

Efficient Experimental Design Framework for Reliable Parameter Identification of Electro-Thermal Models

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Abstract: Electro-thermal models commonly rely on experimentally identified parameters to predict temperatures in power electronic systems. However, even with a physically reasonable model structure, arbitrarily selected experimental cases may leave some parameters unidentifiable and degrade prediction capability. This paper proposes an experimental design framework with an information-sufficiency criterion linking prescribed parameter variations to measurable temperature responses. Singular value decomposition (SVD) of the parameter-sensitivity matrix identifies weak parameter directions, whose corresponding temperature responses are compared with a practical detectability threshold. The framework is demonstrated using a nonlinear electro-thermal model with thermal coupling and validated on four independently power-controlled MOSFETs representing multiple devices. Unguided and framework-guided selections yield fitting errors of 2.161°C and 1.413°C , but prediction errors of 28.236°C and 0.462°C at the same validation case. A broader analysis over experimental case selections also shows an increase in prediction error as temperature response falls below the proposed criterion. These results show that the proposed framework can guide experimental case selection to improve electro-thermal model prediction reliability.

Keywords: electro-thermal modelling; thermal coupling; nonlinear thermal model; singular value decomposition; experimental design; power electronic devices

1. Introduction

Thermal behaviour is an important design consideration in power electronic devices and systems, particularly for reliability assessment, lifetime estimation, and safe operation under high power density [1–4]. Accurate temperature prediction is therefore important when evaluating device stress and operating limits. Finite-element method (FEM) simulations can provide detailed spatial information but can be computationally demanding for repeated evaluation [5].

A widely used alternative is to represent the relation between power loss and temperature rise using simplified electro-thermal models. Rather than resolving the complete spatial temperature field, these models approximate the dominant thermal relationships using a limited number of parameters that can be identified from power-loss and temperature measurements. Once identified, they can be evaluated efficiently over different operating conditions. Depending on the application, electro-thermal models may describe the self-heating response of each device [6], account for thermal coupling between neighbouring heat sources [7], or incorporate nonlinear thermal behaviour with varying levels of detail [8–13].

Even when the model structure is physically reasonable, reliable parameter identification is not guaranteed. Arbitrarily selected experimental cases may leave some parameters unidentifiable when the measured temperature responses contain insufficient parameter information, potentially degrading prediction outside the fitting cases.

Sensitivity- and information-based approaches have been used to assess experimental information and guide experimental design in other parameter-identification problems. In analog circuits, sensitivity analysis has been used to identify component deviations from measured voltage changes [14] and to arrange diagnostic tests by selecting excitation values and measurement nodes such that parameter deviations produce sufficiently large voltage variations for locating and identifying faulty circuit parameters [15]. In battery modelling, information-based experimental design has been used to optimize current excitation profiles [16] and electrochemical-impedance measurement frequencies [17] for improved parameter estimation. Recent studies have also applied model-based experimental design to input-trajectory selection for thermal-model parameter identification in permanent-magnet synchronous machines [18] and to Bayesian selection of informative heater positions and power conditions for parameter identification in thermoacoustic models [19]. These studies demonstrate that reliable parameter identification depends not only on the estimation method, but also on whether the selected experiments produce sufficiently informative responses. However, for electro-thermal parameter identification, a practical criterion that guides experimental design based on measurement detectability remains insufficiently established.

To address this problem, this paper proposes an experimental design framework with an information-sufficiency criterion to guide case selection before experimentation based on practical measurement detectability. Singular value decomposition (SVD) of the parameter-sensitivity matrix identifies weak parameter directions and evaluates the detectability of their temperature responses. The framework is demonstrated using a formulated electro-thermal model and validated on a hardware platform, showing that selections not satisfying the criterion can exhibit substantially degraded prediction despite apparently acceptable fitting error, while a probability analysis shows a relatively low probability of unguided selections satisfying the criterion.

2. Electro-Thermal Modelling

Despite representing similar thermal behaviours, electro-thermal models may differ in assumptions, complexity, and nonlinear trends [6–13]. Naturally cooled devices may show stronger heat transfer as temperature rises [9], whereas temperature-dependent material properties may increase thermal resistance in power devices [10, 20]. Variables such as pressure may also be relevant under specific conditions [21]. Therefore, the model here is formulated for the prototype by balancing physical relevance, accuracy, and complexity.

2.1. Nonlinear Self-Heating Term

For the investigated prototype, the nonlinear self-heating term is based on natural convection from discrete devices to the surrounding air. If the heat-transfer coefficient is assumed constant, the temperature rise is proportional to the power loss,

$$P = hA\Delta T, \quad R_{th} = \frac{\Delta T}{P} = \frac{1}{hA}, \quad (1)$$

where P , A , h , and ΔT denote the dissipated power, effective heat-transfer area, heat-transfer coefficient, and temperature rise, respectively. Under natural convection, h depends on the temperature difference between the surface and ambient air, which can be described using the Nusselt–Rayleigh relation.

$$Nu_L = \frac{hL}{k}, \quad Nu_L = CRa_L^m, \quad (2)$$

where L is the characteristic length, k is the thermal conductivity of air, and C and m are empirical constants. The Rayleigh number is given by

$$Ra_L = \frac{g\beta\Delta TL^3}{\nu\alpha}, \quad \Delta T = T_s - T_{amb}, \quad (3)$$

where β , ν , and α are the thermal expansion coefficient, kinematic viscosity, and thermal diffusivity of air, respectively. For air, β is approximated from the film temperature as

$$T_m = \frac{T_s + T_{amb}}{2} = \frac{2T_{amb} + \Delta T}{2}, \quad \beta \approx \frac{1}{T_m}. \quad (4)$$

Assuming the remaining air properties are constant gives

$$Ra_L \propto \frac{\Delta T}{2T_{amb} + \Delta T}. \quad (5)$$

Combining this scaling relation with (1), the self-heating relation of device i is written as

$$P_i = K_i \frac{\Delta T_{i,\text{self}}^{m+1}}{(2T_{\text{amb}} + \Delta T_{i,\text{self}})^m}, \quad (6)$$

where K_i is the fitted self-heating coefficient, m is the nonlinear exponent, and temperatures are on absolute scale.

Equation (6) is formulated for natural-convection cooling, in which the heat-transfer coefficient varies with the temperature difference through the Nusselt–Rayleigh relation. Under forced-air or liquid cooling, the heat-transfer coefficient also depends on the imposed flow conditions and fluid properties. Therefore, the self-heating relation and its parameters may require modification or recalibration for the cooling mechanism under consideration.

2.2. Linear Coupling Term and Complete Model

The dominant self-heating contribution is modelled nonlinearly by (6), whereas thermal coupling, which contributes relatively less to the temperature rise, is simplified to a linear term to avoid unnecessary model complexity. The temperature rise at device i due to the power loss at j is

$$\Delta T_{i,j} = R_{ij} P_j, \quad (7)$$

where R_{ij} is the thermal resistance from device j to i . Symmetric thermal coupling is assumed, such that $R_{ij} = R_{ji}$.

The complete model will be fitted sequentially, with the coupling parameters in (7) identified first, followed by the self-heating parameters in (6). The steady-state total temperature rise of device i is expressed as

$$\Delta T_i = \Delta T_{i,\text{self}} + \sum_{\substack{j=1 \\ j \neq i}}^N R_{ij} P_j. \quad (8)$$

The electro-thermal model in (8), which combines natural-convection-based nonlinear self-heating with linear thermal coupling, is formulated for the investigated prototype and serves as a representative steady-state model for demonstrating the proposed framework. Its nonlinear implicit self-heating relation also provides a nontrivial case for sensitivity evaluation. Within the steady-state setting, however, the proposed framework is not restricted to this particular model and can be applied to other electro-thermal models, provided that the sensitivity relation between parameter changes and temperature responses can be evaluated. The construction of this relation for the model considered here and the resulting experimental design criterion are presented in Sections 3 and 4, respectively.

The formulation presented in this work does not include thermal dynamics. Its application to transient conditions, such as power cycling and other dynamic operating conditions, therefore requires extending both the information-sufficiency criterion and the model-sensitivity evaluation to account for time-dependent responses.

3. Parameter-Sensitivity Matrix

To assess whether the selected experimental cases provide sufficient information for identifying the parameters of the model in (8), the effect of parameter changes on the predicted temperature responses is first considered. The parameter-sensitivity matrix describes this relation and provides the basis for the experimental design criterion in Section 4.

3.1. Sensitivity Matrix Formulation and Numerical Evaluation

Each thermal experiment case is defined by the power-loss of the heat-generating devices. For the q -th experiment case, the power-loss vector is written as

$$\mathbf{P}^{(q)} = \begin{bmatrix} P_1^{(q)} & P_2^{(q)} & \cdots & P_N^{(q)} \end{bmatrix}^T. \quad (9)$$

For the q -th power condition, the model in (8) predicts the steady-state temperature-rise vector as

$$\Delta \mathbf{T}^{(q)} = \mathbf{f}(\mathbf{P}^{(q)}, \boldsymbol{\theta}), \quad (10)$$

where $\boldsymbol{\theta}$ is the fitted parameter vector. The sensitivity relation is then written as

$$\delta \Delta \mathbf{T} \approx \mathbf{J} \delta \boldsymbol{\theta}. \quad (11)$$

$$\boldsymbol{\theta} = [K_1 \quad \cdots \quad K_N \quad m \quad R_{12} \quad R_{13} \quad \cdots \quad R_{(N-1)N}]^T. \quad (12)$$

Let p denote the number of fitted parameters in (12). Each experimental case provides N temperature responses, so its local sensitivity matrix has dimensions $\mathbf{J}^{(q)} \in \mathbb{R}^{N \times p}$ and is defined as

$$\mathbf{J}^{(q)} = \frac{\partial \mathbf{f}(\mathbf{P}^{(q)}, \boldsymbol{\theta})}{\partial \boldsymbol{\theta}}. \quad (13)$$

Because the nonlinear self-heating relation in (6) implicitly defines $\Delta T_{i,\text{self}}$, its sensitivities are evaluated after numerically solving the relation. Let $\mathcal{T}_i^{(q)}(K_i, m)$ denote the numerical solution for $\Delta T_{i,\text{self}}^{(q)}$ at the fixed values of $P_i^{(q)}$ and T_{amb} . Around representative nominal values $K_{i,\text{nom}}$ and m_{nom} , the self-heating sensitivities are approximated using central finite differences as

$$s_{K_i}^{(q)} = \left. \frac{\partial \Delta T_{i,\text{self}}^{(q)}}{\partial K_i} \right|_{K_{i,\text{nom}}, m_{\text{nom}}} \approx \frac{\mathcal{T}_i^{(q)}(K_{i,\text{nom}} + \varepsilon_{K_i}, m_{\text{nom}}) - \mathcal{T}_i^{(q)}(K_{i,\text{nom}} - \varepsilon_{K_i}, m_{\text{nom}})}{2\varepsilon_{K_i}}, \quad (14a)$$

$$s_{m_i}^{(q)} = \left. \frac{\partial \Delta T_{i,\text{self}}^{(q)}}{\partial m} \right|_{K_{i,\text{nom}}, m_{\text{nom}}} \approx \frac{\mathcal{T}_i^{(q)}(K_{i,\text{nom}}, m_{\text{nom}} + \varepsilon_m) - \mathcal{T}_i^{(q)}(K_{i,\text{nom}}, m_{\text{nom}} - \varepsilon_m)}{2\varepsilon_m}, \quad (14b)$$

where ε_{K_i} and ε_m are the finite-difference perturbation steps applied about the nominal values. In this work, $\varepsilon_{K_i} = 10^{-5} \text{ W}/^\circ\text{C}$ and $\varepsilon_m = 10^{-5}$ are used to numerically evaluate the self-heating sensitivities. For computational efficiency, repeated solutions of the implicit self-heating relation are obtained using a precomputed inverse interpolation table. The coupling sensitivities follow directly from (7). Under the symmetric-coupling assumption,

$$\frac{\partial \Delta T_i^{(q)}}{\partial R_{ij}} = P_j^{(q)}, \quad \frac{\partial \Delta T_j^{(q)}}{\partial R_{ij}} = P_i^{(q)}. \quad (15)$$

For the four-device model and the parameter ordering in (12), the local sensitivity matrix is therefore

$$\mathbf{J}^{(q)} = \left[\begin{array}{ccccc|ccccc} s_{K_1}^{(q)} & 0 & 0 & 0 & s_{m_1}^{(q)} & P_2^{(q)} & P_3^{(q)} & P_4^{(q)} & 0 & 0 & 0 \\ 0 & s_{K_2}^{(q)} & 0 & 0 & s_{m_2}^{(q)} & P_1^{(q)} & 0 & 0 & P_3^{(q)} & P_4^{(q)} & 0 \\ 0 & 0 & s_{K_3}^{(q)} & 0 & s_{m_3}^{(q)} & 0 & P_1^{(q)} & 0 & P_2^{(q)} & 0 & P_4^{(q)} \\ 0 & 0 & 0 & s_{K_4}^{(q)} & s_{m_4}^{(q)} & 0 & 0 & P_1^{(q)} & 0 & P_2^{(q)} & P_3^{(q)} \end{array} \right] \in \mathbb{R}^{4 \times 11}. \quad (16)$$

The first four columns describe the device-specific self-heating coefficients, the fifth column describes the shared nonlinear exponent, and the remaining columns describe the symmetric coupling parameters.

For a combination of Q experiments, the complete sensitivity matrix is obtained by stacking the local sensitivity matrices:

$$\mathbf{J} = \begin{bmatrix} \mathbf{J}^{(1)} \\ \mathbf{J}^{(2)} \\ \vdots \\ \mathbf{J}^{(Q)} \end{bmatrix}, \quad \mathbf{J} \in \mathbb{R}^{NQ \times p}. \quad (17)$$

The corresponding temperature responses are stacked in the same order, giving

$$\begin{bmatrix} \delta \Delta \mathbf{T}^{(1)} \\ \delta \Delta \mathbf{T}^{(2)} \\ \vdots \\ \delta \Delta \mathbf{T}^{(Q)} \end{bmatrix} \approx \begin{bmatrix} \mathbf{J}^{(1)} \\ \mathbf{J}^{(2)} \\ \vdots \\ \mathbf{J}^{(Q)} \end{bmatrix} \delta \boldsymbol{\theta} = \mathbf{J} \delta \boldsymbol{\theta}. \quad (18)$$

Thus, each block of N rows represents the temperature responses from one experimental case, while each column represents one fitted parameter. Stacking the matrices combines the parameter information provided by all selected cases.

3.2. Nominal Parameter Selection

The nominal values introduced in (14) serve only as evaluation points for numerically calculating the self-heating sensitivities used to construct **J**. They are not imposed as fixed values when the model parameters are fitted to the measurements. In this work, the nominal nonlinear exponent is first selected as $m_{\text{nom}} = 0.35$, near the upper range associated with the natural-convection behaviour described in Section 2. After fixing this exponent, the nominal self-heating coefficient is selected based on the effective thermal resistance of the heat-sink assemblies used in the experimental platform. To relate the coefficient to this physical quantity, an equivalent thermal resistance is defined from (6) as

$$R_{\theta,\text{eq}}(\Delta T_{\text{self}}) \equiv \frac{\Delta T_{\text{self}}}{P} = \frac{1}{K_{i,\text{nom}}} \left(\frac{2T_{\text{amb}} + \Delta T_{\text{self}}}{\Delta T_{\text{self}}} \right)^{m_{\text{nom}}}. \quad (19)$$

At $T_{\text{amb}} = 20^\circ\text{C} = 293.15\text{ K}$ and over the representative self-heating temperature-rise range of $40\text{--}50^\circ\text{C}$, using an equivalent thermal resistance of approximately 8°C/W , corresponding to that of these heat-sink assemblies, gives $K_{i,\text{nom}} = 0.31\text{ W/}^\circ\text{C}$ for all four devices. The electro-thermal model used in this work is the complete model in (8), with the nonlinear self-heating term given by (6). Equation (19) is used only to select $K_{i,\text{nom}}$ for the numerical sensitivity calculations. If the heat-sink assembly is changed while the same self-heating model remains applicable, only $K_{i,\text{nom}}$ needs to be updated using (19) before recalculating the sensitivity matrix. The proposed framework and information-sufficiency criterion are independent of the numerical value of $K_{i,\text{nom}}$, so the remaining procedure is unchanged.

4. Experimental Design Criterion

Before conducting the physical experiments, a combination of experimental cases is selected from a pool of all possible cases and evaluated using the information-sufficiency criterion in (31). If the criterion is not satisfied for all SVD parameter-change directions, another combination is selected and analysed. In this work, a greedy search with exchange-based refinement is used to find a combination satisfying the criterion. The search begins with no selected cases. At each greedy step, every remaining candidate is temporarily added to the current combination, and the candidate producing the best result according to the information-sufficiency evaluation is retained. This process continues until the desired number of cases is reached, which is four for the hardware validation in Section 5. The resulting combination is then refined through one-case exchanges. At each iteration, all possible replacements of one selected case with one unselected case are evaluated, and the best improving exchange is retained. The refinement terminates when no improving exchange is found or after 50 iterations. To improve the reliability of the search, five additional case combinations were randomly initialized and subjected to the same exchange-based refinement. The resulting five refined combinations were compared with the refined greedy-search combination, and the combination with the best information-sufficiency result was retained. A fixed random seed was used for reproducibility.

The search algorithm is used to reduce the computational effort required to find a case combination satisfying the information-sufficiency criterion. An exhaustive evaluation of all possible combinations could also identify a suitable combination, but it would require substantially greater computational time and resources. The proposed framework and information-sufficiency criterion are therefore independent of the search algorithm and can be used with exhaustive evaluation or other search methods. The overall procedure is shown in Figure 1.

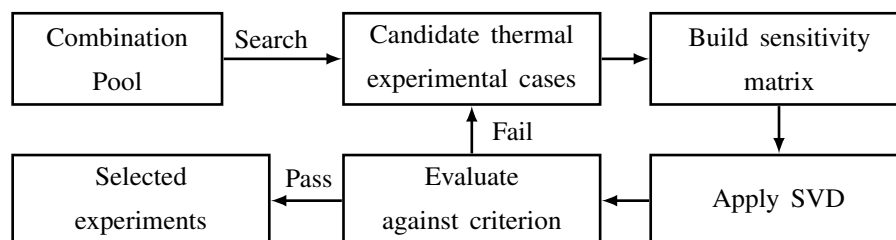


Figure 1. SVD-assisted thermal experiment selection procedure.

A basic requirement for fitting p parameters is that the selected experimental cases provide at least p independent temperature equations. For the parameter vector in (12),

$$p = N + 1 + \frac{N(N-1)}{2}, \quad (20)$$

which gives $p = 11$ for the four-device model considered in this work. Since Q experimental cases produce NQ rows in the complete sensitivity matrix, the corresponding requirements are

$$NQ \geq p, \quad \text{rank}(\mathbf{J}) = p. \quad (21)$$

The dimensional requirement in (21) therefore gives the theoretical lower boundary

$$Q \geq \left\lceil \frac{p}{N} \right\rceil. \quad (22)$$

For the four-device model, $N = 4$ and $p = 11$, giving a minimum of three experimental cases. Thus, fewer than three cases cannot provide enough temperature equations for the fitted parameters. However, three cases only provide the minimum number of equations required for full rank. Whether full rank is actually achieved depends on the sensitivity matrix of the selected cases. Furthermore, achieving full rank only confirms that the parameter effects are mathematically independent. Some parameter variations may still produce only a very small change in the temperature response, making their effects difficult to distinguish in practical measurements.

Therefore, rank alone is not sufficient, and the magnitude of the temperature response must also be evaluated. The proposed information-sufficiency criterion requires the prescribed parameter variations along each SVD parameter-change direction to produce a practically detectable temperature response. A variation is first prescribed for each model parameter. The diagonal matrix of these prescribed variations is written as

$$\mathbf{D}_\theta = \text{diag}(\Delta\theta_{1,\max}, \dots, \Delta\theta_{p,\max}), \quad (23)$$

where $\Delta\theta_{k,\max}$ is the prescribed variation of parameter k . A parameter change is expressed relative to these prescribed variations as

$$\delta\theta = \mathbf{D}_\theta \delta\tilde{\theta}, \quad (24)$$

where $\delta\tilde{\theta}$ is a dimensionless parameter-change vector whose components describe fractions of the corresponding prescribed variations. Substituting this relation into (11) gives

$$\delta\Delta\mathbf{T} \approx \mathbf{J}\mathbf{D}_\theta \delta\tilde{\theta} = \bar{\mathbf{J}}\delta\tilde{\theta}, \quad \bar{\mathbf{J}} = \mathbf{J}\mathbf{D}_\theta, \quad (25)$$

where $\bar{\mathbf{J}}$ is the normalised sensitivity matrix. It relates parameter changes expressed relative to their prescribed variations to the corresponding temperature responses. The normalised sensitivity matrix is then decomposed by SVD as

$$\bar{\mathbf{J}} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T, \quad \bar{\mathbf{J}}\mathbf{v}_i = \sigma_i\mathbf{u}_i, \quad (26)$$

where $\mathbf{v}_i$ is the i -th parameter-change direction expressed relative to the prescribed variations, $\mathbf{u}_i$ is the corresponding temperature-response direction, and the singular value σ_i indicates the magnitude of that response.

To evaluate the temperature response over the prescribed parameter variations, a change along the i -th direction is written as

$$\delta\tilde{\theta}_i = \alpha_i\mathbf{v}_i, \quad \delta\theta_i = \mathbf{D}_\theta\alpha_i\mathbf{v}_i. \quad (27)$$

The factor α_i scales the direction until the largest absolute component of $\alpha_i\mathbf{v}_i$ reaches unity. It is therefore given by

$$\alpha_i = \frac{1}{\|\mathbf{v}_i\|_\infty} = \frac{1}{\max_k |v_{i,k}|}. \quad (28)$$

This scaling causes at least one parameter to reach its prescribed variation, while the remaining parameters do not exceed their corresponding prescribed variations. Substituting the scaled direction into (26) gives

$$\begin{aligned} \delta\Delta\mathbf{T}_i &\approx \bar{\mathbf{J}}(\alpha_i\mathbf{v}_i) = \alpha_i\sigma_i\mathbf{u}_i, \\ \|\delta\Delta\mathbf{T}_i\|_2 &= \sigma_i\alpha_i, \end{aligned} \quad (29)$$

where $\|\mathbf{u}_i\|_2 = 1$. Thus, $\sigma_i\alpha_i$ is the temperature-response magnitude associated with the prescribed parameter variation along the i -th parameter-change direction.

For a combination of experimental cases, the least-detectable temperature response is determined by the weakest parameter-change direction and is defined as

$$\eta = \min_i (\sigma_i\alpha_i). \quad (30)$$

The combination is considered to contain sufficient information when

$$\eta > e_T, \quad (31)$$

where e_T is the prescribed temperature-response threshold. This condition is equivalent to requiring $\sigma_i \alpha_i > e_T$ for every parameter-change direction.

In this work, the prescribed variations are $\Delta K_{i,\max} = 0.01 \text{ W/}^\circ\text{C}$, $\Delta m_{\max} = 0.01$, and $\Delta R_{ij,\max} = 0.02 \text{ }^\circ\text{C/W}$. These values represent the maximum deviations considered acceptable for the fitted parameters and can be selected according to the required parameter-identification accuracy. Selecting smaller prescribed variations imposes a stricter requirement because smaller parameter changes must produce detectable temperature responses. Based on the $0.1 \text{ }^\circ\text{C}$ resolution of the thermometer used for the experiments in Section 5, $e_T = 0.2 \text{ }^\circ\text{C}$ is selected as the temperature-response threshold.

For the four-device model, varying each device power loss from 2 to 9 W over ten discrete levels gives 10^4 candidate cases. Figure 2 shows the estimated probability that a randomly selected combination satisfies (31) as the number of selected cases and the power-loss range vary.

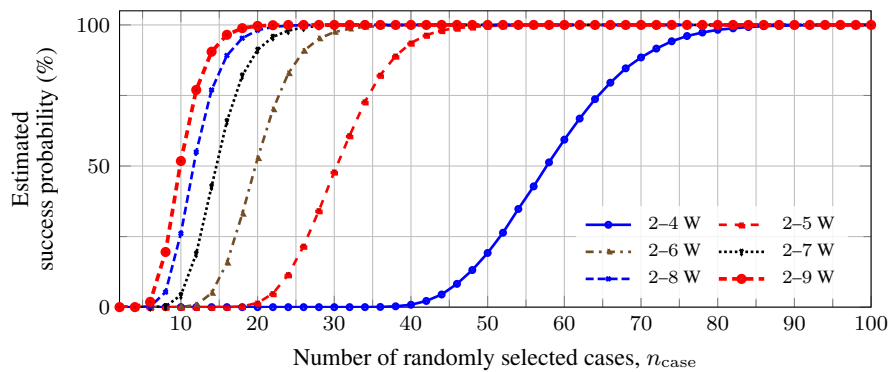


Figure 2. Estimated success probability of randomly selected experimental case combinations satisfying the information-sufficiency criterion, computed from 10^5 samples per condition at $T_{\text{amb}} = 20 \text{ }^\circ\text{C}$.

The probability generally increases with the number of selected cases, but a narrower adjustable power-loss range requires substantially more cases to reach a similar probability. A probability of approximately 52% is reached using 10 cases over the 2–9 W range, 20 cases over the 2–6 W range, and 58 cases over the 2–4 W range. A wider range produces more distinct temperature responses, whereas cases drawn from a narrower range provide more similar sensitivity information. Therefore, the number of experimental cases alone does not determine information sufficiency; the range of power-loss conditions represented by those cases is also important.

5. Experimental Validation and Results

The proposed framework is validated on the hardware platform shown in Figure 3b, which consists of four independently power-controlled MOSFETs used as controllable heat sources representing multiple devices.

The power loss of each device is varied within approximately 2–9 W for the fitting cases, while the validation case lies outside this range. To compare the selection quality using the same amount of fitting data, both the unguided and framework-guided combinations contain four experimental cases. The framework-guided combination is selected using the greedy search with exchange-based refinement. For this selection size, the 10^4 candidate cases form approximately 4.16×10^{14} different four-case combinations. A success probability analysis based on random sampling from this combination space estimates the probability of an unguided combination satisfying (31) in all directions to be below 0.01%, as shown in Figure 2. The resulting steady-state temperature rises are measured using an OMEGA OM-HL-EH-TC thermocouple thermometer and used to fit the model in (8), while a FLIR ONE Pro thermal camera is used only for thermal imaging.

For the experimental validation, the steady-state temperature rise and power loss of each device were first obtained from measurements of the prototype. The parameters of the electro-thermal model in (8) were then fitted using SciPy in Python. First, nonnegative linear least squares was used to determine the symmetric thermal-coupling coefficients R_{ij} in (7). With these coefficients fixed, the nonlinear self-heating parameters K_1 – K_4 and m in (6) were determined using bounded nonlinear least squares, subject to $K_i \geq 0$ and $0.05 \leq m \leq 0.6$. The nonnegative constraint on K_i ensures physically meaningful passive self-heating behaviour, while the bounds on m were

selected with reference to the natural-convection Nusselt–Rayleigh relation, with additional range provided for fitting flexibility.

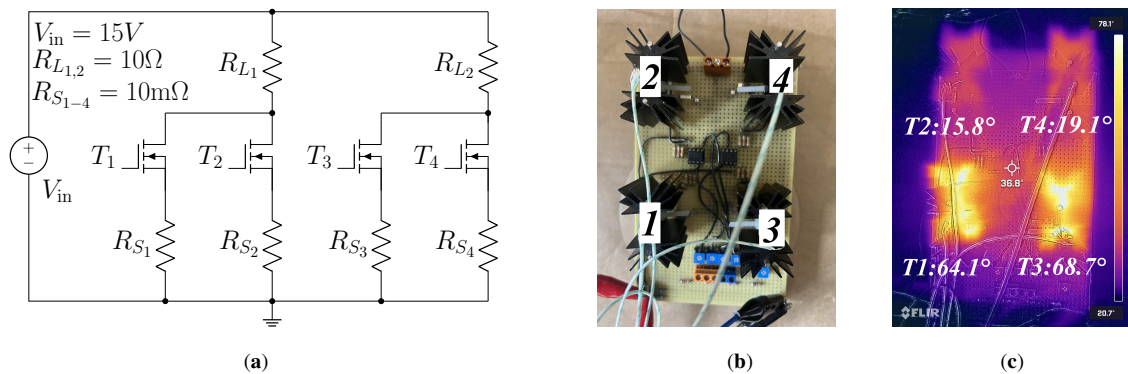


Figure 3. Circuit diagram, experimental setup and thermal image of the laboratory prototype for validation. (a) Schematic using IRFZ44N MOSFETs controlled by LM358 op amps. (b) Prototype. (c) Thermal image.

For comparison, the unguided combination shown in Table 1 was selected using engineering intuition to cover the high and low limits of the fitting-case power range. It includes all-high and all-low operating conditions together with two complementary mixed-power conditions in which Devices 1–2 and Devices 3–4 alternate between high and low power. This selection provides broad operating coverage without evaluating its information sufficiency using the proposed criterion.

Table 1. Device power losses (W) for the experimental cases.

Case Device	Unguided				Framework-Guided				Validation
	1	2	3	4	1	2	3	4	
No. 1	8.9	2.3	8.5	2.2	2.1	8.7	8.3	2.3	9.3
No. 2	8.9	2.3	8.4	2.1	8.8	2.0	8.4	2.1	1.5
No. 3	2.2	8.4	9.0	2.2	9.0	8.3	9.0	8.6	10.1
No. 4	2.4	8.3	8.9	2.3	9.0	9.0	2.0	2.0	1.8

For the models fitted using the unguided and framework-guided combinations, the root-mean-square error (RMSE) across the four device temperatures over the fitting cases was 2.161 °C for the unguided combination and 1.413 °C for the framework-guided combination. At the same validation case, which requires model extrapolation because it lies outside the 2–9 W power range used for fitting and has a power pattern not represented by the fitting cases in Table 1, the prediction RMSE was 28.236 °C and 0.462 °C, respectively.

For a broader comparison, models were fitted using all 1820 four-case combinations formed from 16 experimental cases, including the two in Table 1, and evaluated at the validation case in Table 1, which is not included among the 16 cases. The results are shown in Figure 4.

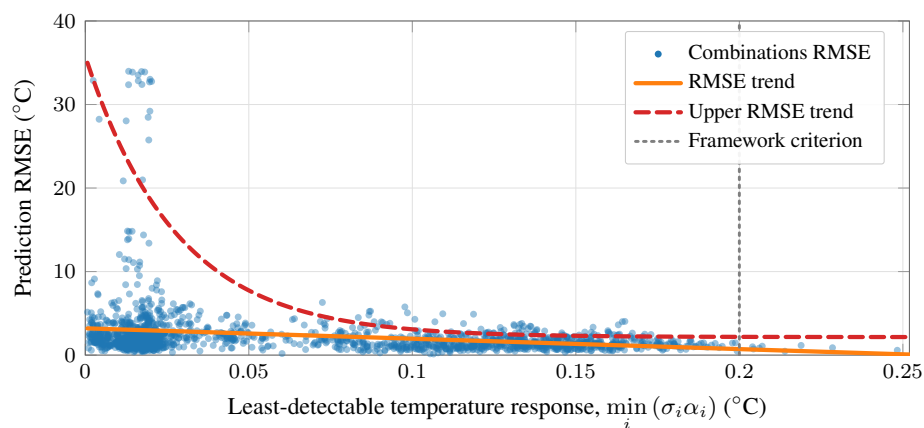


Figure 4. Relationship between prediction RMSE at the validation case and the least-detectable temperature response among the parameter-change directions of each four-case combination, calculated using (31).

The RMSE trend was obtained by ordinary least-squares linear regression using all 1820 combinations. For the upper RMSE trend, the least-detectable temperature-response range was divided into 20 equal-width intervals, and the 99th-percentile RMSE within each interval was calculated. An exponential function was then fitted to these values using nonlinear least squares.

The linear trend indicates an increase in prediction error as each combination's least-detectable temperature response decreases, while the exponential upper RMSE trend also shows that the error becomes substantially more dispersed. The 8 combinations satisfying the framework criterion yield RMSE values of 0.462–1.161 °C, whereas the remaining 1812 combinations span 0.136–33.976 °C.

Despite using the same model structure, the same number of fitting cases, and the same validation case, the fitted models exhibit substantially different prediction performance. This demonstrates that reliable prediction depends not only on the model structure or amount of experimental data, but also on whether the selected cases contain sufficient information for reliable parameter identification, as demonstrated by the results of the proposed framework.

6. Conclusions

Accurate temperature prediction is important for reliability assessment, lifetime estimation, and safe operation of power electronic devices and systems, particularly under high power density. Electro-thermal models provide a practical means of predicting device temperatures for these purposes. However, this paper shows that even a physically reasonable electro-thermal model can produce large prediction errors when the selected fitting cases contain insufficient parameter information. In addition, the number of possible experimental case combinations is extremely large, while only a small fraction are informative enough for reliable parameter identification. The proposed framework therefore supports the experimental design process by guiding case selection through an information-sufficiency criterion that assesses whether prescribed parameter variations produce practically detectable temperature responses, with SVD used to identify weak parameter directions. Experimental results show that criterion-satisfying selections yield low prediction RMSE with a narrow error range, whereas prediction errors generally increase and become more dispersed as the least-detectable temperature response falls below the criterion. More broadly, as the framework is formulated from the parameter-sensitivity relation rather than a specific model structure, it is applicable to other electro-thermal models for which the parameter sensitivities can be evaluated.

7. Biographies of the Authors

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Author Contributions

J.P.: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing—original draft preparation, writing—review and editing, and visualization; D.D.-C.L.: conceptualization, methodology, resources, writing—review and editing, supervision, and project administration; C.-K.L.: conceptualization, methodology, resources, writing—review and editing, supervision, and project administration. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement

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Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

The research idea, methodology, results, and conclusions were produced and verified by the authors without using any artificial intelligence tools. The authors used OpenAI GPT-5.6 and Grammarly only to improve grammar, wording, and readability.

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