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Enhancing High-Power-Density Converter Design: A Data-Driven Analysis of MOSFET and Heatsink Selection

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Abstract— MOSFETs are commonly used switching devices in high-power-density converters thanks to their fast-switching frequency. However, their on-state resistance and high switching frequency result in undesirable heat dissipation, which leads to thermal management challenges. To prevent device overheating, failure, and safety hazards, heatsinks for cooling are essential. This study aims to address the optimal combined selection of MOSFETs and heatsinks for designing high-power-density converters by analyzing extensive MOSFET and heatsink data from electronics distributors and utilizing data imputation to handle missing data related to MOSFET and heatsink specifications. This paper establishes a comprehensive data-driven model, supported by data imputation, that estimates the converters' power dissipation and temperature of MOSFETs and heatsinks based on design parameters including voltage levels, current levels, costs, and volumes. Predicting power dissipation and junction temperature under varying design parameters aids engineers in making suitable choices during the practical design process.

Keywords—MOSFET, Heatsink, Power dissipation, Selection.

I. INTRODUCTION

In modern power electronics systems, converters are indispensable for their power transfer and voltage conversion functions. These converters are critical in various applications, including renewable energy systems [1], electric vehicles [2], and industrial automation [3]. The design of high-power-density converters is crucial for improving system efficiency, reducing volume, and lowering costs [4]. The metal-oxide-semiconductor field-effect transistor (MOSFET) is favored in high-power-density converters for their efficiency, low on-state resistance, fast switching, and high current handling. However, at high frequencies and large currents, they generate significant heat due to on-state resistance and switching losses.[5]. Failure to adequately dissipate this heat may lead to device overheating, malfunction, or safety hazards. Therefore, selecting suitable power-switching devices and heatsinks is essential in the design process.

Engineers have adopted advanced modeling techniques for converter components to overcome the limitations of traditional methods, which rely on manufacturer datasheet parameters for simplified models predicting MOSFET performance [5]. These basic models, focusing on electrical characteristics like on-state resistance, threshold voltage, and switching times, are useful for initial design and comparison. Advanced techniques, such as physics-based models [6] and computational simulations [7], provide more accurate predictions by considering detailed physical phenomena. However, when considering practical design, engineers often need to consider more than just one single specific model. They need to consider a broader range of factors and clearly understand an entire type of device, ensuring that the design is robust and reliable under various conditions.

Research based on models derived from data provided by manufacturers or distributors has been conducted for various components, including capacitors, inductors [8], and MOSFETs [9]. However, these datasets frequently contain missing values, which can complicate the analysis and affect the accuracy of the derived models [10]. Missing data can result from various factors, such as incomplete reporting by manufacturers, inconsistencies in data collection methods, or errors in data entry [11]. Consequently, addressing these gaps is crucial for ensuring the reliability and robustness of research findings, as well as for enhancing the predictive capabilities of models used in component performance evaluation and optimization.

II. METHODOLOGY

This paper proposes a data-driven analysis and machine-learning modeling approach to predict power dissipation, and junction temperature based on a converter's voltage and current ratings and cost parameters using comprehensive data from manufacturers. This predictive capability assists in selecting the most suitable MOSFETs and heatsinks. As a result, the overall system performance and cost efficiency are optimized. Additionally, this approach reduces the need for extensive testing, speeding up the development process. The framework of the approach is shown in Fig. 1.

A. Stage 1: Data collection

Stage 1 involves collecting data on MOSFETs and heatsinks from commercial electronics distributors. Electronics distributors' interfaces and design tools have become significantly more interactive recently. The enhanced digitization and accessibility of data enable extensive, comprehensive, and nearly exhaustive collection of component information, including electrical characteristics, and pricing. Compiling this comprehensive database makes it possible to build a machine-learning model capable of revealing the internal relationships between different parameters, thus aiding in more precise component selection.

Compared to obtaining data from manufacturer datasheets, sourcing data from distributors offers greater convenience and accessibility. Distributors typically provide essential information like rated voltage and current, which is readily available. However, this convenience comes with certain drawbacks. Detailed parameters, such as MOSFET turn-on and turn-off times, are often missing, making it challenging to calculate switching losses at specific frequencies accurately. This lack of detail represents a significant limitation of relying on distributor data. Additionally, errors may arise during data entry — either through incorrect inputs or omissions — or due to missing information in the original datasheets. As a result, the data obtained from distributors may contain gaps that could impact the accuracy of subsequent analyses.

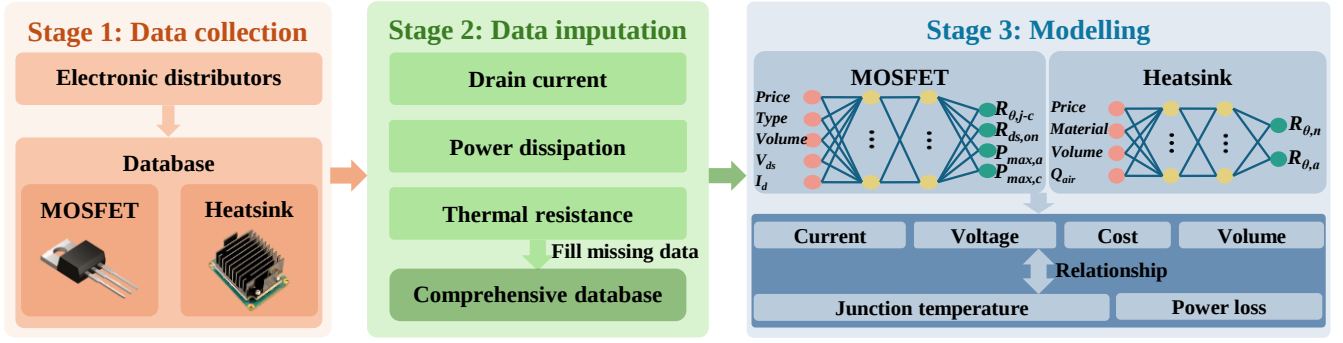


Fig. 1. Framework of data-driven analysis process of MOSFETs and heatsinks.

For MOSFETs, key parameters acquired from distributors include price, rated drain to source voltage V_{ds} , type, rated drain current at 25°C ambient temperature $I_{d,a}$, rated drain current at 25°C case temperature $I_{d,c}$, drain-source on-state resistance $R_{ds,on}$, maximum power dissipation at 25°C ambient temperature $P_{max,a}$, maximum power dissipation 25°C case temperature $P_{max,c}$, and volume. Specifically, $P_{max,a}$ refers to the maximum conduction power dissipation for a MOSFET without a heatsink at 25°C ambient temperature, ensuring the junction temperature remains within safe limits. Similarly, $P_{max,c}$ represents the maximum conduction power dissipation for a MOSFET with an infinite heatsink at 25°C ambient, also ensuring the junction temperature remains within safe limits. Volume is determined based on the package type. Therefore, these parameters are considered during data imputation.

For heatsinks, the key parameters obtained from distributors include price, material, air flow rate Q_{air} , volume, thermal resistance under natural convection cooling $R_{\theta,s-a,natural}$ and forced air cooling $R_{\theta,s-a,forced}$.

B. Stage 2: Data imputation

After collecting data from distributors, Stage 2 employs data imputation techniques to fill in the missing data. Data imputation is a method used to estimate and fill in missing values within a dataset, aiming to create a complete dataset for analysis [12]. This technique is particularly useful when some data points are missing, but the remaining information is still valuable for understanding and decision-making. While the data provided by distributors is generally more accessible and can be easily acquired, it often lacks certain critical details. For instance, specific details like the MOSFETs' $I_{d,a}$ is sometimes missing from the data provided by distributors, which is crucial for accurately modeling the thermal performance of the converter. A basic strategy to handle incomplete datasets is to discard samples containing missing values. However, this approach results in the loss of potentially valuable data, which might still provide significant insights despite its incompleteness [13]. Data imputation ensures a more complete dataset without sacrificing important information. This approach helps balance data completeness and accuracy, leading to more informed design decisions.

Traditional imputation methods such as mean imputation, nearest-neighbor imputation, and regression imputation often fall short when handling high proportions of missing data or complex data distributions. The Generative Adversarial Imputation Network (GAIN) method is proposed to address this problem [14], which is based on Generative Adversarial Networks (GANs). The GAIN method leverages the GAN

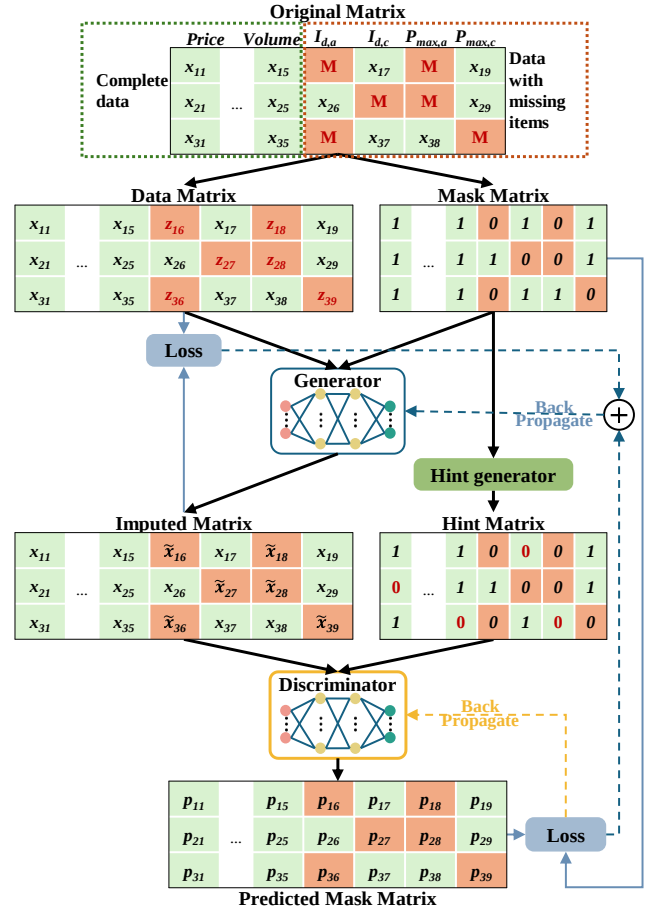


Fig. 2. Data imputation process of MOSFETs data with GAIN method

framework, consisting of a generator and a discriminator which are neural networks. The generator aims to generate values to fill in the missing data, while the discriminator's goal is to distinguish between the real data and the imputed data [15]. Through this adversarial training mechanism, the generator progressively improves the realism and quality of the imputed data.

In this study, the GAIN method is applied to impute missing values in datasets of MOSFETs and heatsinks parameters obtained from distributors. These datasets include key characteristics but contain some missing entries. Fig. 2 shows the GAIN imputation process for MOSFET data. In the Fig. 2, x_{ij} represents the data originally present in the distributor's database, M indicates missing values, z_{ij} is random noise ranging from 0 to 0.01, $\tilde{x}_{ij}$ is the generated imputed value, and p_{ij} is the probability that the discriminator

predicts the current position as original data. For the MOSFET dataset, parameters including price, V_{ds} , type, $R_{ds,on}$, and volume are complete, while $I_{d,a}$, $I_{d,c}$, $P_{max,a}$, $P_{max,c}$ have missing values that required imputation. The imputation process using the GAIN method begins by organizing the incomplete data into a data matrix, where missing values are initially replaced with random noise. A corresponding mask matrix is created to indicate the locations of these missing values. The generator then uses this data and mask matrix to predict the missing values, aiming to produce imputed data that closely resembles the true data. A unique feature of GAIN is the use of a hint matrix, which provides the discriminator with partial information about the original data, helping it better assess the authenticity of the imputed values. The discriminator evaluates the authenticity of the imputed data by predicting which values are real and which are generated, using the hint matrix as a reference. During training process, the generator and discriminator engage in a process of adversarial learning. The generator aims to minimize the discriminator's ability to distinguish between real and imputed data, while the discriminator strives to improve its accuracy in detecting the imputed values. Over multiple iterations, this adversarial process leads to the generator becoming more adept at producing high-quality imputed data.

Similarly, in the heatsink dataset, parameters including price, material, air flow rate (Q_{air}), and volume are complete, while $R_{\theta,s-a,natural}$ and $R_{\theta,s-a,forced}$ had missing values. These are also imputed using the same GAIN method.

C. Stage 3: Modelling

Stage 3 involves building neural network models for MOSFETs and heatsinks using the comprehensive database. In the model training of MOSFETs, the inputs are price, type, volume, drain to source voltage V_{ds} , and maximum continuous drain current $I_{d,a}$ and $I_{d,c}$, outputs are drain-source on resistance $R_{ds,on}$, thermal resistance $R_{\theta,j-c}$, maximum power dissipation $P_{max,a}$ and $P_{max,c}$. The thermal resistance $R_{\theta,j-c}$ is calculated as:

$$R_{\theta,j-c} = \frac{T_{j,max} - 25^{\circ}\text{C}}{P_{max,c}} \quad (1)$$

where, $T_{j,max}$ is the maximum junction temperature.

In the model training of heatsinks, inputs are price, material, air flow rate Q_{air} , and volume, outputs are thermal resistance $R_{\theta,s-a,natural}$ and $R_{\theta,s-a,forced}$.

After obtaining the models of MOSFETs and heatsinks, we can predict the power dissipation P , maximum power dissipation $P_{max,a}$ and $P_{max,c}$, and junction temperature T_j for various combinations of MOSFETs and heatsinks. The maximum power dissipation $P_{max,a}$ and $P_{max,c}$ can be predicted by the neural networks directly. Given the $R_{ds,on}$ and the thermal resistances of the MOSFET and heatsink, the power dissipation and junction temperature can be estimated by (2) and (3). Due to the absence of switching loss data from the distributor database, the calculation of P is simplified to consider only conduction losses.

$$P = I_d^2 R_{ds,on} \quad (2)$$

$$T_j = T_a + P(R_{\theta,j-c} + R_{\theta,c-s} + R_{\theta,s-a}) \quad (3)$$

where the I_d is the drain current, $R_{\theta,c-s}$ is the thermal resistance from the case to the mounting surface of the semiconductor, $R_{\theta,s-a}$ represents the thermal resistance of heatsink.

This enables us to evaluate numerous design scenarios without needing extensive physical prototyping. Subsequently, the relationships between total volume, power dissipation, and temperature with voltage levels, current levels, and costs can be analyzed. By understanding these interactions, engineers can make more informed decisions to optimize overall system performance, balance trade-offs, and reduce costs.

III. RESULTS

Data for 41,536 MOSFETs and 113,863 heatsinks are extracted from a mainstream distributor's database in Stage I. Due to severe data gaps in some devices, data screening is performed. For MOSFETs, data samples with missing values for price, drain-to-source voltage, type, drain-source on-state resistance, and package type are discarded. Data samples with missing price, material, and volume values are discarded for heatsinks. After this screening process, 27,053 MOSFETs and 112,271 heatsinks are retained for the next stage of data imputation.

A. Data imputation results (Stage II)

TABLE I presents the statistical information of MOSFETs' $I_{d,a}$ and $I_{d,c}$, and $P_{max,a}$ and $P_{max,c}$ before and after imputation. It can be observed that after imputation, the mean and standard deviation of the imputed data are slightly adjusted compared to the original data, indicating that the imputation process has slightly shifted the data distribution. For instance, the mean value of $I_{d,a}$ decreased from 13.73 A in the original data to 12.15 A in the imputed data, while its standard deviation decreased from 20.19 A to 17.89 A. Similarly, for $I_{d,c}$, the mean decreased from 57.50 A to 51.95 A, with a reduction in the standard deviation from 68.60 A to 60.33 A. The imputation of $P_{max,a}$ and $P_{max,c}$ following a similar trend, the imputed data shows a slight change in mean and standard deviation, ensuring that the overall data distribution remains consistent and the dataset's statistical integrity is preserved.

TABLE II displays the statistical information of heatsinks' $R_{\theta,s-a,natural}$ and $R_{\theta,s-a,forced}$ before and after imputation. For $R_{\theta,s-a,natural}$, the mean thermal resistance increased significantly from 12.64°C/W in the original data to 22.79°C/W after imputation, with a corresponding increase in the standard deviation from 11.95°C/W to 13.15°C/W. This considerable change is primarily due to the large amount of missing data in the original heatsink dataset provided by distributors, particularly for natural convection parameters. The imputation process had to introduce a broader range of values to account for the large gaps, potentially reflecting a more diverse set of heatsinks in the dataset. In contrast, the imputation of $R_{\theta,s-a,forced}$ resulted in only minimal changes, with the mean value slightly decreasing from 11.16°C/W to 11.10°C/W, and the standard deviation remaining almost unchanged at around 6.78°C/W. This stability indicates that the original dataset already had a relatively complete and consistent set of values for $R_{\theta,s-a,forced}$, requiring minimal adjustment through imputation. Overall, these results demonstrate that the imputation process effectively filled in the missing values, particularly for natural convection, while maintaining the statistical integrity of the dataset.

Fig. 3 shows the comparison of the distributions of MOSFETs' maximum continuous drain current $I_{d,a}$ and $I_{d,c}$, and maximum power dissipation $P_{max,a}$ and $P_{max,c}$ before and after imputation. The imputed data distributions are very close to the original data distributions, as evidenced by the minimal differences in their shapes and central tendencies. 0 shows the comparison of the distributions of heatsinks' thermal resistance $R_{\theta,s-a,natural}$ and $R_{\theta,s-a,forced}$ before and after imputation. The distribution of $R_{\theta,s-a,natural}$ shows some changes due to the higher amount of missing data, while the distribution of $R_{\theta,s-a,forced}$ remains largely similar to that of the original data.

Overall, the imputation process successfully reduced the data gaps and provided a more robust and comprehensive dataset, enabling more reliable analysis and modeling of MOSFET and heatsink performance.

TABLE I. STATISTICAL INFORMATION OF MOSFETs PARAMETERS FOR ORIGINAL AND IMPUTED DATA.

Parameters	Data type	Amount	Mean	Standard deviation
$I_{d,a}$ (A)	Original data	10861	13.73	20.19
	Imputed data	27053	12.15	17.89
$I_{d,c}$ (A)	Original data	20157	57.50	68.60
	Imputed data	27053	51.95	60.33
$P_{max,a}$ (W)	Original data	12595	3.79	21.27
	Imputed data	27053	6.08	19.22
$P_{max,c}$ (W)	Original data	21089	146.27	175.99
	Imputed data	27053	121.99	165.38

TABLE II. STATISTICAL INFORMATION OF HEATSINKS PARAMETERS FOR ORIGINAL DATA AND IMPUTED DATA

Parameters	Data type	Amount	Mean	Standard deviation
$R_{\theta,s-a,natural}$ ($^{\circ}\text{C/W}$)	Original data	1845	12.64	11.95
	Imputed data	112271	22.79	13.15
$R_{\theta,s-a,forced}$ ($^{\circ}\text{C/W}$)	Original data	111270	11.16	6.77
	Imputed data	112271	11.10	6.78

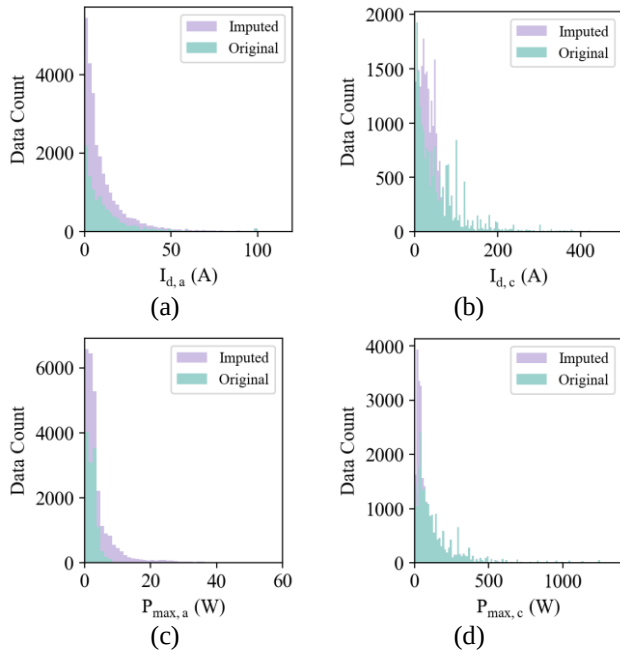


Fig. 3. Distribution of imputed and original data of MOSFETs' (a) $I_{d,a}$ (b) $I_{d,c}$ (c) $P_{max,a}$ (d) $P_{max,c}$.

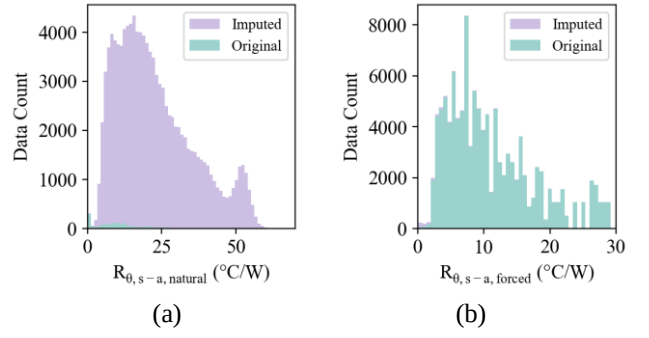


Fig. 4. Distribution of imputed and original data of heatsinks' (a) $R_{\theta,s-a,natural}$ and (b) $R_{\theta,s-a,forced}$.

B. Modelling results (Stage III)

The component modelling is performed via Artificial Neural Network (ANN), with the dataset divided into a 70% training set, 15% validation set, and 15% test set. The training and validation sets are used to train the model and monitor its performance, while the test set is used to evaluate the model's performance on unseen data [16].

The effectiveness of the imputation process and model performance is evaluated using two key metrics: Mean Squared Error (MSE) and the Coefficient of Determination (R^2).

MSE measures the average squared difference between actual and predicted values, with lower MSE indicating higher accuracy. It is calculated as:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4)$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of data samples.

R^2 indicates how well the model explains the variance in the data, ranging from 0 to 1, with higher values showing better model performance. It is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5)$$

where $\bar{y}$ is the mean of the actual values.

Fig. 5 shows the fitting performance of the MOSFETs on the test set. Table 3 displays the fitting results for MOSFETs' $R_{ds,on}$, $R_{\theta,j-c}$, $P_{max,a}$ and $P_{max,c}$ under the same model before and after data imputation. Table III shows the MSE has been reduced, indicating that the predictions are more accurate. Additionally, the R^2 has increased, which means the model now better explains the variability of the response data around its mean. This improvement suggests that the imputation has successfully addressed the missing data problem, resulting in more robust and reliable model performance. So, we can have greater confidence in the model's predictions and its overall effectiveness in capturing the underlying patterns in the data.

Fig. 6 illustrates the fitting performance of heatsinks on the test set. Table IV shows the fitting results for the heatsinks' $R_{\theta,n}$ and $R_{\theta,a}$ before and after data imputation, after data imputation, the Mean Squared Error (MSE) has decreased, and the R^2 has increased. The substantial improvement in $R_{\theta,a}$ is particularly notable due to its initial high data missing

rate, which required significant imputation adjustments. This indicates that while the model's performance for $R_{\theta,n}$ is already robust, the imputation has considerably improved the accuracy of $R_{\theta,a}$, addressing its previous data deficiencies.

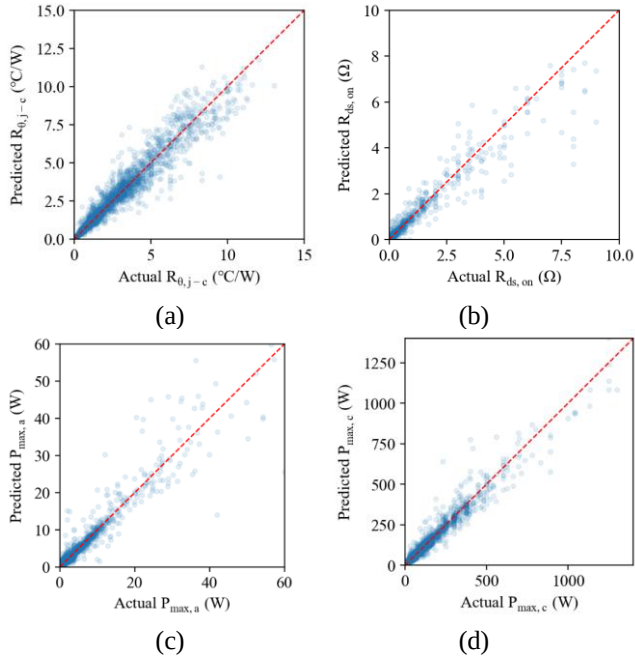


Fig. 5. Modeling performance of MOSFETs' (a) $R_{d,on}$ (b) $R_{\theta,j-c}$ (c) $P_{max,a}$ and (d) $P_{max,c}$.

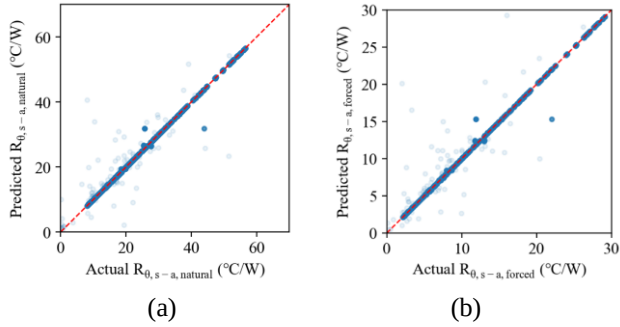


Fig. 6. Modeling performance of heatsinks' (a) $R_{\theta,s-a,natural}$ and (b) $R_{\theta,s-a,forced}$.

TABLE III. MOSFETs MODELING PERFORMANCE OF ORIGINAL DATA AND IMPUTED DATA

Parameters	Data type	MSE	R ²
$R_{\theta,j-c}$ ($^{\circ}\text{C/W}$)	Original data - test set	1.5268	0.7359
	Imputed data - test set	0.4233	0.9256
$R_{ds,on}$ (Ω)	Original data - test set	0.1096	0.5649
	Imputed data - test set	0.0897	0.9251
$P_{max,a}$ (W)	Original data - test set	7.0843	0.8160
	Imputed data - test set	6.0527	0.9190
$P_{max,c}$ (W)	Original data - test set	1625.8731	0.9126
	Imputed data - test set	1091.5994	0.9527

TABLE IV. HEATSINKS MODELING PERFORMANCE OF ORIGINAL DATA AND IMPUTED DATA

Parameters	Data type	MSE	R ²
$R_{\theta,s-a,natural}$ ($^{\circ}\text{C/W}$)	Original data - test set	1.4430	0.9750
	Imputed data - test set	0.2275	0.9951
$R_{\theta,s-a,forced}$ ($^{\circ}\text{C/W}$)	Original data - test set	49.2796	0.6533
	Imputed data - test set	0.7620	0.9950

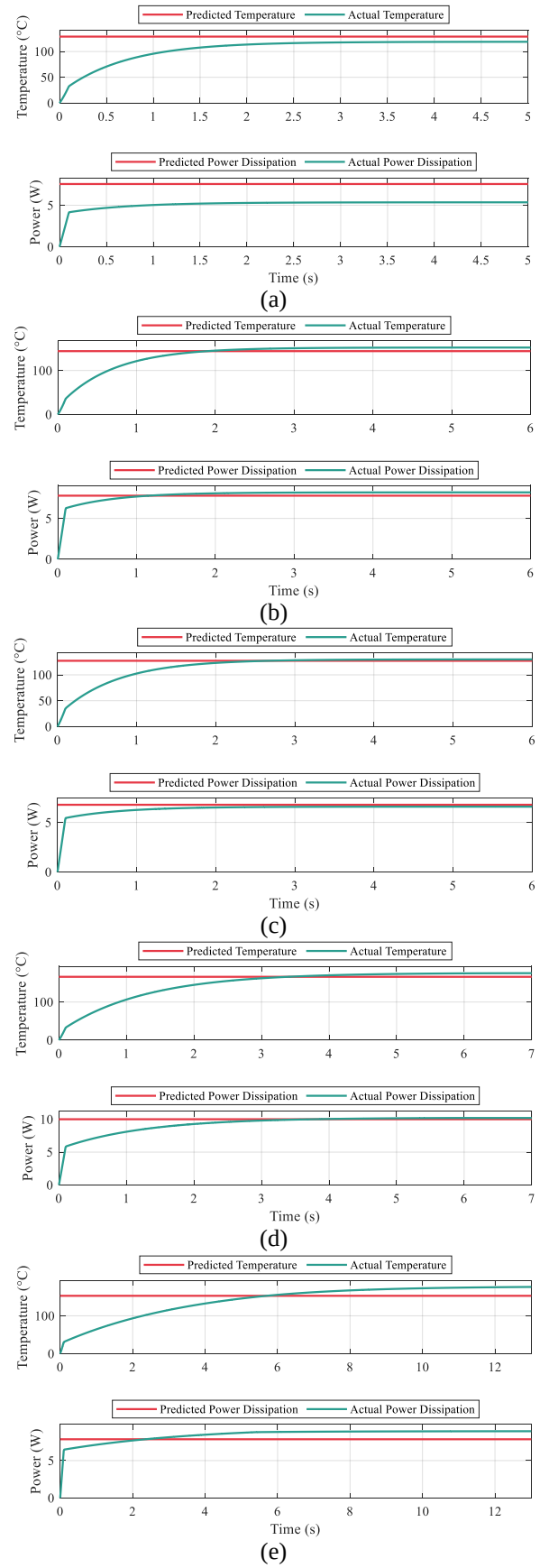


Fig. 7. Predicted junction temperature vs. actual junction temperature and predicted power dissipation vs. power dissipation of the MOSFET and heatsink $R_{\theta,s-a,natural}$ (a) 'E4M0045075J2', 16.00 $^{\circ}\text{C/W}$ (b) 'C3M0045065J1', 14.81 $^{\circ}\text{C/W}$ (c) 'C3M0060065J', 14.85 $^{\circ}\text{C/W}$ (d) 'E3M0075120J2', 14.12 $^{\circ}\text{C/W}$ (e) 'C3M0065100J', 16.03 $^{\circ}\text{C/W}$.

IV. VALIDATION

A random selection of 50 MOSFETs (with thermal models provided by the manufacturer in PLECS) and 50 heatsinks, amounting to a total of 2,500 simulations, is used for validation through MATLAB/Simulink and PLECS joint simulations with a drain current of $I_{d,a}$. Due to inherent errors in data imputation and model training, as well as the fact that the values provided by manufacturers are typically typical rather than precise, there are unavoidable discrepancies in the predicted junction temperature and power dissipation. Despite these challenges, the simulations provide valuable insights into the performance of different component combinations. Five randomly selected cases are shown for validation, as shown in the Fig. 7. The actual junction temperatures in these five cases differed from the predicted values by 8.05°, 4.23°C, 1.72°C, 4.74°C, and 15.14°C, respectively. The discrepancies between the actual and predicted power dissipation are 2.28W, 0.41W, 0.19W, 0.19W, and 1.08W, respectively. The MSE for junction temperature among 2,500 simulations is 27.81, and the MSE for power dissipation is 3.92.

V. CONCLUSION

This paper proposes a data-driven analysis method and machine-learning modelling technique to guide the design of high-power-density converters. Data imputation is utilized to handle missing data, ensuring data integrity and quality. Neural network models are constructed to predict the power dissipation, and junction temperature for various MOSFET and heatsink combinations. The data imputation and neural network models facilitate accurate predictions and provide a comprehensive analysis of the relationships between coupling parameters. Utilizing data imputation through GAIN has led to significant performance improvements in the prediction of MOSFET and heatsink models, reducing errors and enhancing the fit. The validated results demonstrate relatively low prediction errors, with the MSE for junction temperature being 27.81 and the MSE for power dissipation being 3.92 among the 2,500 simulations.

Future research will focus on selecting the best combinations of components and better refinement of the data imputation process to align more closely with real-world conditions. This will further enhance the accuracy of the predictions and the overall robustness of the model, leading to better-informed design decisions and improved converter performance.

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