputs and outputs	Requires large, labelled datasets, generalization can be challenging, limited knowledge.
LLMs	Knowledge-based driven, learn independently	Vast PE knowledge base, natural language understanding, contextual information	May attract cost, data privacy issues, potential bias, security, hallucination

3. Power electronics design and the prospect of large language model

The demand for more energy-efficient electrical systems is increasing. However, the design process of electrical systems remains the same. In [4], it is reported that more than 12 months are needed for efficient converter and inverter design. Table 4 provides a more comprehensive time for each design process stage based on Fig. 7. This time frame would differ based on the designer's experience, project objectives and complexity. Power electronics research is now focusing more on sustainability, innovative designs and electronics as a key goal. Technological advances need to include power electronics design process optimizations to improve energy efficiency and sustainability [110]. The lack of an AI tool that integrates system design phases is a major issue. Most design tools and processes use manual calculations and human expertise. Research by [54] adapted artificial neural network-based to automate power electronic design. The process optimizes design using reliability metrics and links them to design parameters. Another research by [111] studied machine learning models for electronic circuit design to reduce human error and generate layouts automatically. Another study by [112] suggested an AI circuit design enhancer to speed up design and optimization. They employed a genetic algorithm, NSGA-II algorithm, and artificial neural network optimized circuit design. In [3], design of framework for IoT has been investigated using hybrid deep learning. In addition, [3] proposed a design framework for IoT enable for autonomous vehicle application. Their result demonstrated a promising result in improving accuracy and speed up design. Another research by [113] investigated combined AI-driven stage design with traditional Chinese opera stage design and reported improved design performance. A study by [114] reported current approach to power electronics design lacks automation which limits production, applications, and penetration. Other studies include [54,115–123] also follow the same pattern. However, their approach ignores the entire power of electronics integrating every step of the design process such as conception, specification, mathematical modelling, simulation, prototyping, testing, certification, and mass production. This limits the potential of how AI can improve power electronics design. These will help in innovating and iterating power electronics more rapidly and productively. Therefore, researchers and designers are working on novel strategies to meet the demands and advancement of the field.

Recent advancements in fine-tuning techniques for LLMs in power electronics have demonstrated their potential for optimization, security, and design automation in PE. Research by [124] proposed an LLM-based agent using the Pandapower library to optimize power system states, with a secondary agent verifying compliance with GOST 32144-2013 standards, resulting in improved

Table 4
Power electronic design process stages and estimated time.

Electronic design process stage	Estimated time (weeks)
Conceptual design	0–4
Design Specification	1–6
Computation/Mathematical modelling	1–8
Simulation	1–12
Design parameter optimization	0–8
Prototyping (PCB layout, Schematic design, Component selection)	4–12
Code/Software development	1–8
Hardware testing and debugging	2–12
Set up, integration and system testing	4–8
Certification and compliance testing	4–8
Final prototyping and validation	6–10
Mass production	Ongoing (months)

optimization outcomes with GPT-4-Turbo, GPT-3.5, and Claude-2.1. A study by [125] investigated security threats in cyber-physical power systems (CPPS), emphasizing domain-specific fine-tuning and rigorous validation to mitigate risks. Another research by [126] introduced an LLM-based multi-agent framework leveraging zero-shot prompting for automated PE controller design, reducing design cycle times. In [127], a human-in-the-loop (HITL) framework combining interactive learning and fine-tuning for routine and innovative engineering tasks, enhancing success rates and adaptability for complex problems is proposed. A study by [128] developed PE-GPT, a multimodal LLM integrating retrieval-augmented generation (RAG) and metaheuristic algorithms for modulation design and circuit optimization, achieving a 35.6% accuracy improvement. In [129], a LP-COMDA is proposed using physics-informed LLM integrating surrogate models and optimization algorithms, achieving a 63.2% error reduction in low-data scenarios through physics-informed fine-tuning. In this research, we propose a hybrid approach integrating prompt engineering, transfer learning, and RAG to enhance the contextual relevance and domain-specific accuracy for power electronics design. Our method combines theoretical constraints with adaptive, data-driven learning for multi-objective design optimization, bridging the gap between theoretical modelling and practical application in different power electronics scenarios. Table 5 provide a summary of recent works on LLM fine-tune techniques for PE.

Table 5
Recent LLM fine-tuning techniques in power electronics.

Study	Technique	LLM models used	Application focus	Key outcome
[124]	Prompt engineering	GPT-4-Turbo, GPT-3.5, Claude-2.1	Power system optimization	Improved voltage deviation results
[125]	Transfer learning	Fine-tuned LLMs	CPPS security threat detection	Enhanced anomaly detection accuracy
[126]	Zero-shot prompting	LLM Agents	PE control design	Reduced design cycle time
[127]	Prompt engineering, Iterative learning	ChatGPT, Claude, Bard	Routine & novel PE tasks	Improved task-solving flexibility
[128]	RAG, Metaheuristics	PE-GPT	Modulation & circuit design	35.6% accuracy improvement
[129]	Physics-informed fine-tuning	LP-COMDA	Modulation design automation	63.2% error reduction, 33x faster design
This work	Prompt engineering, Transfer learning, RAG	Open-AI Custom LLM	Multi-objective PE design	Enhanced adaptability and practical performance

In [130], AI design automation based on a graph neural network model to reduce circuit design time is proposed. Their results show equal performance to manually optimized design system which save designers weeks of design time. However, this approach did not consider the complete electronic design process. In addition, it is difficult to generalize the overall design time because each power electronics design task depends on the type, aim, specification, and complexity of the system. Another research by [131] stated that power electronics system productivity, reliability, and flexibility improve when the design process methodology is improved. They proposed a design tool called ‘Power Electronics Design 4.0 (PED 4.0)’ which includes five power electronics design stages as specifications, topologies selection, simulations, prototype, and production. However, the proposed method did not include design computation, modelling, code or software development, certification, or compliance. Fig. 7 shows an extended version including design computations, modelling, coding, certification, and compliance.

The flowchart in Fig. 7 shows a systematic approach to power electronics design from concept to mass production. Starting with the objective and design concept (O&CD), the process develops the initial specification and requirements (SP/R). Computational, or mathematical modelling (C/MM) creates a design specification that meets the goal. A computation or mathematical modelling that is successful, followed by a simulation and optimization (S&O). The initial design requirement is compared to simulation results. Successful simulation-driven design iteration leads to prototype creation, including component selection (CS), schematic creation (SC), and printed circuit board (PCB) creation. Software development, hardware testing, debugging, and system test setup follow the

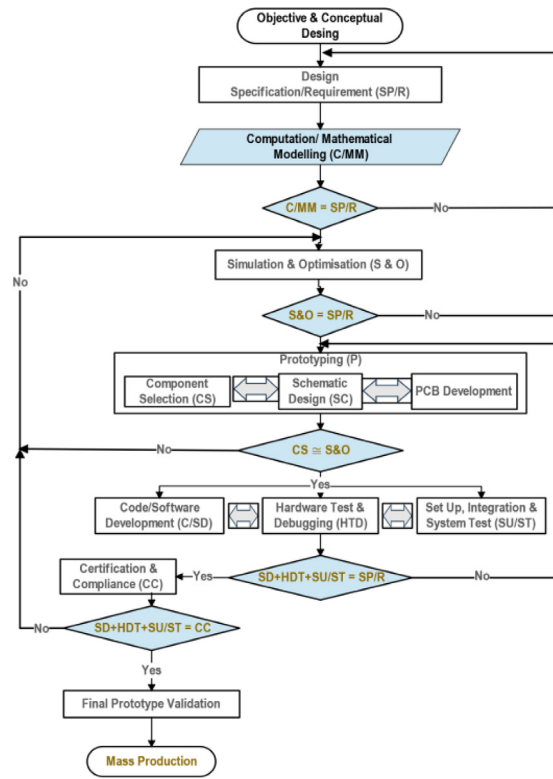


Fig. 7. PE design framework.

prototype. After a successful prototype test, regulatory standards established certification and compliance (CC) and final prototype validation (PV). CC and PV success indicate mass production readiness.

It is necessary to assess the design process of power electronic systems and propose novel approaches integrating AI to facilitate an effective shift towards sustainable power systems design and development. The escalating demand for more energy-efficient electrical systems affects design time. This is where LLMs such as GPT will be able to make the process easier. GPT models can generate coherent, contextually appropriate text and conduct a wide variety of natural language processing (NLP) tasks due to the advanced transformer architecture proposed by Google and vast training data. Their scalability and adaptability make them quite suitable for applications both in research and the real world. This allows the update of design support systems for researchers and engineers with LLMs, improving productivity, reducing errors, and saving large costs. The following section discussed LLMs. A summary of existing AI design assistant tools including a High Frequency Power Electronics (HFPE) LLM proposed in this research are provided in Table 6, indicating strength and capabilities at each design stage of PE design.

4. Large language model AI

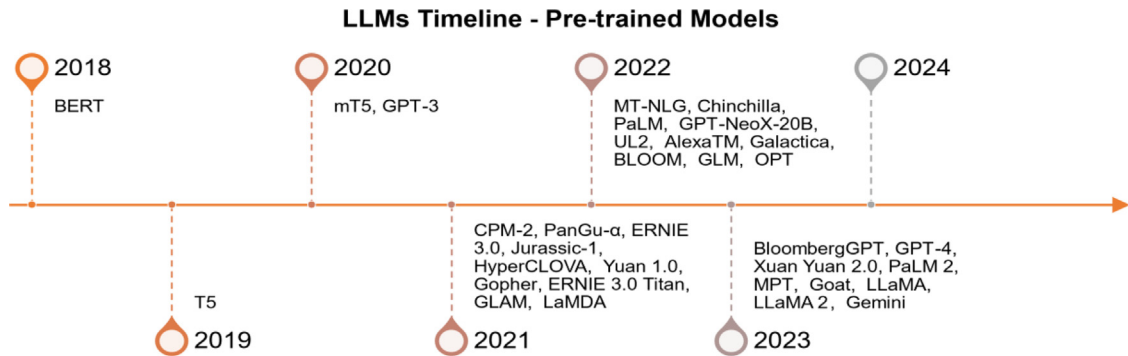
Large language models have demonstrated capabilities recently in natural language processing (NLP) due to their ability to understand and generate human-like text [142]. These models are trained over vast amounts of data to either process or generate text with a great degree of accuracy due to the attention mechanism in the transformer architecture [143]. This transformer architecture (TA) becomes more intelligent to be able to learn, generate, translate, summarize, and answer questions related to both text and numerical data. This makes an interesting area of research for design performance analysis to investigate the feasibility of LLM in the fast-tracking PE design process. In addition, LLMs can be developed for design automation and optimization of distinct phases involved in power electronics design. Starting from interpreting the design requirements to documentation generation, parameter optimization, and performance simulation, LLMs increase the productivity of design and reduce the risk of errors. With an increase in information, computing power, and AI algorithms, LLMs have the potential to revolutionize the design of power electronics processes. The TA was proposed by Google in 2017 [143], which uses traditional recurrent, and convolutional neural networks with self-attention mechanisms as shown in Fig S4 in the supplementary information document. The various kinds of position recordings include using decoder or encoder or encoder–decoder models. The attention calculates, at every word in a sequence, the relative value and relevance of words concerning other words in that sequence based on Eq. (1) as reported in [143]. Where Q represents the query matrix, K is the key matrix, and V is the value matrix, K^T transpose of the matrix K , and d_k dimension of the key vectors. The

Table 6

Collection of HFPE design assistant tools applied in PE including the prospect of LLMs.

Ref	Tool	AI technique	Applications	O&CD	SP/R	C/MM	S&O	CS	SC	PCB	CC	MP
[132]	CADY AI	Natural language with computer vision	Automatic electrical schematic inspection	↓	↓	↓	↓	↓	↓	↑	↑	↓
[133]	MagNet Princeton	Machine learning	HF simulation, Optimization	↓	↓	↑	↑	↓	↓	↓	↑	↓
[134]	Flux.AI	Machine learning	PCB design assistant	↓	↑	↓	↓	↑	↓	↑	↑	↓
[135]	M2Spice Princeton	Machine learning	HF, SPICE Netlist generation	↓	↓	↓	↑	↓	↓	↑	↓	↓
[136]	CoupL Princeton	Non-AI advanced modelling	Design optimization	↓	↓	↑	↑	↑	↓	↓	↓	↓
[137]	Frenetic.AI	Machine learning	Magnetics optimization, Simulation	↓	↓	↓	↑	↑	↑	↓	↑	↓
[138,139]	PowerBrain.AI	Machine learning with advanced OpenAI LLMs	HF magnetic components design, Core loss analysis	↓	↓	↑	↑	↓	↓	↓	↑	↓
[140]	AI-Mag	ANN, Finite element method	HF inductor modelling	↓	↓	↑	↑	↓	↓	↓	↑	↓
[141]	Open magnetics	Machine learning	Magnetics design, Simulation	↓	↓	↑	↑	↓	↓	↑	↑	↓
This paper	High Frequency Power Electronics (HFPE)	Machine learning with advanced OpenAI LLMs	Power electronics design assistant	↑	↑	↑	↓	↑	↓	↓	↑	↓

Applicability & Strength: ↑ Full Capability ↓ Partial Capability.

**Fig. 8.** Trends of LLMs pre-trained AI models timeline.

functions of each part of the transformer architecture are summarized in Table S1 in the supplementary information document. LLMs have developed more capabilities in response to the growing need for machines to perform complex language tasks, as language models are essential to human communication and self-expression. These state-of-the-art artificial intelligence systems are capable of processing, generating, and generalizing to multiple tasks with coherent communication. From statistical to neural language modelling, and from pre-trained language models (PLMs) to LLMs, NLP has advanced historically. A substantial number of LLMs are being developed by researchers that can be applied to various tasks. Figs. 8 and 9 show an increasing in the number of released LLMs and LLMs proposed over the years collected from Databricks. These timelines show the developments and patterns of natural language processing in different fields over the years.

$$[H]A(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (1)$$

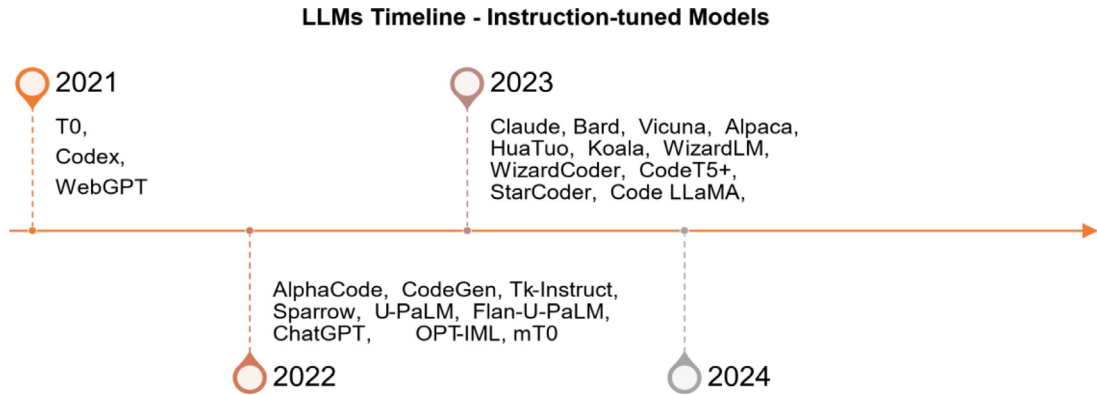


Fig. 9. Trends of LLMs instructions tuned AI models timeline.

4.1. LLMs framework-based OpenAI for power electronics design

LLMs represent a new development in artificial intelligence [144]. Their evolution can be related to earlier neural network architectures, which paved the way for more advanced models like transformers. Fast-paced development in artificial intelligence is impacting different industrial activities, including power electronics. Generative pre-trained transformers (GPT) developed by OpenAI can enhance design strategy to ensure reliability and improve productivity reported by [144,145]. The development trend of the instructions-tuned foundation model of OpenAI is shown in Fig S5 in the supplementary information document. Fig. 10 presents the design framework integrated with LLN-AI Design Assistant. This reduced the design time as opposed to the traditional framework of Fig. 7. In this process, the knowledge regarding PE is provided to the AI, and hence researchers and engineers can efficiently respond to and make design changes, thus reducing the iteration process by a tremendous amount. It automates activities connected to Objective and Conceptual Design (O&CD), Specification and Requirement (SP/R), Computation and Mathematical Modelling (C/MM), Component Selection (CS), Coding plus Schematic Design (C/SD), and Certification and Compliance (CC) to reduce human effort and the possibility of errors. MATLAB, being used for simulation and other AI implementation methods, makes the workflow smooth from conceptual design to mass production without waits due to manual transitions. Real-time feedback from the AI helps in shortening the decision cycle and brings down revision and validation times. Moreover, automating component selection, schematic design, and PCB development accelerates the prototyping phase itself. This approach avoids the tedium of the process, and much consumption of time as compared to the traditional framework, which relies exclusively on manual intervention. Thus, it provides ways in which the overall design time can be reduced under the proposed sequential design processing framework.

This proposed sequential LLM design processing framework has the potential to shorten the total time spent on the overall design. For a given defined objective and design concept (O&CD) with initial specification and requirements (SP/R), the mathematical expression of the AI framework can be represented by the following (2) to (6).

$$AI_R = Model(K) \rightarrow \begin{cases} Repeat, & \text{if } AI_R \neq SP/R \\ Proceed, & \text{if } AI_R = SP/R \end{cases} \quad (2)$$

$$C/MM \rightarrow \begin{cases} Revise, & \text{if } C/MM \neq SP/R \\ Proceed to S/O, & \text{if } C/MM = SP/R \end{cases} \quad (3)$$

$$Start_{Prompt} \rightarrow (S) \rightarrow Optimize(S) \rightarrow (S \approx SP/R) \rightarrow P \rightarrow (CS \approx S) \rightarrow (SD + HTD + SU/ST = SP/R) \quad (4)$$

$$AI_{re-prompt} \rightarrow LLM - AI \rightarrow Open AI - Based Model \rightarrow AI_R \rightarrow \text{If } AI_R = SP/R \quad (5)$$

$$End_{Prompt} \rightarrow V \& M, \text{ if } HTD + SU/ST = CC \quad (6)$$

where S and P are simulation and prototyping, respectively. SC schematic design, PCB printed circuit board development, CS combined schematic design, HTD hardware test & debugging, SU/ST set up integration & system test, SP/R specification and requirements to be met, CC certification standardization, AI_R AI response, K embedded knowledge, M mass production, V validation. This can further be expressed as (7) to (9), respectively.

$$S \rightarrow Optimize(S) \rightarrow \begin{cases} Repeat, & \text{if } S \neq SP/R \\ P, & \text{if } S \approx SP/R \end{cases} \quad (7)$$

$$P = SC + PCB \rightarrow \begin{cases} Repeat, & \text{if } CS \neq S \\ Proceed to Testing, & \text{if } CS \approx S \end{cases} \quad (8)$$

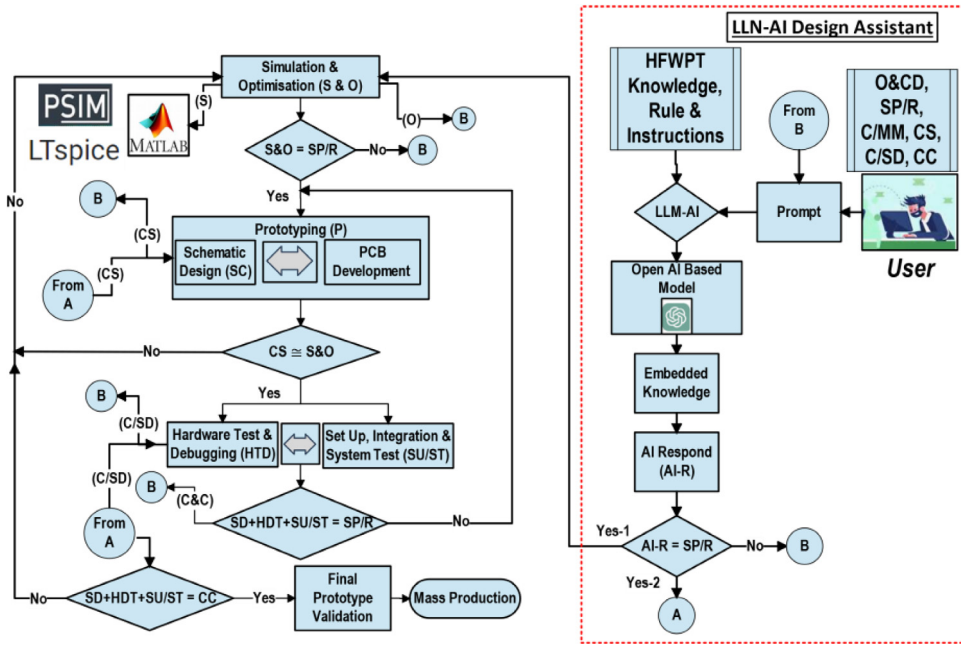


Fig. 10. PE design automation framework based on LLM instruction tune AI model.

$$HTD + SU/ST \rightarrow \begin{cases} \text{Repeat,} & \text{if } SD + HTD + SU/ST \neq SP \\ V/M, & \text{if } SD, HTD, SU/ST = CC \end{cases} \quad (9)$$

Total design time T for a non-AI framework and AI framework can be expressed in (10) and (11), respectively.

$$T_{Non-AI} = T_{SP/R} + T_{C/MM} + T_{S/O} + T_P + T_{CSD} + T_{HTD} + T_{SU/ST} + T_{TCC} + T_V \quad (10)$$

$$T_{AI} = T_{SP/R,AI} + T_{C/MM,AI} + T_{S/O,AI} + T_{P,AI} + T_{CSD,AI} + T_{HTD,AI} + T_{SU/ST,AI} + T_{TCC,AI} + T_{V,AI} \quad (11)$$

The total design time savings can be expressed as (12).

$$\Delta T = T_{Non-AI} - T_{AI} \quad (12)$$

Substituting Eqs. (10) and (11) into (12) would give (13), and introducing a saving factor α_i , the total AI design time reduction can be expressed as (14), where each T_i is the time for stage i in the non-AI framework.

$$\Delta T = (T_{SP/R} - T_{SP/R,AI}) + (T_{C/MM} - T_{C/MM,AI}) + \dots + (T_V - T_{V,AI}) \quad (13)$$

$$\Delta T = \sum \alpha_i \cdot T_i \quad (14)$$

Fig. 11 shows a framework of how to create a customized model from an OpenAI base model; this ranges from data sources to the end user. It involves a pathway of different stages: data collection, followed by base model selection, then embedding and fine-tuning following certain rules and orders, and testing with refinements before deployment for practical use. The model's knowledge base is primarily based on reputable published sources from IEEE, Scopus, and Texas Instruments. In this research, 2000 pages of data were used to fine-tune the model for high frequency AC inverter and wireless power application design based on the design automation framework present in Fig. 10.

Fig. 12 shows the procedure used to create LLM-AI assistant called 'High Frequency Power Electronic (HFPE)' to design HFWPT system. The based model is design to accept data into its knowledge section, process the uploaded data through embedding such as retrieval-augmented generation and fine-tuning, until reaching the objective instructions and rules. If the objective is not reached, there is a need to go back to refine the instructions, improve the data quality in the knowledge section. The model keeps learning from the uploaded data based on its based training and provided instructions. It answers user query, gets further training as it operates with the based generative large language model to keep advancing. The model can make changes over time by taking feedback from users and performance reviews. There is a constant need for updated and further finetuning the models to improve for best performance. The application programming interface (API) allows developers to interact with and utilize the AI model programmatically. Table 7 provides a summary of the AI algorithm used in power electronics-based design applications stages

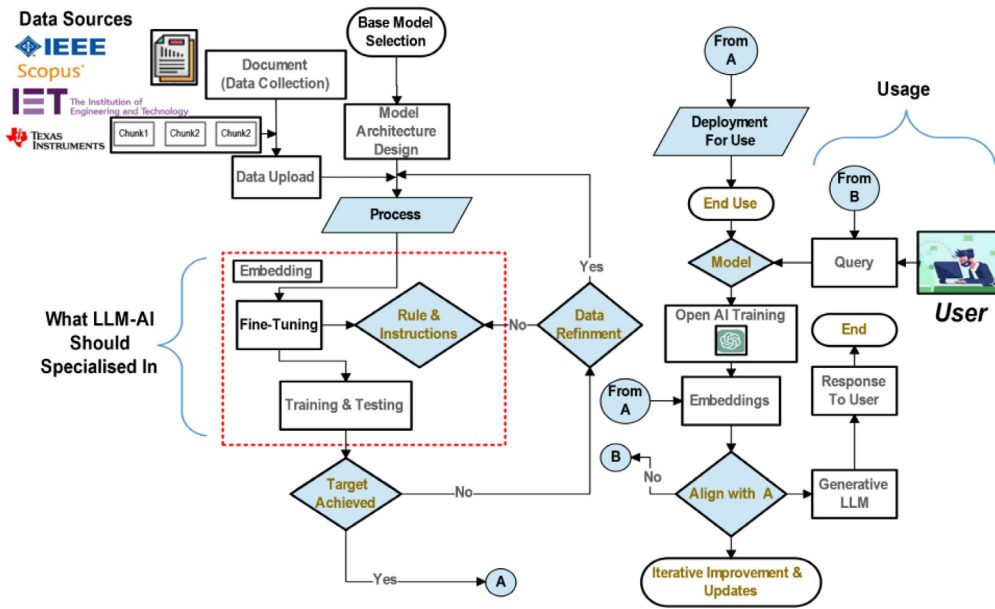


Fig. 11. LLM framework development for fine-tuning and creating customized GPT for power electronics design.

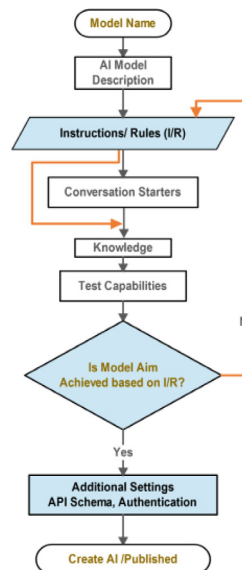


Fig. 12. High Frequency Power Electronic (HFPE) customized LLM-AI creating procedure for power electronics design.

indicating strength at each stage including LLM. The next section discussed a case study with the practical demonstration of the LLM AI assistant in the design and analysis of HFWPT systems. Simulations were run, and literature analysis was used to validate the proposed LLM-driven design.

Table 7

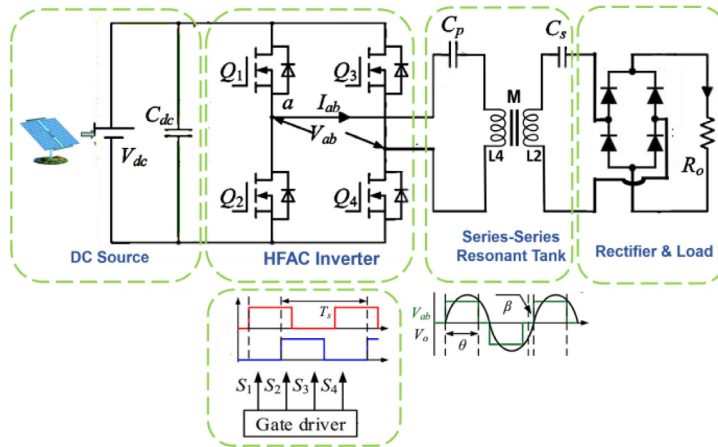
AI algorithm applications based on stages of PE design process.

Ref	AI algorithm	O&CD	SP/R	C/MM	S&O	CS	SC	PCB	CC	MP
[98]	Expert systems	↓	↓	↓	↑	↓	↓	↓	↓	↓
[87,100,146,147]	Fuzzy Logic	↓	↓	↓	↓	↓	↓	↓	↓	↓
[29,32,60]	GA (Genetic Algorithm)	↓	↓	↓	↑	↓	↓	↓	↓	↓
[51,52,72]	NSGA-II	↓	↓	↓	↑	↓	↓	↓	↓	↓
[45,76,148]	PSO	↓	↓	↓	↑	↓	↓	↓	↓	↓
[50,68]	ABC	↓	↓	↓	↑	↓	↓	↓	↓	↓
[47]	ACO	↓	↓	↓	↑	↓	↓	↓	↓	↓
[48,70]	DE	↓	↓	↓	↑	↓	↓	↓	↓	↓
[30,53,149,150]	ANN	↓	↓	↓	↑	↓	↓	↓	↓	↓
[73,75,151]	ANN-GA	↓	↓	↑	↑	↓	↓	↓	↓	↓
[76,152]	ANN-PSO	↓	↓	↑	↑	↓	↓	↓	↓	↓
[83–85]	RL	↓	↓	↑	↑	↓	↓	↓	↓	↓
[22,153]	UL	↓	↓	↑	↑	↓	↓	↓	↓	↓
[37,108]	SL	↓	↓	↑	↑	↓	↓	↓	↓	↓
[107,154]	Metaheuristic Methods	↓	↓	↓	↑	↓	↓	↓	↓	↓
Proposed in this work	LLMs based on GenAI	↑	↑	↑	↓	↑	↓	↓	↑	↓

Applicability & Strength: ↑ Full Capability ↓ Partial Capability.

5. LLM-AI-driven design of HFWPT (Case study 1)

Wireless power transfer (WPT) has been studied since the 1880s by Nikola Tesla [155,156]. Research and development in semiconductor materials like wide band gap devices, has made the development of high-frequency wireless power electronics working at high power density, low size [157], and enhanced performance possible [158]. These materials operate at lower losses, higher voltages and temperatures which enables system miniaturization and development of compact systems. Recent progress in Silicon carbide (SiC) and gallium nitride (GaN) based switches has made wireless power systems operate at even higher frequencies by designing an effective AC power inverter. Fig. 13 shows a simplified circuit diagram of the HFWPT system.

**Fig. 13.** Basic simplified circuit diagram of series-series HFWPT system.

High-frequency wireless power transfer (HFWPT) technology particularly in the tens of kilohertz to megahertz range, has experienced major advancements. In a recent study performed by [159], a wireless power transfer system operating at a frequency of 6.78 MHz was presented. The system exhibited an efficiency of 95% for a power level greater than 1 kW. Another research by [160] based on an inductive power transfer system having a nominal power of 2 kW and a frequency of 3.39 MHz demonstrated a peak efficiency of 95% when delivering an output of 3 kW. These advances prove the possibility of high efficiency and high power in systems that work at high frequencies [161]. High-frequency wireless power transmission yields higher power density and is more compact, making it suitable for high-power applications with minimal coupling requirements [162]. High-frequency wireless power transfer technology has applications in various fields such as electric vehicle charging [163], smart grid systems [164], wireless charging of portable biomedical electronic devices [165], and high-power applications with low coupling requirements. However, it faces challenges and limitations. A comprehensive review by [166] discussed challenges including design, prototypes, international standards, and commercialization of both dynamic and static WPT. Research by [167–169] reported that series-series (SS) topology is suitable for high-frequency magnetic resonance wireless power transfer. Eqs. (15) to (21) are used in modelling and designing

wireless power transmission systems, which are resonant at high frequencies based on SS topology. They provide the calculation of the resonant frequency (f_o) of an LC circuit, governed by the inductance and capacitance of the LC components as shown (15). A coil inductance depends on the number of turns (N), coil circular radius(R), the permeability of space (μ_o), the relative permeability (μ_r), and the G.M.R of the wire (r) as shown in Eqs. (16).

$$f_o = \frac{1}{2\pi\sqrt{L_o C_o}} \quad (15)$$

$$L_o = N_o^2 R \mu_o \mu_r \left[\ln \left(\frac{8R}{r} \right) - 2 \right] \quad (16)$$

where f_o represent primary (f_1) and secondary (f_2) side frequency, while (L_o) represent primary side inductance (L_1) and secondary side inductance (L_2) as represented in Fig. 14. The primary capacitance (C_p) can be calculated considering the secondary inductance, secondary capacitance (C_s), and primary inductance as shown in (17). The coupling coefficient (k) is a constant ranging from $0 \leq k \leq 0.5$ for a loss coupling, and complete mathematical modelling of HFWPT is discussed in [167]. These provide an estimate of the degree of magnetic coupling existing between two inductors in which (M) is the mutual inductance. The quality factor is the measure of the efficiency of the resonant circuit and is calculated as the ratio of inductive reactance to resistance on the primary and secondary sides where $\omega = 2\pi f$. Q_p and Q_s can be calculated for the primary and secondary sides using Eq. (19). Maximum efficiency can be calculated using Eq. (20) considering the coupling coefficient and quality factors of the primary and secondary sides, or currents through the primary and secondary sides with load resistance, primary and secondary resistances as shown in Eq. (21). These equations provide the basis for designing wireless power transfer.

$$C_p = \frac{L_2 C_s}{L_1} \quad (17)$$

$$k = \frac{M}{\sqrt{L_1 L_2}} \quad (18)$$

$$Q = \begin{cases} \frac{\omega L_1}{R_1}, & \text{For Primary Side} \\ \frac{\omega L_2}{R_2}, & \text{For Secondary Side} \end{cases} \quad (19)$$

$$\eta = \frac{k^2 Q_1 Q_2}{(1 + \sqrt{1 + k^2 Q_1 Q_2})^2} \quad (20)$$

$$\eta = \frac{I_2^2 R_L}{I_1^2 R_1 + I_2^2 R_2 + I_2^2 R_L} \quad (21)$$

5.1. WPT simulation

The HFWPT system is designed using LLM-AI-driven design assistance as proposed in Section 3. After the creation, finetuning and successful deployment of the LLM-AI. It is prompted to design an HFWPT using the design specifications as reported in [167]. The input design specifications are shown in Table 8. The proposed design was simulated in MATLAB to analyse and compare with the results reported in [167]. The LLM proposed design was simulated and the results output was used to design optimized the filter using an iterative prompt approach between the LLM and simulation output. The HFPE often provide potential values of the design using based on design equations provided in the knowledge section and instructions during creation and fine tuning. The parameter values can be further refined or optimized to meet the design requirement. The MATLAB simulation block presented in Fig. S6 in the supplementary information documents, which includes a gate drive, high-frequency inverter, high-frequency wireless power system, rectification, and a resistive load. A 'Chat sheet' and video of HFPE-AI driven design showing all the prompts and responses is provided in the supplementary sections of this paper.

Table 8
Input design specification.

Parameter	[167]	HFPE LLMs-AI (This work)
Frequency (Hz)	41 500	41 500
Circular coil radius (cm)	3.8	3.8
Primary & Secondary turns	25	25
G.M.R of the wire (mm)	3.5	3.5
Primary & Secondary resistance (Ω)	0.0714	0.0714
Resistive load (Ω)	150	150
Duty ratio	0.75	0.75

5.2. WPT LLM-driven design results

The results of the LLM-AI-driven design of the HFWPT and validation are shown in Figs. 14 to 15 and Table 9, respectively. The sinusoidal nature of both the voltage and current waveforms shows that the system is conducting the necessary function within the specified frequency range. This type of waveform analysis is crucial for designing and optimizing WPT systems to ensure efficient

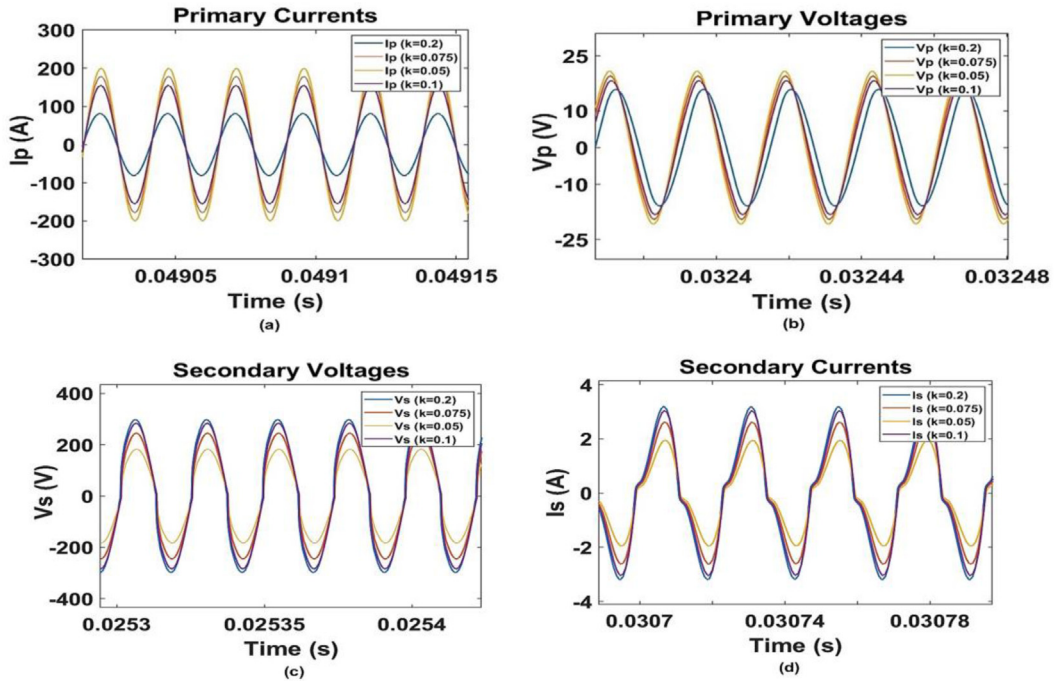


Fig. 14. HFPE-AI proposed HFWPT design at 1 cm spacing, 41.5 kHz, (a) and (b) primary currents, and voltage, (c) and (d) secondary voltage and currents.

power transfer and minimize losses. The graphs presented in Fig. 14 illustrate the waveforms of primary and secondary currents and voltages for a wireless power transfer system under different coupling coefficient (k) values. The primary current and voltage waveform at $k = 0.2, 0.1, 0.075$, and 0.05 significantly changes in amplitude corresponding to changes in the coupling coefficient, with the highest amplitude observed for $k = 0.2$ and the lowest for $k = 0.05$ (Fig. 14a and b). A similar trend is on the secondary side (Fig. 14c and d), where the amplitudes decrease as (k) decreases. These results provide a clear visual representation of how the coupling coefficient impacts the performance of the wireless power transfer system, like the result reported in [3].

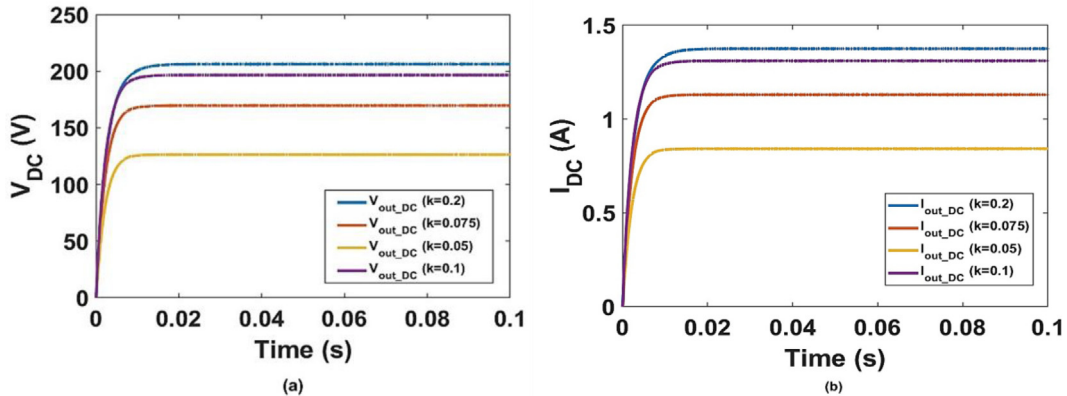


Fig. 15. HFPE-AI proposed HFWPT design system output DC (a) voltage, (b) current.

The overall DC output in Fig. 15, shows a steady state of current at approximately 1.4 A and voltage at approximately 200 V at $k = 0.2$. A decrease in current and voltage indicated a decrease in power output as the value of k decreased from 0.2 to 0.05 indicating a decrease in efficiency. This agrees with the results reported in other literature. The HFPE-AI was also used to optimize the output fillers and provide a potential supplier of suitable components to proceed to the prototype. The design parameters computation was completed in seconds. The complete design including filter parameter optimization was completed in minutes. The currents, proposed by the LLM-AI driven design assistant may be due to potential issues such as incorrect quality factor assumption. The HFPE-AI design assistance assumes a $k = 0.2$ to calculate the mutual inductance of the WPT system. Future work should focus on investigating the trade-off and dependability of LLM AI WPT systems-driven design and adopt other advanced LLM AI techniques. Further insight into the overall output DC performance shows that the AI-designed system works correctly under the expected

conditions, thus making the 250 V potentially applicable to electric vehicles (EV). In addition, the ability of the HFPE-AI design assistance to assist with component selection based on specific design applications has demonstrated the potential of reducing design time at the stage of prototyping. Appropriate component ratings selection reduces losses and improves system robustness. The overall design is achieved by simply prompting an AI that is finetuned for a specific system design to show the feasibility of automation and reducing design time of the O&CD, SP/R, C/MM, CS, C/SD, and CC as proposed in Fig. 7. Table 9 compares the design output of the HFPE AI proposed design validation against a reference design reported in [167]. Both designs operate at 41.5 kHz, with a circular coil radius of 3.8 cm, 25 primary and secondary turns each, and wire G.M.R of 3.5 mm. The HFPE AI was prompted to design an HFWPT system based on the specifications reported in [167]. The reference paper uses 73.43 μH for primary and secondary self-inductances, slightly differing from the LLMs-AI design calculated value of 73.6 μH with a standard deviation (SD) of 0.0085. The LLMs-AI design also calculated the mutual inductance of 14.72 μH , 7.36 μH , 5.52 μH , and 3.6 μH for k_1 , k_2 , k_3 , and k_4 , respectively, which is not reported in [167]. The primary and secondary compensation was obtained to be 0.2 μF , the same as the referenced paper (SD = 0). To ensure proper spacing, the efficiency decreases as k decreases, with an SD of 42.9, 20.1, 0.3, 18.3 compared to the simulation in [167] and 44.5, 21.8, 1.9, 16.6 compared to the experiment in [167]. The closest LLM-AI-driven design efficiency is 36.4% with $k_3=0.075$, SD of 0.3 and 1.9 compared to 36.0% and 33.6% in [167], respectively. These results show the potential of LLMs AI to optimize the design process of power electronics systems. These improvements could increase engineers' and researchers' productivity, enhance performance and efficiency, and maintain consistency in design parameters.

Table 9

Output comparison of HFPE (LLMs-AI) design with [167].

Parameter	[167]		LLM-AI (This work)				Standard Deviation							
	Sim	Exp	k_1 (0.2)	k_2 (0.1)	k_3 (0.075)	k_4 (0.05)	[167] Simulation				[167] Experiment			
							k_1	k_2	k_3	k_4	k_1	k_2	k_3	k_4
Primary & Secondary Self-inductance (μH)	73.43	73.43	73.6	73.6	73.6	73.6	0.085				0.085			
Mutual Inductance (μH)	–	–	14.72	7.36	5.52	3.68	–	–	–	–	–	–	–	–
Primary & Secondary series capacitance (μF)	0.2	0.2	0.2	0.2	0.2	0.2	0	0	0	0	0	0	0	0
Efficiency (%)	36	33.6	96.6	64.4	36.4	10.1	42.9	20.1	0.3	18.3	44.5	21.8	1.9	16.6

6. LLM-AI-driven design of HFAC inverter (Case study 2)

High-frequency alternating current (HFAC) systems first proposed by NASA for space equipment, have found applications in a variety of fields due to their simpler structure, higher power density, and transmission efficiency compared to traditional DC systems. Fig. 16 shows a simplified LCLC HFAC system circuit diagram. HFAC system eliminate the need for AC–DC and DC–AC therefore fewer components are required in the system resulting in higher reliability [170]. The switching network generates a high-frequency quasi-square-wave voltage to convert the DC voltage into HFAC voltage or current. Increasing the switching frequency allows miniaturization of inverters and reduces cost. However, this creates several challenges, including switching and magnetic losses. The challenge can be improved by proper design methods, topology, drive circuits, and magnetic components. This makes HFAC suitable as a second case study to investigate the feasibility of LLM-driven design. Wide band gap (WBG) devices such as Silicon Carbide (SiC) and Gallium Nitride (GaN) are at the front end of the HF system [171]. The WBG devices enable system to work at high frequency switching employing soft switching technique zero voltage switching (ZVS) and zero current switching (ZCS) within the system. HFAC systems have many applications and detailed studies have been reported in [172,173]. For example, [174] investigated control strategy in HFAC. Their results show that proportional integral resonant (PIR) control shows better performance and lower total harmonic attenuation capability. As such, the PIR control is adopted in the LLM-driven design. Full information about the design including design correlations can be found in the supplementary documents. Preliminary studies in HFAC reported various advantages, including flexibility in meeting different voltage requirements, ease of electrical isolation with compact high-frequency transformers, fewer components, and reduced system integration complexity. Phase-Shift Modulation (PSM) is one of the essential control strategies in HFAC systems and is utilized in high-efficiency applications with reduced switching losses. As such the power flow in the LLM-driven design is controlled by PSM through an adjustment of the phase angle between the input and output voltage waveforms. This technique substantially minimizes switching losses by permitting ZVS and ZCS soft switching [175–179]. The LCLC HFAC simulation was conducted using PSIM. Design specification from [174] is adopted to allow the LLM-driven design validation and assessment.

The PSIM simulation block as shown in Fig. S7 in the supplementary information document includes a Texas Instrument (TI) second-order low pass filter (LPF) UAF42, PIR controller, phase shift modulation logic gate to drive the high-frequency AC inverter, and a resistive load using the HFAC H-bridge topology. The complete PIR circuit diagram and all other necessary information can be found in Fig S8, Fig S9 and Table S3 in the supplementary documents, respectively. A 'Chat sheet' and video of HFPE-AI driven design showing all the prompts and responses are also provided in the supplementary sections of this paper. The design equations for the HFAC and the complete specification of the inverter can also be found in Table S1 in the supplementary documents.

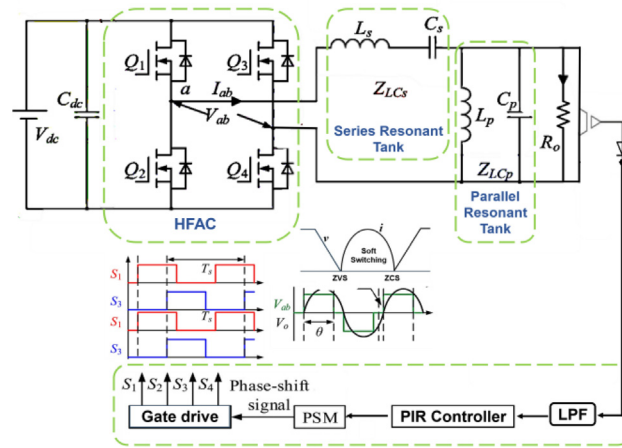


Fig. 16. Circuit diagram of single-phase HFAC.

The LLM-AI is prompted to design a 130 W HFAC inverter using the design specifications as reported in [174]. The results of the LLM-AI-driven design of the LCLC HFAC inverter and validation are shown in Figs. 17 to 18 and Table 10, respectively. The HFPE-AI proposed HFAC design operating at 25 kHz demonstrates balance electrical dynamics. Fig. 17(a) illustrates the resonant current I_{ab} , maintaining a sinusoidal waveform with consistent amplitude which is common in optimal resonance circuit. The corresponding H-bridge arm voltage V_{ab} exhibits a square waveform, aligning with the expected operational behaviour of a high-frequency inverter topology working based on phase shift modulation. Fig. 17(b) shows the achieved zero voltage switching (ZVS) and zero current switching (ZCS) within the system. ZVS is achieved in leg B as shown in the plot of voltage and current IDS_D across switch CD. Similarly, ZCS is achieved in leg A as shown in the plot of voltage and current IDS_B across switch CD. Soft switching achieved in the system's design minimizing switching losses and ensuring high efficiency. These results closely align with those reported in the reference paper [174], and further detailed comparisons can be found in Table 10. This comprehensive illustration underscores the practical application of the LLM-driven design.

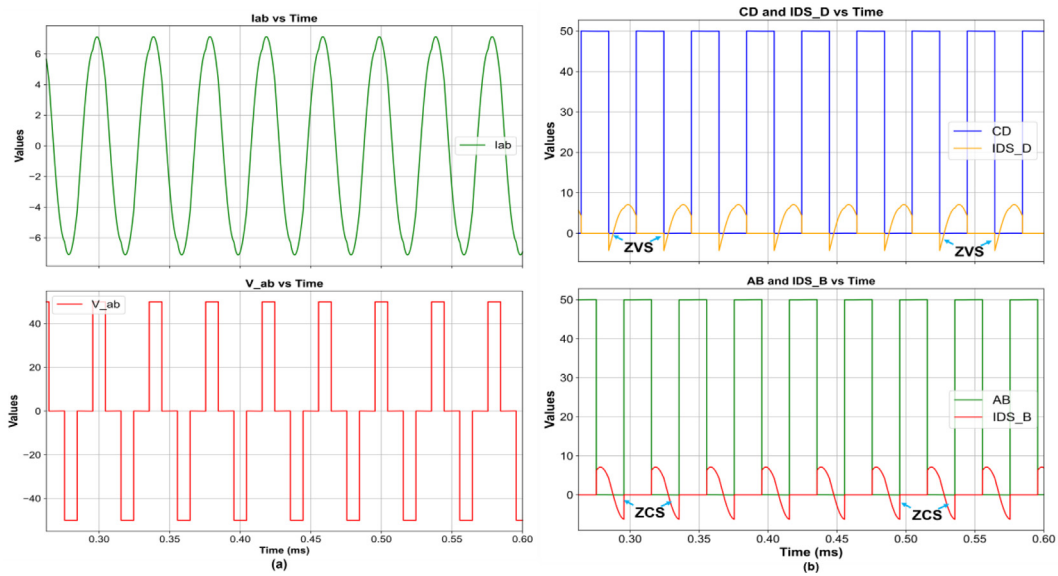


Fig. 17. HFPE-AI proposed HFAC design at 25 kHz (a) resonant current, and H-bridge arm voltage (b) ZVS and ZCS achieved, respectively.

The proposed AI design output performance is presented in Fig. 18 showing the output current I_o and voltage V_o . The simulation results show a total harmonic distortion (THD) of 1.23% and a peak voltage of 41.6 V, compared to the experimental results from the reference paper, which reported a THD of 1.65% and a peak voltage of 39.4 V [174]. While the simulation values differ slightly from the experimental data, this is expected due to the inherent differences between simulations and experiments. Further detailed comparisons can be found in Table 10 with the reference data to validate the LLM-AI-driven design.

Table 10 provides a detailed comparison of the HFPE (LLMs-AI) design results from this study with the reference work [174], highlighting key electrical parameters and performance metrics. The load resistance in this work is 6.03 Ω as proposed by the

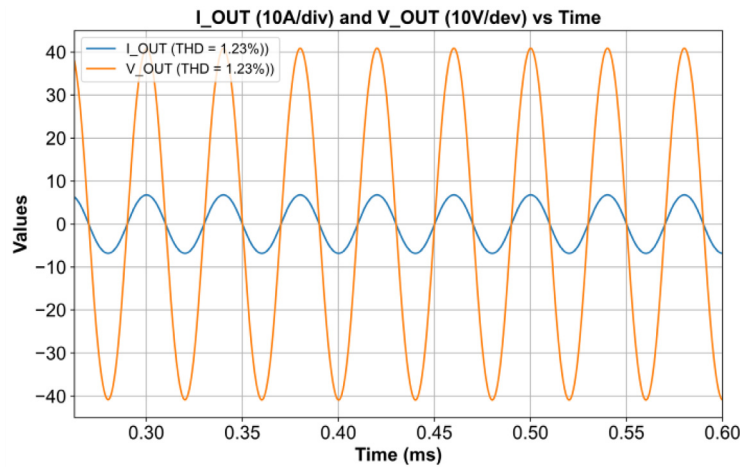


Fig. 18. HFPE-AI proposed HFAC design output currents, and voltage with THD at 25 kHz.

LLMs-AI, closely matching the reference value of 6.00 Ω , with a standard deviation (SD) of 0.03 Ω . The series capacitance and inductance also align well with the reference values, showing minimal deviations with SDs of 0.102 μF and 0.004 μH , respectively, while both designs maintain a series resonant frequency of 25 kHz without any deviation. The parallel network shows moderate deviations, particularly in inductance, with an SD of 11.34 μH , reflecting possible slight errors from the LLMs-AI design approach. The output voltage of 41.6 V in this study is slightly higher than the reference value of 39.4 V, with an SD of 1.56 V, demonstrating an improvement in voltage amplitude. Additionally, the total harmonic distortion (THD) achieved is 1.23%, lower than the reference value of 1.65%, with an SD of 0.30%, as reported in [174]. The simulation efficiency for the proposed design is 92.91%, with a SD of 1.59%, compared to the reference simulation efficiency of 94.50%. These results collectively demonstrate the potential LLMs-AI design assistant approach in high-frequency AC applications, which can be extended to other areas. A Wilcoxon signed-rank test was conducted to compare the Ref. [174] and LLMs-AI (this work). With a p -value of 0.50, the test revealed no significant difference between the two groups. This indicates that we fail to reject the null hypothesis, suggesting that there is no evidence of a systematic difference between the reference paper and the LLM-AI design. The complete Wilcoxon statistical test can be found in the data spreadsheet in the supplementary information section.

Table 10

Output comparison of HFPE (LLMs-AI) design with [174].

Parameter	[174]	LLMs-AI (This work)	SD
Method	Experiment	Simulation	
Load resistance (Ω)	6.00	6.03	0.03
Reactance of series capacitor (Ω)	–	17.28	–
Series capacitance (μF)	0.47	0.37	0.102
Series inductance (μH)	110.00	109.996	0.004
Series resonant frequency (kHz)	25.00	25.00	0.00
Reactance of parallel capacitor (Ω)	–	3.54	–
Parallel capacitance (μF)	1.80	1.81	0.01
Parallel inductance (μH)	17.00	28.34	11.34
Parallel resonant frequency (kHz)	–	37.50	–
Output voltage (V)	39.4	41.6	1.56
Total harmonic distortion (%)	1.65	1.23	0.30
Efficiency (%) - Experimental	93.33	–	–
Efficiency (%) - Simulation	94.50	92.91	1.59

7. Discussion and future research direction

AI algorithms are used in various sectors to personalize and simplify interactions, and tasks, or solve problems. This creates an interesting and novel opportunity for the integration of LLMs, such as GPT, within the processes of designing power electronics. The approach has prospects that can make the design process much faster, with reduced potential for errors, and increased productivity in current trends and future demands in the field of power electronics. ChatGPT, published by Open AI in 2022, is one of the fastest-adopted AI technologies in history and marks a new AI beginning in 2023. It is based on natural language processing and is used to understand and enhance predictions of algorithms in various sectors. Machine learning incorporates random forest methods for clustering, regression, and classification. Regression presents a statistical methodology that predicts continuous values of target variables, based on their relation to the input factors. In the applications of a control system, an intelligent controller can use regression analysis to build mathematical models of dependencies between the input signals and control variables. The concept of

Table 11
Prospect of LLMs AI applied to power electronics design.

Design phase	Applications of LLMs	Description
Objective & Conceptual	Generating design concepts	Analyzes large datasets of existing designs to propose new configurations.
	Refining specifications	Interprets user inputs and compares them with industry standards to refine design specifications.
Design specification & Requirement	Requirements analysis	Utilizes natural language processing to extract and analyse requirements from technical documents and stakeholder inputs.
	Specification verification	Automatically checks the consistency and completeness of specifications against known standards and prior projects.
Computation/ Mathematical modelling	Parameter optimization	Automates the optimization process by exploring potential solutions and leveraging historical data.
	Performance simulation	Integrates with simulation tools to run and interpret simulations, suggesting modifications for improvement.
	Model-based design	Uses mathematical models to simulate and validate system behaviour under various operating conditions.
Simulation & Optimization	Sensitivity analysis	Identifies critical design parameters and assesses their impact on overall system performance.
	Scenario testing	Runs multiple simulations to evaluate system robustness and performance across different scenarios.
Prototyping	Automated component selection	Analyzes design requirements to recommend suitable components based on availability, cost, and performance.
	Prototyping assistance	Generates detailed instructions and documentation for creating prototypes, ensuring accuracy and efficiency.
Code/Software development	Code generation	Automatically generates code for embedded systems based on design specifications and models.
	Software validation	Uses LLMs to validate software against design requirements and industry standards.
Hardware test and debugging	Automated test generation	Creates test cases and procedures for hardware validation using patterns learned from historical test data.
	Fault diagnosis	Analyzes test results to diagnose faults and suggest corrective actions.
Set up, Integration and system test	System integration support	Provides integration guidelines and checks compatibility between different subsystems.
	End-to-End testing	Executes comprehensive tests to ensure all system components work together seamlessly and meet design specifications.
Certification and compliance	Generating technical documentation	Automatically generates comprehensive documentation, including design descriptions and testing procedures.
	Compliance checks	Analyzes design against industry standards and regulatory requirements, suggesting modifications for compliance.
Final prototype validation	Final system validation	Ensures the final prototype meets all design and performance criteria through rigorous testing and validation.
Mass production	Production optimization	Provides recommendations for scaling up production efficiently while maintaining quality standards.
	Continuous improvement	Analyses production data to suggest ongoing improvements and optimizations in the manufacturing process.

using LLMs for the optimization of design processes in power electronics has been relatively new. While applications of LLM cut across quite a few domains, there is very little on record about its applications in power electronics design time reduction and accuracy improvement. Future work would include impact assessment to identify trade-offs, where researchers have used LLMs in the prediction of material properties, and parsing design documents, specifications, and simulation results for optimal power electronics design. This research into exploring the integration of LLMs like GPT in the design process of power electronics bridges an important gap in the current methodologies by leveraging advanced AI to drive design efficiency and accuracy. This work will advance the field of power electronics, and this application of LLMs in the engineering design process will set a concrete precedent for other such developments. Table 11 highlights how LLMs can enhance various stages of the power electronics design process, from conceptual design to compliance checks, by automating and optimizing key tasks.

The integration of LLMs into power electronics design presents both opportunities and challenges. One significant challenge is the dependency on large datasets. LLMs require extensive amounts of data for training and fine tuning to function effectively, which in the context of PE design may not always be readily available. LLMs' reliance on large datasets not only raises concerns about data availability but also about the quality of the data. Potential biases can affect the generalization ability of the models, limiting their effectiveness across different PE applications. Implementing LLMs in PE design is computationally intensive, often necessitating

Table 12

Future research directions for LLMs in power electronics design.

Research direction	Potential research areas	Description
Advanced LLMs AI algorithms		
Hybrid models	Combining LLMs with other AI techniques	Integrate LLMs with RL or graph neural networks (GNNs) for enhanced performance.
Generalization ability of LLMs	Mitigating hallucination and improving accuracy	Explore possibility cross-reference model outputs with trusted databases and simulation tools to validate accuracy in critical applications like PE design.
Meta-learning	Models learning to learn	Reduce the need for extensive fine-tuning by enabling models to adapt more quickly to new tasks.
Explainability and transparency	Making LLMs more explainable and transparent	Develop techniques to help PE engineers understand model decisions, increasing trust and facilitating adoption.
Real-time implementation of LLMs		
Real-time design optimization	Developing real-time optimization algorithms	Improve the performance and efficiency of power electronics systems with reduced computational latency within simulation platforms such as MATLAB, PSIM, ALTIUM, etc.
Edge computing	Deploying LLMs closer to the source of data	Reduce latency and enhance real time processing capabilities for applications like adaptive control in power converters.
Interdisciplinary collaboration		
Collaborative platforms	Platforms for sharing data, models, and insights across disciplines using LLMs	Accelerate research and development through joint projects and a multidisciplinary approach.
Cross domain knowledge transfer	Methods for transferring knowledge across domains using LLMs	Adapt techniques from other fields for power electronics design.
Educational initiatives	Promoting integration of AI and power electronics in education	Need for a new generation of engineers skilled in both AI and power electronics leveraging the advancement in LLMs.
Data-driven design, optimization and sustainable		
Big data analytics	Developing more AI algorithms and analytics to simplify power electronics design	Reveal patterns and trends from large datasets to inform design decisions. Improve efficiency and stability of renewable energy generation, storage, and distribution by system troubleshooting during design, or maintenance.
Predictive maintenance	Developing predictive maintenance strategies using LLMs	Enhance the reliability and lifespan of power electronic systems by predicting failures and optimizing maintenance schedules. Optimize charging/discharging cycles, predict energy demand, and ensure efficient utilization.
Digital twins	Creating digital twins of power electronics systems using LLMs	Enable real-time monitoring and optimization through simulations of physical systems. Analyses and optimizes grid operations, detect faults and integrate distributed energy resources.

high-performance hardware and substantial energy consumption. Proprietary constraints can limit access to model or level of fine tuning, potentially leading to models that lack robustness or bias. Future research should focus on creating LLM not depending on foundation model to shared datasets and exploring data augmentation techniques to mitigate these issues. Another challenge lies in the potential bias and ethical considerations associated with AI models during creation or fine tuning. Bias in training data can lead to inaccurate results, which is concerning in various applications of power electronics. Addressing this requires developing methods for bias detection and correction, as well as establishing ethical guidelines for AI use in PE. This requirement can be a barrier, especially for smaller organizations with limited budgets. For smaller organizations or projects with tight budgets, the practicality of implementing LLMs is a critical issue. High costs associated with creating and fine tuning can make adoption challenging. The financial investment required for deploying LLMs includes not only computational resources but also ongoing maintenance and updates. The total cost for the OpenAI ‘Team workspace’ used is \$25 per seat/month for the monthly subscription. This is crucial for ensuring that the AI models remain effective as technologies and design requirements evolve. The ability of LLMs refers to their capacity to apply learned knowledge to new and varied situations in electronics design based on continuous data update that can also be a financial burden. Potential users and creators may find these costs as a barrier, potentially widening the gap between large and small organizations in technological capabilities. Ethical implications are equally important, especially in sensitive applications like power electric and sourcing data from data base like Scopus, IEEE, google scholar etc. The use such data may raises concerns about accountability, transparency, and the potential for unintended consequences. More case study of LLM driven design of PE is need. In addition, strategies to enhance real world applicability, such as incorporating stochastic elements and experimental validation are ares for future research directions. To address these issues the following mitigations can be adopted as outline in [Table 12](#). [Tables](#)

13 and 14 outline the challenges and future research directions for integrating LLMs into power electronics design, with potential advancements and applications to PE.

Table 13

LLMs implementation limitations.

Type	Mitigation strategies	
Data availability and quality	Data diversification	Incorporate a wide range of data sources to enhance model robustness.
	Bias mitigation techniques	Employ algorithms specifically designed to detect and reduce bias in AI models.
	Poor-quality data, including inaccuracies, biases, or inconsistencies, impacts model performance	Use reliable data sources for data gathering Encourage industry collaboration to develop comprehensive datasets while respecting proprietary boundaries. Implement rigorous data validation and cleaning processes to ensure accuracy and consistency. Use robust data preprocessing techniques to handle biases and inconsistencies.
	Efficient model development	Explore the development of smaller, more efficient models requiring less data without compromising performance.
Computational costs and resource demands	Model Optimization	Research into model compression and optimization to reduce computational load.
	Cloud computing	Utilize cloud services for scalable resources without significant upfront investment.
	Algorithm efficiency	Develop more efficient algorithms tailored to PE applications to lower resource demands.
Accessibility for smaller organizations	Open-source platforms	Leverage open-source AI tools and models to reduce costs.
	Shared resources	Participate in consortiums or partnerships to share computational resources and expertise.
	Training and education	Invest in training programmes to build in-house capabilities, minimizing reliance on external specialists.
Generalization ability of LLMs	Hallucination	Design clear and specific prompts to guide the model towards accurate and relevant outputs. Ensure that datasets undergo rigorous validation to identify and remove inaccuracies or inconsistencies. Data from standard data base should be use which include web of science, Scopus, IEEE, etc
	Broad training data	Use diverse datasets covering a wide range of scenarios and conditions.
	Transfer learning	Apply knowledge gained from one domain to another, reducing the need for extensive retraining.
	Continuous Learning	Implement mechanisms for models to learn incrementally from new data over time.
Practical barriers and ethical implications	Ethical frameworks	Establish clear ethical guidelines for AI deployment in PE, focusing on transparency and responsibility.
	Regulatory compliance	Ensure that AI applications meet all regulatory standards and certifications required in the industry.
	Stakeholder engagement	Involve a broad range of stakeholders, including policymakers, industry experts, and the public, in discussions about AI integration.

Table 14

LLMs challenges and potential solutions for implementation.

Challenge	Description	Potential solutions
Data availability and quality		
Domain-specific data sensitive	Highly data sensitive as the functionality depends on data used for development and fine tuning.	More additional case studies are required. Encourage collaboration between academia, industry, and research organizations to create comprehensive datasets based on a reliable database. Integrate empirical data through simulations or other AI models.
Model adaptation and customization		
Fine-tuning complexity	Requires expertise in both AI and power electronics to fine-tune models successfully.	Use pretrained models on large, general datasets or fine-tune-based domain-specific datasets. Implement techniques such as dropout or early stopping to prevent overfitting.
Computational requirements		
High training costs	Significant computational resources are required for training and fine tuning LLMs	Use cloud platforms to access scalable resources on a pay-as-you-go basis.

8. Conclusion

We have reviewed AI applied in power electronics and proposed the potential of LLMs in electronic design. This study provides key information on implementing a large language model AI assistant tool including challenges, limitations and future research

directions. Two case studies – high-frequency wireless power transfer design and HFAC system design – are presented to investigate the design approach. A ‘Chat sheet’ and video of the case studies have been provided in the supplementary section. The designs were compared with reference designs available in the literature. Additionally, we proposed an LLMs-AI driven design framework to improve the design process. Advancement in design methodologies and design tools such as LLM-AI driven design has the potential to streamline the design process of power electronic. LLM-AI driven design optimization enables quicker iteration, significantly reduces development cycles, and fosters innovation in power electronics design. Advancements in LLM-AI driven design, have the potentials to revolutionize the design process of power electronics, including conceptualization, modelling, rapid prototyping, component selection, parameter optimization, and validation. This can significantly decrease the time required to produce a circuit board. Furthermore, LLM has the potential to unify the design framework for power electronics with a combined knowledge-based assistance data base. The use of AI methodology has significant prospects in PE design, and LLMs including OpenAI GPT, have the capabilities of understanding and processing technical specifications, design parameters, and optimization of power electronics which can generate new design ideas. This paper highlights trends in methodology usage together with advantages, limitations, and future research directions for AI algorithms in power electronics. In addition, LLM perspectives with interconnections among relevant AI algorithms, core functions, and applications are also discussed.

Declaration of Generative AI and AI-assisted technologies in the writing process

A generative AI called High Frequency Power Electronic (HFPE) was specifically created and optimized to investigate the feasibility of LLM as PE design assistant. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

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Appendix A. Supplementary material

A supplementary document, data, complete ‘Chat sheet’ and video of the LLM-AI driven designs of the case studies are provided. Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.compeleceng.2025.110248>.

Data availability

Data will be made available on request.

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Revolutionizing power electronics design through large language models: applications and future directions

Ibrahim, Khalifa Aliyu; Luk, Patrick Chi-Kwong; Luo, Zhenhua; Ng, Seng Yim; Harrison, Lee

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