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The Potential of Machine Learning for Thermal Modelling of SiC Power Modules - A Review

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***Abstract*—The introduction of silicon carbide(SiC) has reduced the superiority of traditional silicon-based power module packaging strategies. As packaging strategies become increasingly complex, classical thermal modelling tools often prove inadequate in balancing efficiency with accuracy. Integrating these tools with machine learning (ML) can significantly enhance their application potential. This discussion commences by addressing the pressing issues in thermal modelling of SiC modules, specifically the challenges associated with multiple heat sources and heat spreading. During the design stage, ML models can swiftly simulate the thermal response of various packaging strategies, aiding engineers in eliminating ineffective options. In the monitoring phase, the employment of a digital twin enables a deeper investigation into degradation phenomena. This article reviews the current status and explores the potential applications of ML in thermal modelling of SiC power modules.**

***Index Terms*—ML, Thermal modelling, SiC, power module**

I. Introduction

With the substantial growth of the electric vehicle (EV) market [1], power devices for EVs have entered a phase of rapid development, driven by significant increases in energy density. This surge has facilitated the development and renewal of related processes and technologies [2] [3]. The SiC (SiC) metal-oxide-semiconductor field-effect transistor (MOSFET), an alternative to the silicon insulated gate bipolar transistor (IGBT), offers higher switching frequencies, accommodating higher energy densities and operating temperatures [4] [5]. However, challenges with SiC MOSFET arise from the parallel connection of multiple chips [6], where cost control and the need for increased output power exacerbate issues such as heightened parasitic inductance [7]. Fig.1 illustrates the development of SiC power semiconductors from ROHM and Wolfspeed's commercially available devices, depicting their evolution from the initial rapid increase in device power (first two data sets) to the current phase of maintaining low losses while preserving output power (last two data sets). Under high-frequency operations, a multi-chip design may lead to power and thermal imbalances across the chips, ultimately compromising reliability [8] [9]. To address these challenges,

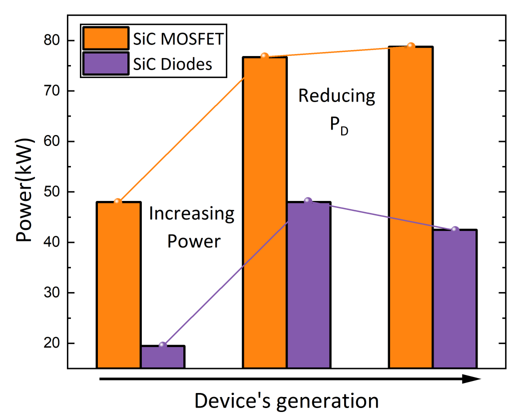


Fig. 1. Generation iteration of discrete SiC power components: The first two generations represent a rapid increase in power during the early stages; the last two generations reduce the dissipated power while maintaining the output power [10] [11] [12] [13] [14] [15].

numerous complex packaging strategies have been developed [16] [17] [18]. Nonetheless, existing thermal modelling methods struggle to accurately capture the thermal behaviour of these packages while maintaining efficiency. Although finite element methods (FEM) can reproduce the physical fields inside these packages, they require significant computational time and extensive post-processing of results. For instance, after extracting the transient thermal response curve from FEM analyses, it is necessary to integrate it into a Foster RC thermal network and perform a series of mathematical transformations and deconvolutions to ascertain the structure functions (R_{th}, C_{th} distributions) [19]. Further challenges include complex thermal coupling effects, anisotropic thermal conductivity of materials (thermal spreading), and issues related to multiple thermal paths (double-sided cooling).

Concurrent with the rise of the EV industry is the advancement of AI technology [20], driven by the demand for autonomous driving and the growth in GPU computational power. As considerations expanded to industrial applications, the concept of utilising AI to address power module challenges naturally emerged.

The aim of this paper is to explore the potential of applying AI in the thermal modelling of SiC power devices. Firstly, it describes two challenges in the thermal modelling process: the presence of multiple heat sources and the effects of thermal spreading. Subsequently, it outlines two traditional thermal modelling techniques alongside innovative ML applications for device design. Finally, the article summarises the application of AI in real-time monitoring.

II. Challenges

A. Multi-heat sources

As SiC technology matures and finds broader application, traditional silicon-based power modules are increasingly being replaced. Unlike silicon, the material properties of SiC and its immature fabrication processes contribute to lower yields [21] [22]. To manage costs, manufacturers utilise smaller SiC chips, which individually possess a lower current-carrying capacity than their silicon counterparts [23]. With the escalating power demands of EVs, these smaller chips are often connected in parallel, forming Multi-chip Power Modules (MCPM) [24] [25] [26] [27]. The layout of these chips is crucial, as it influences the performance parameters and reliability of the module. In [28], a circular symmetric layout is employed to optimise current distribution among the chips and reduce voltage spikes. Although this multi-chip layout allows for more design flexibility and a smaller module footprint, it also results in strong thermal coupling effects among multiple heat sources, leading to thermal reliability issues due to uneven temperature distribution [29]. Consequently, layout optimisation becomes essential in managing multiple heat sources within MCPM. In [30], a good design of the electro-thermal model led to an 18.1% reduction in the module's maximum temperature. Furthermore, adhering to the design principle of aligning the paralleling chip perpendicular to the current direction, a module designed to avoid current imbalance under transient input conditions was developed in [8].

However, despite the effectiveness of these optimisation methods in reducing temperature and current imbalances, these configurations still necessitate significant modelling resources during the preliminary design phase to validate diverse ideas. Integrating ML with thermal modelling techniques can significantly reduce the resources required.

B. Thermal Spreading

In addition to the heat sources, the heat path also requires careful design. Shorter thermal paths undoubtedly result in lower steady thermal resistance; however, such a design can affect the switching performance of the device [31] and the transient thermal performance. Accurate heat path modelling is necessary to identify the optimal heat path design that achieves a balance between electrical and thermal performance [32] [33]. However, thermoelectric coupling is beyond the scope of this review paper; therefore, this subsection focuses on heat-spreading effects in the heat path of a power module as illustrated in Fig.2.

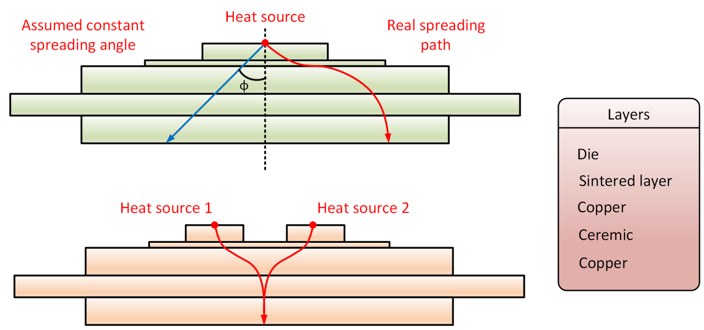


Fig. 2. Comparison of Assumed Constant Spreading Angle vs. Real Heat Spreading Path in Multilayer & Multichip Power Modules.

Initially, thermal engineers used a fixed angle to account for the heat spreading effects; in [34], a fixed spreading angle model was extended to the dynamic field, allowing the model to predict the transient thermal response. The heat spreading angle Φ is defined as the angle between the heat path and the vertical axis (Fig.2) and is often assumed to be 45 degrees. However, employing a fixed thermal diffusion angle is clearly not accurate [35], and the origin of the 45-degree assumption is not well-documented, making it more of a widely accepted convention among thermal engineers rather than a scientifically established fact.

In [36], the error of a fixed 45-degree diffusion angle is evaluated. The results show that the mismatch of the 45-degree assumption is within acceptable limits for single-layer structures (20%); however, in multilayer structures and in power modules with multiple chips (multiple heat sources), the assumption fails to accurately predict the thermal behaviour of the structure. Therefore, there is a need to apply more accurate spreading angle models when modelling modern MCPMs. Furthermore, in [37], a concept of an equivalent heat spreading angle derived from local heat flux density is presented. Based on this concept, the entire heat path can be approximated by a truncated cone heat spreading model. Simultaneously, this model can be extrapolated to a certain extent to different structures, thus demonstrating potential for practical application.

In addition to the direct use of spreading angles to model heat paths, the thermal spreading effect can similarly be approximated as a type of thermal resistance. In [38], an analytical solution for this thermal resistance is provided in the field of power electronics. Subsequently, in combination with the classical thermal network approach, heat spreading resistance was included in the RC network model of the power module, corrected for the thermal diffusion angle according to the properties of each material layer [39]. Heat spreading resistance is also significant in LED applications.

The resistance calculated for the LED substrate is one to two orders of magnitude larger than that resulting from a one-dimensional through-plane calculation [40]. Employing materials with higher lateral thermal conductivity in LEDs is one strategy to optimise this issue [41], and it is evident that this approach also applies to the MCPM discussed in this paper.

III. Modelling & Design techniques

This section outlines several techniques commonly used in the thermal design. These include thermal networks and FEM. The subsequent paragraph explores current applications of ML in thermal design of power modules.

A. Classic Technics

1) Thermal Network: RC thermal networks, including the Foster and Cauer network models (Fig.3), are a widely used modelling technique in industry. The Foster model essentially fits the thermal impedance (Z_{th}) profile directly using RC parameters, which, in this model, lack physical significance. Conversely, a Cauer model can convey the physical meaning of the internal layers, achievable through a mathematical transformation from an established Foster model. Currently, with the increasing complexity of packaging strategies, traditional one-dimensional thermal networks can no longer satisfy the demands of technology, necessitating an update to the model.

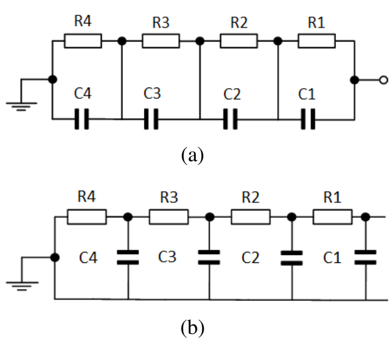


Fig. 3. a).4 stage Foster network b).4 stage Cauer network.

In [42], a 3D lumped thermal impedance model is constructed and utilised to study the effect of the distance between the IGBT chip and the diode. The findings indicate that the model can accurately predict the thermal coupling effect at various distances. As the layout becomes more compact, the thermal coupling impedance between the chips increases, suggesting a stronger thermal coupling effect. Subsequently, this model was applied to the long-term wind power mission profile [43] and results of the network model correlate well with those obtained from FEM.

Similarly, in [44], the improved thermally coupled 3D thermal network is segmented into constant and time-varying, non-constant parts by examining the effects of solder layer degradation. Furthermore, in [45], the structure function was employed to verify the influence of thermal coupling effects and solder layer degradation on the transient thermal response of the structure. As solder layer degradation progresses, heat increasingly concentrates in the central area, causing the temperature distribution among multiple chips to become non-uniform, and resulting in more extreme current distributions within the module due to variations in temperature-dependent electrical parameters. Utilising thermal modelling in conjunction with real-time data to precisely determine device degradation and adjust power distribution across multiple chips in a power module presents a potential avenue for further research.

In [46], an equivalent 3D thermal network with reduced scale is constructed, the model's efficiency enhanced by directly fitting the equivalent thermal path from the simulation results for multiple simultaneous heat sources. In [47], the bidirectional thermal paths of two different LEDs are characterised by a straightforward thermal network model, considering the top thermal paths. The findings underscore the necessity of accounting for the bidirectional thermal path for accuracy. A 3D thermal network model of a modular multilevel converter system is developed in [48], which incorporates multiple thermal paths of the sub-module and the ambient temperature difference caused by the device in this thermal network.

The initial step in ML involves extracting feature parameters; the RC network, validated by engineering applications as a parametric thermal model, meets this requirement effectively. Applying ML to RC thermal networks may significantly enhance the capabilities of both methods.

2) FEM: FEM is currently one of the most prevalent modelling methods, involving the following steps: 1) Create a 3D model of the object; 2) Discretise the 3D model; 3) Determine the boundary and initial conditions, along with material properties, according to the desired physical field; 4) Compute. Given its numerous advantages and established maturity, further details on this method will not be shown here.

Multi-physics FEM modelling is a key focus in the development of SiC power modules. Prominent examples include fluid-solid coupling modelling for two-phase flow heat sinks and immersion heat sinks [49] [50], as well as coupled electro-thermal simulations [51], among others.

B. ML Application

Research combining ML with power modules has primarily focused on control and monitoring, with only a minor portion dedicated to the thermal modelling and design of the modules [52]. The aim of applying ML in thermal modelling is to predict the performance, which can be determined through direct fitting, temperature field prediction, and thermal network. Thus, the literature reviewed in this subsection is broadly categorised into three directions: 1) Directly learning from the temperature field distribution. 2) Learning and fitting the non-linearity between the design parameters of the module and critical parameters. 3) Combining ML with thermal network model, which are adept at predicting transient thermal consequential effects due to the inherent properties of the thermal networks.

The training efficiency of a neural network depends on its structure and the specific application. The size of the training set can vary significantly according to the requirements(see Fig. 4); however, generally, the efficiency of a well-designed algorithm will consistently surpass that of a more classical structure. For instance, ACO-BPNN [53] combines the Ant colony optimisation method with neural networks to achieve the desired accuracy with fewer than 200 training datasets.

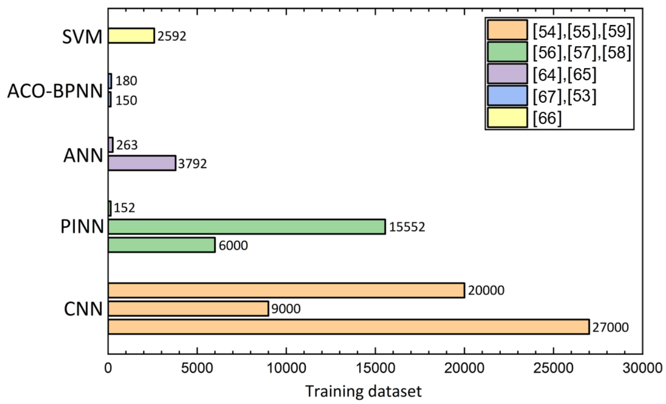


Fig. 4. Amount of training datasets for different ML structures: Convolutional neural network(CNN), Physics-informed neural network(PINN), Artificial Neural Network(ANN), Ant Colony Optimization-Back Propagation Neural Network(ACO-BPNN), Support vector machine(SVM) in different researches. The size of the training set can vary significantly according to specific applications.

As FEM is time-consuming, using ML to predict FEM results has become more common. Some researchers have attempted to adapt this type of ML from physical fields to temperature field imaging by constructing a deep CNN model that learns the thermal coupling effects of multi-chip systems in two dimensions [54] [55], and accelerating the model using a Bayesian approach. Overall, the accuracy of the predictions was excellent, and the extrapolation performance was satisfactory; however, such 2D application scenarios are oversimplified, and this approach does not include the applications where the thermal channels are predominantly oriented in the longitudinal direction.

A more reasonable approach is to incorporate physical constraints into the ML methods, specifically using the well-known PINN. Embedding the governing physics equations into the loss function not only reduces the amount of training data required but also enhances the model's extrapolation performance to some extent. For example, in [56], researchers utilised a PINN model to predict the 3D temperature field during direct energy deposition of metals. The model required only 20% of the datasets to achieve satisfactory accuracy compared to a fully data-driven neural network. In [57], the steady-state thermal conductivity of multilayer structures was investigated. Each layer of material was represented by a separate neural network model, which were assembled into a large neural network that fed the results into a physics-informed loss function for back propagation. This approach effectively addresses the challenging thin-layer problem in FEM, where tiny finite cells often cause non-convergence issues. Moreover, this method exhibits excellent extrapolation, particularly in simple multilayer structures such as power modules.

In real cases, data often originate from several sensors and are subject to ambiguous boundary conditions. Owing to these unspecified boundary conditions, FEM frequently struggles to effectively solve this type of inverse problem, whereas PINN is more adept at addressing such 'guessing' challenges. In [58], the inverse temperature field reconstruction of a turbine blade is performed using the PINN method, enabling the model to reconstruct the thermal distribution of the entire blade based on input temperature data from discrete points. However, it has been observed in other studies that ML methods face challenges in accurately predicting results in areas with large temperature gradients. In [59], the researcher addresses regions with significant gradients near the heat sink individually, employing the UNet method.

On the other hand, real measurements often include unavoidable noise, necessitating a certain degree of robustness in the PINN model when handling noisy data. The model presented in [60] demonstrates good accuracy even with the addition of noise and is applicable to the inverse construction problem of transient thermal conductivity for two-dimensional multiple heat sources. In a similar case, the output of the PINN model in [61] is significantly affected by noise, prompting the proposal of a method known as CMCN-PSO to mitigate the noise impact, suggesting that the model's structure influences its noise tolerance.

To summarise, PINN can achieve the same level of accuracy as traditional neural networks using less data if the physics equations are correctly embedded into the loss function, and the inclusion of physics also improves the extrapolation performance of PINN. However, constructing PINN is frustrating when the physics in the problems can not be clear defined. The approach of directly mapping the relationship between input and output reliability parameters will be discussed in the next paragraph.

Utilising the powerful nonlinear fitting capabilities of neural networks to directly learn the nonlinear relationship between input design parameters and output performance parameters appears to be a reasonable alternative.

In [62], an artificial neural network trained with a dataset of cooling curves can predict the transient thermal response of a multi-chip power module (thermally coupled), which serves as a surrogate model to a thermal network. If the time required to train the model is considered, the neural network approach is more costly compared to the thermal matrix method. However, the number of parameters in the thermal matrix grows with the square of the number of heat sources, and an additional experiment is required for each new heat source which consume a lot of time. It is concluded that neural networks may offer advantages in configurations with a more chips. Similar research was conducted in [63], where several artificial neural networks with varying structures were employed to predict the transient thermal response of

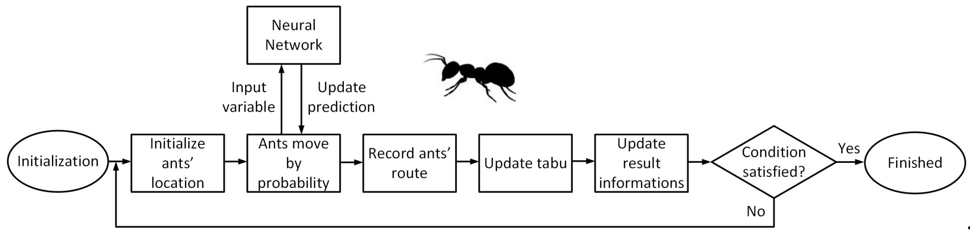


Fig. 5. ACO-BPNN configuration [53].

the power module. Likewise, in [64], [65], and [66], neural networks are utilised to predict the thermal response of the module; [64] extends the transient prediction based on [66], and [65] constructs an optimisation model using two artificial neural networks, where the first predicts the temperatures of the transient junction with various design parameters, and the second forecasts the corresponding life consumption.

In [67] and [53], an ACO-BPNN optimisation algorithm (Fig.5) is used to optimise the design of the redistribution layer and the optimal chip placement in a panel-level fan-out SiC power module. A similar algorithm in [68] is used to optimise the size of the DBCs and the chip spacing in the power module. This algorithm for optimising the design can be seen as an application of the prediction algorithm discussed previously. As the model is extended, more parameters can be taken into account, such as cost [69], performance requirements, and so forth. However, solely considering the mapping relationship between parameters does not fundamentally reflect the insight into the physical relationship between parameters, which can lead to a lack of extrapolation performance of such an approach.

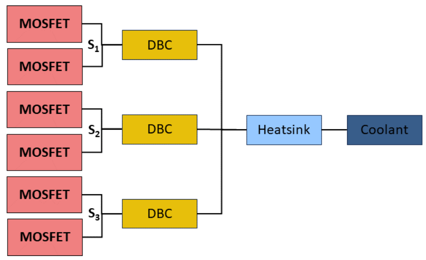
Applying ML to classical thermal network methods has received scant attention from researchers, despite thermal networks being more amenable to learning by neural networks as parametric physical models and having demonstrated considerable accuracy in industrial applications. In the field of monitoring, the thermal network evolves into a self-tuning thermal model when combined with a ML approach [70], which necessitates minimal computational resources to accurately predict the junction temperature and thermal correspondence of a power module. Similarly, ML is employed in [71] to fit the nonlinear thermal resistance and heat capacity at the heat convection interface in a power module, thereby enhancing the accuracy of the thermal network. Although current applications combining thermal networks and ML methods are limited, this approach will gain more traction as ML is used more in industry.

IV. Real time model - digital twin

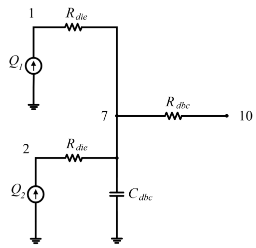
Recently, due to the rapid advancement in technology and the increasing complexity of systems, monitoring variations in a parameter of interest within these systems, such as the junction temperature within a power module during testing or real operational conditions, has become challenging. Additionally, in many cases, it requires considerable time and financial resources to conduct tests to understand the physics of failure in complex devices. To surmount this limitation in the reliability analysis of microelectronics, digital twin technology proves invaluable. The concept of the digital twin originated in the 1960s when NASA utilised a replica of Apollo 13 on Earth to explore different rescue scenarios. Since then, as the application of this technology has broadened to various fields, multiple definitions of digital twin have emerged in the literature. Nonetheless, these definitions concur that a digital twin is an integrated multiphysics, multiscale, and probabilistic simulation that replicates the life of a physical system [72]. The definition of a digital twin model also hinges on the level of detail and the accuracy of the simulation. At lower levels of accuracy, a digital twin is characterised as a three-dimensional model, comprising physical elements, simulations or virtual twins, and the connections between them [73]. Conversely, at a higher level of accuracy, a five-dimensional digital twin can optimize the simulation's accuracy [74].

This concept can also be found in research related to the context of this paper. For instance, in [75], an accurate FEM model of the MOSFET and the cooling system of a boost converter has been employed to extract the 2D Cauer network model. This model, considered a digital twin, is utilised to measure the temperature and heat flux across different layers. Similarly, in [76], an accurate 3D model, referred to as a digital twin, is employed for design optimization, while in [77], the parameters of the thermal model of the MOSFET are estimated by using measured values. At the five-dimensional level, to monitor a system over time, the uncertainty in the estimated parameter of interest can be significantly influenced by measurement uncertainty and the model uncertainty. In an accurate digital twin model, these factors should be taken into account. In this regard, in [73], a digital twin model is defined as a 2D thermal network of MOSFET within a dual three-phase inverter to estimate their thermal profile. For each pair of MOSFET, a temperature sensor is installed on the copper layer, and the thermal model of the entire system has been established (see Fig.6). To mitigate model and measurement uncertainty, an Extended Kalman Filter has been employed to update the model parameters using noisy data from sensors. The results indicate that the model updates quickly and its predicted values rapidly converge to the true value.

Moreover, in complex systems for modeling the physical element, ML techniques can be employed as the digital twin of the real device. For instance, in [78], a deep neural network has



(a)



(b)

Fig. 6. (a)Power module structure (b) A branch in the thermal model of the inverter, including a DBC and two MOSFET blocks [73].

been trained using data generated from FEM to estimate the junction temperature of a power switch. In [79], experimental data has been used as a substitute for simulation data to train an AI model to estimate junction temperature, thus overcoming the problem of model uncertainty. Although the results of these methods demonstrate a high level of accuracy in estimating the junction temperature, the absence of any optimizer in these models may lead to a loss of accuracy due to variations in the behavior of the device (e.g., material aging and degradation). This addressed in [80], in this research, initially, a numerical model for power loss estimation of a half-bridge inverter has been used, which calculates power loss using average thermal junction, switching frequency, DC bus voltage, and current. Then, the calculated power loss, alongside coolant temperature and coolant flow rate, are used as inputs for a high-precision FEM to estimate the internal negative temperature coefficient (NTC) and junction temperature of each MOSFET. To mitigate uncertainty in both the numerical and FEM models, a deep neural network has been trained in parallel to each model (see Fig.7). Then, the discrepancies between the calculated NTC and measured NTC have used to update the estimated junction temperatures. While the application of AI-driven digital twin

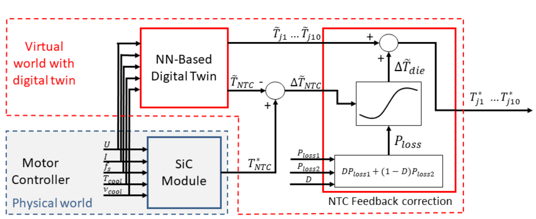


Fig. 7. Architecture of junction temperature estimation method via neural network-based digital twin. [80]

technology is increasingly prevalent, there remains a need for further research in this area. For instance, for modeling the twin, real-time training of nonlinear system identification models can be utilized to estimate the dynamic behavior of the power modules. Additionally, more sophisticated methods such as Reinforcement Learning can be employed to minimize the number of iterations in the optimization procedure. Moreover, the concept of a digital twin can extend beyond model updating and parameter estimation. The application of statistical methods, like the Hierarchical Bayesian approach, can aid not only in estimating system parameters but also in assessing the uncertainty of these parameters and their hyperparameters, and in linking them to the uncertainty of the measured values.

V. Conclusion

The integration of ML with thermal modeling of SiC power modules marks a significant advancement in power electronics. This review examines how ML can enhance the efficiency and accuracy of thermal models for novel power modules, focusing on the challenges posed by multi-heat sources and complex thermal paths in modern SiC modules.

Traditional thermal modeling methods, like FEM, face limitations due to high computational demands and extensive post-processing. This review advocates for ML techniques to overcome these limitations, providing faster and more efficient thermal behavior modeling under various operational conditions.

The concept of a digital twin is introduced as a future vision that employs ML to address complex problems by creating a virtual replica of physical systems, enabling real-time diagnostics and prognostics. This approach improves system behavior prediction under different scenarios and aids in the development and testing of new designs without traditional testing constraints.

In summary, the article highlights the necessity of ML techniques in modern thermal modeling for SiC power modules. The increasing complexity and reliability demands of these modules necessitate rapid thermal modeling methods, which ML can facilitate.

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