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Transient Thermal Modeling of Power Semiconductors for Long-Term Load Profiles

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***Abstract*—This paper presents an improved thermal analysis method focusing on the long-term profiles of power modules. A shift-invariant dictionary method is developed to extract the critical atoms to sparsely represent time series signals. Then the temperature response of the power module can be approximated by a sparse linear combination of basis functions. The performance of the proposed method is compared with the convolution method, the result indicates that the transient junction temperature of the power module can be predicted with less computational effort. The simulation and experimental results also prove that the proposed method can effectively reconstruct the thermal behavior, exhibits good predictive capability and is suitable for temperature prediction under long time scales.**

I. Introduction

In the application of photovoltaics, electric vehicles, wind power, etc., the dynamic mission profiles may introduce complicated loading conditions to the devices, consequently resulting in complicated thermal dynamics [1]. In the meanwhile, reliability depends on the junction temperature of the device, effective loss calculation and thermal simulation techniques are needed to support these designs [2], [3].

To handle the transient thermal analysis under a long-term dynamic load profile, a simplified thermal estimation model is required to quickly estimate the thermal profiles with allowable error. The half-sine loss profile [4], the equivalent discretization of the half-sine loss curve are generally accepted solutions to reduce the computational burden by simple loss profiles [5], [6]. Multi-timescale thermal models, with low speed at small time scales and low accuracy at large time scales, cannot meet the accuracy and speed requirements at the same time [7], [8].

The discussed simplification methods indicated two concerns: 1) it limits the loss profile to periodic half-sine wave, may introduce large errors under dynamic load conditions, 2) the simplified loss model still need to convolve with the thermal impedance, which causes a huge computational burden, especially for long-term estimation.

This paper develops a fast transient thermal modeling based on dictionary learning, which is suitable for long-term thermal analysis with arbitrary power loss profile. Dictionary learning is a representation learning method that aims to find sparse representations of input data in the form of elementary elements and linear combinations of these elementary elements themselves [9]. The fields of signal processing, image processing and fault analysis are all popular areas where dictionary learning is widely used [10], [11]. Dictionary learning methods can also be used for transient thermal modeling.

Under long mission profiles, the low-precision sampling is usually the first choice for the long-scale thermal signals because of its super-large data size. To address this issue, the meaningful features can be learned from time series by performing dictionary learning on highly overlapping time series. Secondly, by comparing their shift-variable versions over different kinds of time series, the signals can be reconstruction, prediction and classification [12]. Previously, several dictionary learning techniques adapted to shift-invariant have been proposed [13]- [15]. In [16], massive wind speed signals are compressed by random sampling and recovered using the time-shift strategy. Meanwhile, many dictionary learning methods have been developed to solve the problem of sparse coding, such as a generalization of the k-means clustering method K-SVD [17]- [18]. Matching Pursuit (MP) is a sparse approximation algorithm which finds the "best matching" [13], [19]. A extensions of MP is orthogonal MP (OMP) [15], [20], which is applicable to high-dimensional signals.

In this paper, power losses and thermal profiles are considered to be time invariant. And these time series data can be modelled as sparse linear combinations of short basis functions (segments) that are executed at different points in the linear order. Therefore, the time series signal can be linearly decomposed into the set of basis functions which represents pre-characterized device behavior, is predicted by shift-invariant dictionary and linear superposition. By dictionary learning, convolution calculation between power loss and thermal impedance can be eliminated, reducing the computational burden of thermal modelling. The predicted results are compared with the temperatures obtained from the simulation and the experimental measurements to confirm the accuracy of the prediction method.

II. Instantaneous Power Losses and Thermal Behaviors Estimation

A. Power Device Loss Distribution

The device loss of the power module includes conduction and switching loss. When the current direction is positive during the power module turn-on, the current $i_C(t)$ flows through the IGBT; when the current direction is negative, the current flows through the diode, and the diode current can be expressed as $i_F(t)$. Therefore, the instantaneous conduction losses of IGBTs and diodes can be expressed as (1) and (2), respectively.

$$P_{cond\_T}(t) = \begin{cases} u_{CE}(i_C(t)) \cdot i_C(t) \cdot M(t) & i_C(t) \geq 0 \\ 0 & i_C(t) < 0 \end{cases} \quad (1)$$

$$P_{cond\_D}(t) = \begin{cases} u_F(i_F(t)) \cdot i_F(t) \cdot (1 - M(t)) & i_F(t) \geq 0 \\ 0 & i_F(t) < 0 \end{cases} \quad (2)$$

where, $P_{cond\_T}(t)$, $P_{cond_D}(t)$represent the conduction losses, $u_{CE}(t)$ and $u_F(t)$ are the conducting voltage of IGBT and Diode respectively. $i_C(t)$ and $i_F(t)$ are the conducting current through the IGBTs and the diodes, and the duty ratio of the power device is $M(t)$.

The turn-on loss E_{on} and turn-off loss E_{off} of IGBT vary nonlinearly with current $i_C(t)$, which is difficult to describe accurately and quantitatively with analytical expressions. Manufacturers generally only provide E_{on} and E_{off} curves for rated current, voltage, or a few modes. Experience shows that converting E_{on} and E_{off} by linearization can meet the needs of engineering calculations. The instantaneous switching losses of IGBT $P_{sw\_T}(t)$ can be calculated as,

$$P_{sw\_T}(t) = \begin{cases} f_{sw} \cdot (E_{on}(i_C(t) + E_{off}(i_C(t)) & i_C(t) \geq 0 \\ 0 & i_C(t) < 0 \end{cases} \quad (3)$$

where, f_{sw} denotes the switching frequency.

In the case of the diode, the turn on energy can be disregarded, only the recovery energy Err is counted. The switching loss of the diode $P_{sw\_D}(t)$ can be deduced as follows,

$$P_{sw\_D}(t) = \begin{cases} f_{sw} \cdot E_{rr}(i_F(t)) & i_F(t) \geq 0 \\ 0 & i_F(t) < 0 \end{cases} \quad (4)$$

Fig. 1(a) shows ideal duty ratio of an inverter for a sinusoidal pulse width modulation (PWM). Based on the above analysis, the current and the instantaneous power losses of IGBT are shown in Fig. 1(b) - (d).

B. Thermal analysis method

The compact thermal network model corresponding to a specific IGBT structure. With the thermal impedance model and instantaneous power losses model, it is possible to calculate the instantaneous junction temperature of the power devices by convoluting the loss and thermal impedance [21].

$$\Delta T_j(t) = \int_0^t \left[\frac{\mathrm{d}P_{loss\_T/D}(z)}{\mathrm{d}z} \right] \cdot Z_{th}(t-z)dz \quad (5)$$

where, Z_{th} is the thermal impendence of power module, $P_{loss\_T/D}$ is the instantaneous losses of IGBT or Diode, $\Delta T_j(t)$ is the temperature fluctuation.

The convolution operation is computationally unfriendly, especially for long mission profiles. To solve this problem, the half-sine loss profiles is equalized to the square profiles, based on the principle of area equality, as shown in Fig. 2. The temperature fluctuations can be given as:

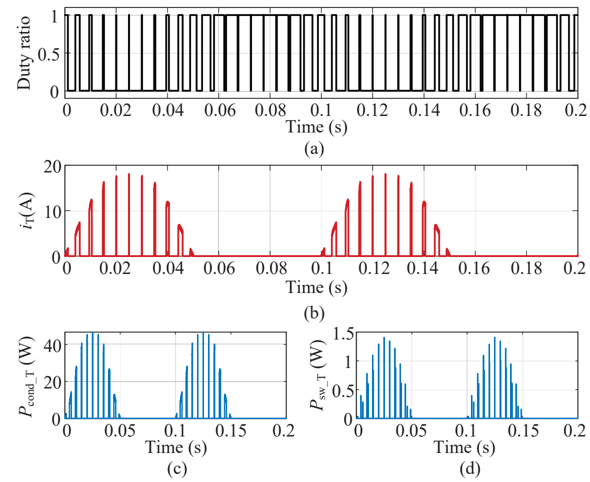

Fig. 1. (a) Duty ratio of the inverter, (b) Instantaneous current of IGBT, (c) Conduction loss, (d) Switching loss.

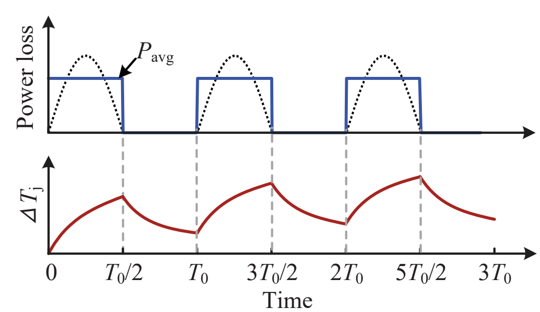

Fig. 2. Junction temperature fluctuation under simplified power losses.

$$\Delta T_j(t) = \begin{cases} P_{avg} \sum_{i=1}^{m} R_{thi} \left(1 - e^{-\frac{t}{\tau_{thi}}}\right), 0 \leq t \leq \frac{T_0}{2} \\ P_{avg} \sum_{i=1}^{m} R_{thi} \left(1 - e^{-\frac{T_0}{2 \cdot \tau_{thi}}}\right) e^{-\frac{t - T_0/2}{\tau_{thi}}} \\ \qquad , \frac{T_0}{2} < t \leq T_0 \\ \vdots \\ P_{avg} \sum_{i=1}^{m} R_{thi} \left(1 - e^{-\frac{T_0}{2 \cdot \tau_{thi}}}\right)^n \left(e^{-\frac{T_0}{2 \cdot \tau_{thi}}}\right)^{n-1} \\ \qquad \cdot e^{-\frac{t-(2n-1)T_0/2}{\tau_{thi}}}, \frac{(2n-1)T_0}{2} < t \leq nT_0 \end{cases} \quad (6)$$

where, R_{thi}, τ_{thi} are the thermal resistance and thermal time constant of i-th RC lump, respectively. m is the order of Foster RC lumps. T_0 is the fundamental period.

It indicates that the temperature fluctuation $\Delta T_j(t)$ for each heating period subjects to the temperature at the each end of the previous heating period. With periodic power consumption, the temperature of each heating period is determined by iteration, has time-ordered and continuity. It will be more complicated for long time scales temperature rise calculating, which will take more calculation time. To further simplify the thermal analysis process, in this paper a dictionary learning-based thermal analysis method is proposed for long-term profile.

III. Proposed Transient Thermal Analysis Method

Shift-invariant sparse representation describes a signal as a linear superposition of atoms in the dictionary. In this paper, a shift-invariant dictionary learning based thermal analysis method is used to obtain the power losses and thermal profiles by extracting the features of the signals.

A. Basic theory of dictionary learning

Assuming that Y is a set of training samples and $D = [d_1, d_2, \cdots, d_N]$ is a dictionary learned from this training sample. The training sample Y can be represented as a linear combination of several atoms in the dictionary D: $Y \approx DA$, where $A = [a_1, a_2, \cdots, a_N]^T$ is the coefficient matrix. If most of the coefficients a_i in the solution vector A are zero or close to zero, that means, only a few atoms are activated to approximate the original signal, it is called sparse approximation. Based on the different objective functions, the dictionary learning can be divided in two ways : sparsity-based and error-based.

$$\min_{D,A} \left\{ \|Y - DA\|_F^2 \right\}, \quad s.t.\forall i, \|A\|_0 \leq k_0 \tag{7}$$

$$\min_{D,A} \{\|A\|_0\}, \quad s.t. \|Y - DA\|_F^2 \leq \varepsilon \tag{8}$$

where ε is the maximum allowable errors, and $\|A\|_0$ represents the zero-order norm, which indicates the number of non-zero coefficients in A, $\|\cdot\|_F$ is the Frobenius norm.

The sparse approximation step is an iterative process that terminates at some predetermined level of sparsity in (7) or tolerance of the model residuals in (8). In this paper, the OMP as an efficient pursuit algorithm is used to search for the best matching atom by continuously searching for the residual vector until a set minimum error range is met.

B. Shift-invariant dictionary learning

The proposed thermal analysis method based on dictionary method is divided into two level: the single pulse dictionary as lower level to get power loss pulse. The higher level dictionary shifts the basis function for different time and extends it by setting the rest to 0 to get a dictionary atom with the same length as the original signal. Fig. 3 illustrates the proposed dictionary method.

The steps of the dictionary learning algorithm are as follows:

1) Input: Time series signal Y with N samples, maximum number of iterations K, maximum allowable error ε.
2) Initialization: The first column of D_1 is initialized by normalized original signal $d_{11} = Y/|Y|$, $A_1^{(1)} = [1, 0, \ldots, 0]$, $A_2^{(1)} = 0$.

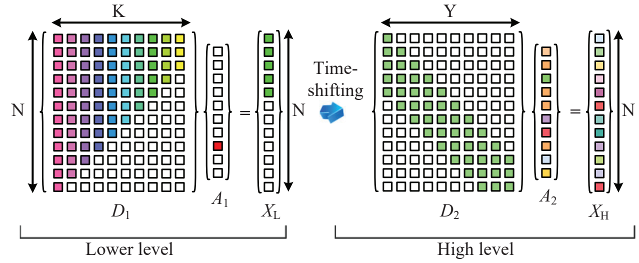

Fig. 3. The schematic diagram of dictionary method.

3) Shift-invariant: Based on the shift-invariant property, the atom d_{1k} is shifted to generate the dictionary $D_2^{(k)}$ in the k-th iteration. And the shift length $Q^{(k)}$ of each atom in $D_2^{(k)}$ is equal to the length of d_{1k}. The number of atoms in $D_2^{(k)}$ can be expressed as:

$$L^{(k)} = \left\lceil N/Q^{(k)} \right\rceil \tag{9}$$

The dictionary matrix $D_2^{(k)} \epsilon R^{N \times L^{(k)}}$ with normalized atoms is constructed by exploiting the time-varying shift-invariant of these time series.

$$D_2^{(k)} = \begin{bmatrix} d_{1k} & & & \\ & d_{1k} & & \\ & & \ddots & \\ & & & d_{1k} \end{bmatrix} \tag{10}$$

4) Matching pursuit: Use the OMP algorithm to find out $D_2^{(k+1)}$ and $A_2^{(k+1)}$ according to (8). The iterative results assign to the lower-level dictionary by updating the lower level atom $d_{1(k+1)}$ with the first column of $D_2^{(k+1)}$. The k-th row of the coefficient matrix $A_1^{(k)}$ equal to 1, and the remaining rows are equal to 0.
5) Iteration: Do 3) and 4) until the maximum number of iteration steps or the maximum allowable error is met.
6) Output: output the reconstructed signal $X_H = D_2 \cdot A_2$ with optimal matching result.

The dictionary $D_1 = [d_{11}, d_{12}, \cdots, d_{1K}] \epsilon R^{N \times K}$ is constructed by each iteration and used as the input to the D_2 dictionary. The sparse matrix A_2 indicates that the best reconstruction of the original signal is achieved within the allowable error by a minimum linear superposition of the atoms in D_2.

C. Proposed thermal method

Based on the dictionary learning method in section B, the reconstructed signal X_P can be generated using dictionary learning by specifying the mean square error ε and the input loss signal P_{loss}, where the error ε is defined as:

$$\varepsilon = \sqrt{\frac{1}{N_P} \cdot \sum_{i=1}^{N_P} \left(P_{loss}(i) - X_P(i)\right)^2} \tag{11}$$

where, N_P is the number of samples in time series P_{loss}. X_P is divided into a number of moderately sized segments d_P,

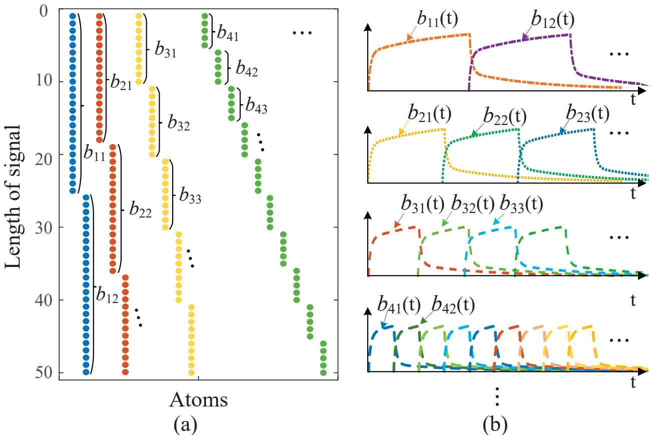

Fig. 4. The shift-invariant dictionary considering thermal coupling. (a) Thermal model composition in terms of the dictionary. (b) Time waveform of the atoms in thermal matrix.

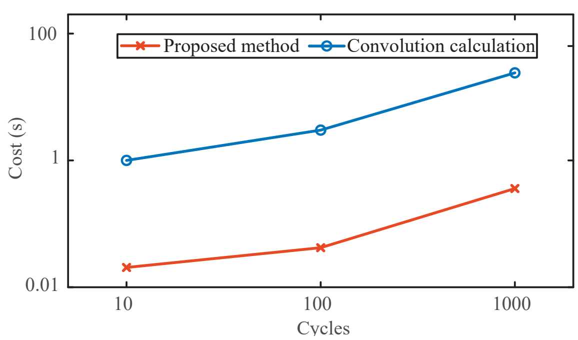

Fig. 5. The computation cost under thermal coupling.

corresponding to a coefficient matrix A_P. d_P is shifted Q_P positions down for each new column in power loss matrix D_P.

Therefore, the atom $b(t)$ of thermal matrix under the pulse power loss $d_P(t)$ for a specific power module structure can be easily calculated according to Equation (5). Since the length of the atom $d_P(t)$ is much smaller than N_P, the computational effort caused by convolution is negligible.

In this study, the thermal signal of a single chip is a linear mixing model, as shown in Fig. 4. Assuming that there are S independent heat source, the observed signal obtained through only one temperature sensor is a linear superposition of the source signals. The fluctuation of junction temperature can analytically be solved by convoluting the loss and thermal impedance.

$$\Delta T_j(S,t) = \sum_{n=1}^{S} \int_0^t \left[\frac{\mathrm{d}P_{loss\_T/D}(n,z)}{\mathrm{d}z} \right] \cdot Z_{th}(n, t-z) dz \tag{12}$$

Based on the dictionary learning result, the reconstructed thermal signal $\Delta T_j(S,t)$ considering thermal coupling can be also modelled as:

$$\Delta T_j(S,t) = \sum_{n=1}^{S} \sum_{k=1}^{Y_n} A_{P\_n,k} \cdot b_{n,k}(t-(k-1)\tau_n) \tag{13}$$

where, the functions $b_{n,k}$ are shift-invariant atoms that represent elementary waveform of the signal and Y_n is the number of atoms. The amplitude of the k-th instance of atom $b_{n,k}$ are denoted by $A_{P\_n,k}$, the corresponding shift time is $\tau_n = t(Q_{P,n})$.

We can see that, the thermal dictionary matrix $B = [b_{11}, b_{12}, \cdots, b_{SY}]$ can be easily constructed by replacing the atom $d_{P\_n,k}$ in the loss dictionary $D_{P\_n,k}$ with atom $b_{n,k}$. It means that the dictionary learning only works once as preprocessing to extract the eigenvalues of power loss and thermal profiles. Comparing with Equation (12), the proposed dictionary learning method in (13) can replace the convolution operation with matrix operation, which can greatly reduce the computational cost.

TABLE I
PARAMETERS OF THE INVERTER

Parameter	Values
DC link Voltage (V_{dc})	300V
Peak value of ac current (I_{ac_peak})	20A
Switching frequency (f_{sw})	5kHz
Filter inductance	4mH
IGBT module	F4-50R12KS4

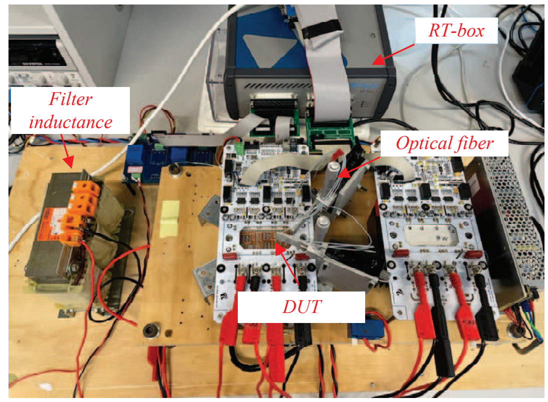

Fig. 6. The photo of the experimental platform.

IV. Validation by Simulations and Experiments

To further confirm the accuracy of the proposed method, the predicted results are compared with the junction temperature obtained by simulation and experiment. To demonstrate the effectiveness of the proposed method, tests are implemented based on a single-phase inverter. The parameters used in the prototype and testing are listed in Table I. The experimental platform used in the prototype and testing is shown in Fig. 6.

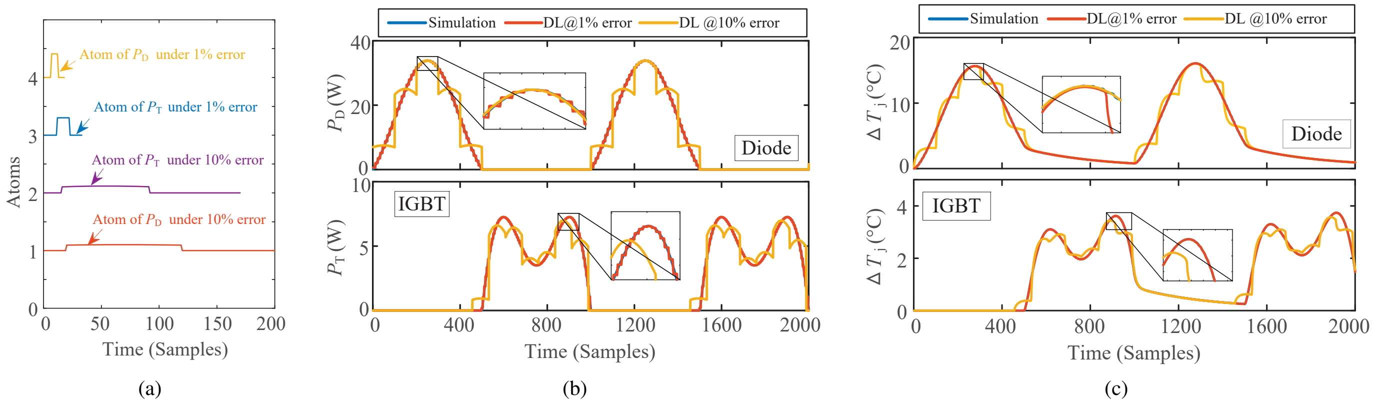

Fig. 7. The comparison of simulation and the dictionary learning (DL) for reconstructed loss signals and junction temperature fluctuation.(a) Atoms in shift-invariant dictionary . (b) Power losses profiles. (c) Junction temperature fluctuation.

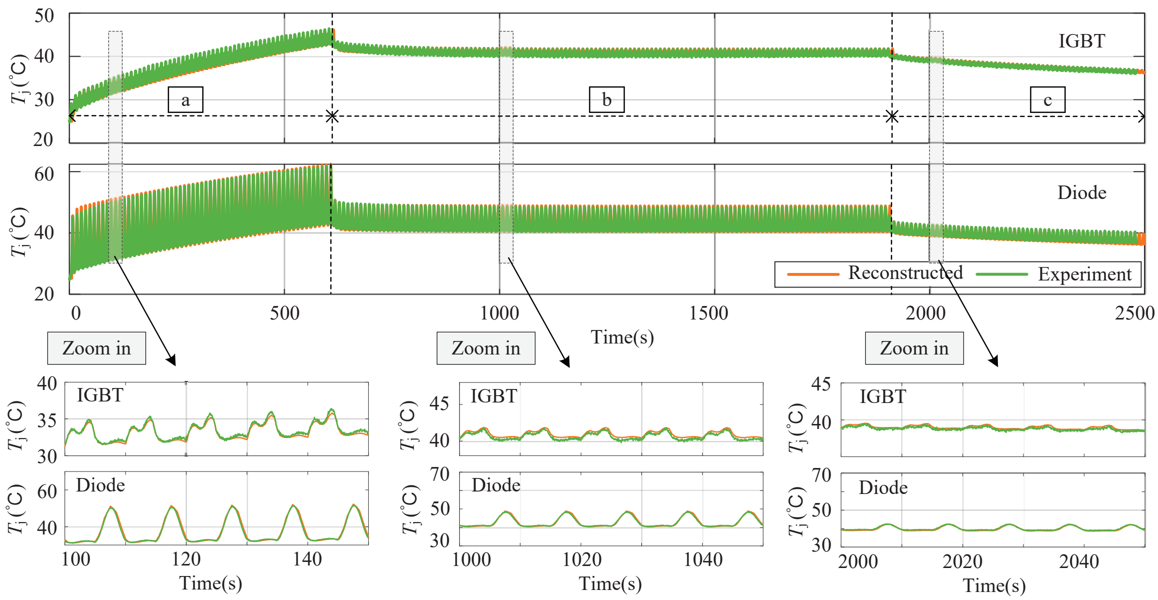

Fig. 8. The comparison of measured and the reconstructed junction temperature profiles under different currents.

A. Result of dictionary learning

Before comparing the results with simulation and experiment, it is necessary to extract the atoms of loss profiles using the proposed dictionary method. The atoms of the thermal response can also be calculated from the atoms of the loss matrix and the thermal impedance of the IGBT module. The computation time of the proposed method can be divided into two parts, the first part is the time for constructing the dictionary and the second part is the time for the linear superposition calculation. However, for a specific IGBT, the dictionary construction process only needs to be performed once, so this time can be neglected.

The computational times for convolution in (12) and the presented model (13) are compared at a maximum allowable error of 1% in Fig. 5. As the number of cycles of the simulation increases, the length of the thermal signal also increases, therefore making the time of both methods increase. In general, the proposed method can significantly reduce the calculation time compared to traditional methods.

B. Comparison with simulation results

Prediction results of the IGBT and diode junction temperatures by the proposed dictionary method are compared with the results obtained by the simulation in PLECS. The dictionary learning results under 1% error and 10% error are considered. Figure 7(a) indicates that smaller errors lead to more atoms to reconstruct the signals, with the increased computational cost. Although the shape of the power losses has a non-negligible effect on the dictionary learning results, the maximum junction temperature fluctuation can be estimated well with an error of no more than 1°C.

In general, the result in Fig. 7 shows that with the same IGBT characteristics applied, the proposed model can give the almost same thermal performance compared to the full physically based device modelling approach.

C. Experimental Validations

The comparison of the junction temperature between the proposed method and the measured by the optical fiber under different currents are shown in Fig. 8. In period a, the peak current flowing through the power module is 20A, while in period b, the peak current is reduced to 10A and in the last period c, the peak current is 5A. And the dynamic performance of the proposed method is verified by varying the peak current.

The temperature dynamic profiles of IGBT and Diode in the inverter are measured in 2500s, and the proposed method takes only 1.2s to complete the temperature prediction. The depicted results show that the proposed method can offer a more accurate estimation of the junction temperature fluctuation with less computational effort. There was little difference and the result was authentic.

V. CONCLUSIONS

This paper presents a fast transient thermal modeling to estimate thermal profiles of the power modules. The sparse matrix is obtained by iterative of the allowable error and linearly superimposed on the dictionary to obtain the temperature response signals. To validate the potency, simulation and experiments are carried out, and the results verified the feasibility of the method. In summary, the presented thermal model performs well in thermal estimation accuracy and computational burden, and is suitable for long-term dynamic load profiles.

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