RC-Based Temperature Prediction Scheme for Proactive Dynamic Thermal Management in Throttle-Based 3D NoCs

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Abstract—The three-dimensional Network-on-Chip (3D NoC) has been proposed to solve the complex on-chip communication issues in multicore systems using die stacking in recent days. Because of the larger power density and the heterogeneous thermal conductance in different silicon layers of 3D NoC, the thermal problems of 3D NoC become more exacerbated than that of 2D NoC and become a major design constraint for a high-performance system. To control the system temperature under a certain thermal limit, many Dynamic Thermal Managements (DTMs) have been proposed. Recently, for emergent cooling, the full throttling scheme is usually employed as the system temperature reaches the alarming level. Hence, the conventional reactive DTM suffers from significant performance impact because of the pessimistic reaction. In this paper, we propose a throttle-based proactive DTM (T-PDTM) scheme to predict the future temperature through a new Thermal RC-based temperature prediction (RCTP) model. The RCTP model can precisely predict the temperature with heterogeneous workload assignment with low constant computational complexity. Based on the predictive temperature, the proposed T-PDTM scheme will assign the suitable clock frequency for each node of the NoC system to perform early temperature control through power budget distribution. Based on the experimental results, compared with the conventional reactive throttled-based DTMs, the T-PDTM scheme can help to reduce 11.4~80.3 percent fully throttled nodes and improves the network throughput by around 1.5~211.8 percent.

Index Terms—Proactive, dynamic thermal management, 3D MPSoC, 3D IC, NoC, DVFS, power budget

1 INTRODUCTION

As the complexity of System-on-Chip (SoC) grows with respect to the technology development, on-chip connections gradually dominate the system performance of Multi-Processor SoC (MPSoC) systems. Because of the characteristics of regularity, mesh-based Network-on-Chip (NoC) has been proposed as a feasible solution for efficient interconnections among the computing elements [1]. Recently, the three-dimensional integrated circuit (3D IC) technologies are promising to provide larger interconnection bandwidth to achieve higher performance [2]. However, because of stacking dies, the high integration density with high operation frequency results in larger power density, which leads to higher temperature. Furthermore, the heterogeneous thermal conductance of different silicon layers makes the 3D NoC-based MPSoC systems suffer from even severer thermal problem [2], [3]. Thermal issue increases the leakage power, which may further increase temperature and thermal runaway [4], [5]. Hence, we aim to solve the thermal issue of mesh-based 3D NoC system in this work.

To keep the system temperature below a certain thermal limit, some dynamic thermal managements (DTMs) were proposed, and they can be classified into temporal DTMs and spatial DTMs [5]. The temporal DTMs slow down the activities of the thermal-emergent nodes (i.e., the temperature of the nodes exceeds the triggering temperature of the DTM) to perform cooling through throttling schemes, such as Global Throttling (GT) [6], Distributive Throttling (DT) [7], and Vertical Throttling (VT) [4]. The Dynamic Frequency Scaling (DFS), Dynamic Voltage Scaling (DVS), Dynamic Voltage and Frequency Scaling (DVFS), Clock Throttling, etc. are the popular techniques to implement the throttling schemes [3], [4], [6], [7], [8], [9], [10], [11]. Because the major concern is to perform emergent cooling as the temperature exceeds the alarming level, the full throttling scheme is usually employed. Hence, the temporal DTMs result in significant performance impact, although they can regulate the system temperature within short cooling time. Fig. 1a shows an example while the conventional reactive VT is involved as the DTM policy. Because the node $A$ is thermal-emergent, it is fully throttled at time 2 for the emergent cooling, which results in rapid performance degradation, as shown in Fig. 1b. Note that each node of NoC contains an IP, an embedded memory, and one router, as shown in Fig. 2. On the other hand, the spatial DTMs [5], [12], [32] can control the system temperature without slowing down the thermal-emergent nodes through power migration. As the temperature exceeds the thermal limit, the packets will be detoured the hotspot region [32]. However, the spatial DTMs need long cooling time because of the thermal
coupling between each node and the heterogeneous thermal conductance between each vertical silicon layer of 3D NoC [5]. Therefore, the throttle-based temporal DTM schemes are adopted in this work due to the better cooling efficiency for the 3D NoC systems.

To mitigate the performance impact while applying the throttle-based temporal DTMs, the proactive DTMs (PDTMs) have been proved as an efficient way to prevent the system from thermal emergency and rapid performance degradation [5]. In [8], Wegner et al. proposed a central control scheme to proactively control the temperature of an NoC system. However, the central control results in serious communication overhead in a large scale NoC system. In [9], Cochran et al. proposed a table-based two-phase PDM. However, the large table requirement is not feasible to apply in an NoC system. In [3], Kang et al. assign the frequency of each element based on the power budget assignment. However, because of the iterative search, the computational complexity is linearly increased with respect to the size of the 3D NoC system, which increases the response time. In [10], Ayoub et al. proposed to use the thermal resistance and thermal capacitance (Thermal RC) model to predict the future temperature and perform temperature control for a memory subsystem. However, it still suffers from the large performance impact due to the memory gating. In [11], Wu et al. proposed to shut down the thermal-emergent node and slow down the nodes, which have high thermal correlated to the thermal-emergent node. However, the performance overhead is large because all thermal correlated nodes will be slow down as one node becomes thermal-emergent.

In this paper, we propose a throttle-based proactive DTM scheme for thermal-aware 3D NoC systems. Figs. 1c, 1d illustrates an example. The T-PDTM can early control the temperature of node A before the thermal emergency at time 2 through partially throttling scheme. Hence, the performance impact can be reduced. The framework of the proposed T-PDTM scheme is shown in Fig. 2. We assume that each NoC node has one embedded thermal sensor and one embedded proactive thermal management unit (PTMU). Based on the result of the predictive temperature \( T_{\text{predict}} \) and the current sensing temperature \( T_{\text{current}} \), the PTMU can early control the percentage of each local node’s activity to perform temperature control. The contributions of this paper are summarized as:

- **A Thermal RC-based temperature prediction (RCTP) model for temperature prediction.** Based on the Thermal RC model [14], a temperature prediction model is proposed, which is performed in the first phase of Fig. 2. The experimental results show that the proposed RCTP model can predict the temperature after 50 ms, and the average prediction error is less than 0.2°C against the measured temperature measurement. Besides, we propose a theoretical analysis to reduce the computational complexity to constant computational complexity (i.e., \( O(1) \)).

- **A throttle-based proactive DTM scheme for early temperature control.** Based on the result of the predictive temperature, the T-PDTM scheme can early control the system temperature. The T-PDTM scheme can be applied to arbitrary throttle-based temporal DTMs (i.e., GT [6], DT [7], and VT [4]). In this paper, we propose a method of frequency assignment to control the percentage of each node’s activity, as shown in the second phase of Fig. 2. As shown in the experimental results, the proposed T-PDTM scheme can help to reduce 11.4~80.3 percent thermal-emergent nodes and improve 1.5~211.8 percent network throughput compared with the conventional reactive throttle-based DTMs.

The rest of this paper is organized as follows. In Section 2, the state-of-the-art throttle-based DTMs and the approaches of PDTM are introduced. In Section 3, the proposed Thermal RC-based temperature prediction model is introduced. With the RCTP model, the throttle-based proactive thermal management (T-PDTM) scheme for the thermal-aware 3D NoC systems is introduced in Section 4. Finally, the conclusion is shown in Section 5.

2 BACKGROUND AND RELATED WORKS

2.1 Throttle-Based Dynamic Thermal Management Schemes for NoC Systems

2.1.1 Global Throttling Scheme [6]

The simplest throttle-based DTM scheme uses global throttling scheme to cool down the network system. When any node of the 3D NoC system achieves the crucial high temperature, the entire system will be slowed down, as shown in Fig. 3a. Although the GT scheme has the benefit of short cooling time, the impact of system availability is huge.

2.1.2 Distributive Throttling Scheme [7]

In [7], Shang et al. proposed a Distributive Throttling scheme, ThermalHerd, to regulate the network temperature, as shown in Fig. 3b. The DT scheme controls the quota of

![Fig. 1. (a), (b) Reactive DTM results in performance impact, and (c), (d) T-PDTM scheme can improve the system performance.](Image 37x572 to 266x720)
incoming traffic of the thermal-emergent node. Because of less throttled nodes, the DT can mitigate the performance impact caused by the GT scheme. However, the DT scheme usually needs long cooling time because of the heterogeneous thermal conductance between each silicon layer of 3D NoC systems.

### 2.2.1 Central Thermal Management for NoC Systems [8]

To early control the temperature of the NoC system, Wegner et al. proposed a mechanism of central temperature control. Based on the Thermal RC model, the future temperature of each node of the NoC can be predicted. By exhaustively searching each DFS step, the clock frequency of each node can be determined based on the information of predictive temperature. The embedded central thermal management unit will assign the clock frequency to each node through sending the instruction packets.

### 2.2.2 Phase-Aware Thermal Prediction Methodology [9]

Cochran et al. proposed to use $k$-means clustering to classify the global workload phases and the corresponding thermal models in offline analysis. By using the performance counter, the transient workload can be measured. Based on the analytic results in offline phase, the projected temperature of each node at each frequency level can be calculated.

### 2.2.3 Energy Efficient Thermal Management for Memory Subsystem [10]

Ayoub et al. proposed to use Thermal RC model to predict the temperature after hundreds milliseconds for a memory subsystem. Based on the results of the predictive temperature, the authors use memory gating and control the fan speed to achieve the energy efficiency under a certain thermal limit. The method has the benefit of low computational complexity.

### 2.2.4 Slack-Based Power Budgeting Frequency Assignment [3]

By following the First Thermodynamic Law [22], the temperature is a function of the total power consumption of each node. Besides, the power consumption linearly depends on the clock frequency. In [3], Kang et al. proposed to assign the frequency of each node based on the slack power budget toward the steady-state temperature. Through iteratively searching the frequency level of the employed DFS, this method can assign the optimal clock frequency for each node under the thermal constraint.

### 2.2.5 Distributed Thermal Management [11]

Because the temperature of one device may be affected by its neighboring components, Wu et al. proposed to calculate the thermal correlation between each pair of devices in offline phase. As one device becomes thermal-emergent in online phase, the proposed distributed thermal management not only shut down the thermal-emergent device but slow down the devices, which have high thermal correlated to the thermal-emergent device.

Although the aforementioned PDTMs can perform better cooling efficiency than the reactive ones, there are some disadvantages, which are not feasible to apply to a high-performance 3D NoC system, as shown in Table 1.

Note that the bold words mean better technical merits. In [8], the extra instruction packets result in long response time and heavy traffic load because of the central temperature control in [9], the large table requirement leads to heavy area overhead due to the offline temperature profiling. In [10], the methods still suffers from the significant performance overhead due to the memory gating. In [3], the computational complexity of the proposed method will be increased with respect to the network size, although it can obtain the optimal frequency assignment. In [11], it is time
the high thermal correlated device in a large scale network system. In addition, the performance overhead is large because all the thermal correlated devices will be slow down as one device becomes thermal-emergent. To solve the aforementioned problems, we propose RCTP model and T-PDTM with low computational complexity and short response time, which will be introduced later.

3 PROPOSED TEMPERATURE PREDICTION SCHEME

3.1 Preliminary

3.1.1 Thermal Model for a 3D NoC System

For a 3D NoC system, there are multiple stacked silicon layers, as shown in Fig. 4a. In [14], the heat flow within a package was modeled by analogous electrical resistor-capacitor (RC) network. Fig. 4b shows a corresponding Thermal RC model of a 3D NoC system with a heat sink. For an X-by-Y-by-Z 3D NoC, the $T_{x,y,z}$ and $P_{x,y,z}$ mean the corresponding temperature and power consumption of the node at the location $(x,y,z)$, respectively. $R_{\text{inter}}$ and $R_{\text{intra}}$ represent the thermal resistance between each vertical silicon layer and each horizontal silicon layer, respectively. $C_{\text{inter}}$ is the thermal capacitance between each vertical silicon layer. For the heat spreader, the $R_{ss}$ and $C_{ss}$ are the thermal resistance and thermal capacitance, respectively. In usual, the heat sink is attached in the one side of the 3D NoC package. To model the heat transfer between the heat sink and ambient, we use the $R_{\text{sink}}$ as the convective resistance of the heat sink.

To achieve the early temperature control, the transient temperature of each node should be derived. By Fourier’s Law, the change of temperature in a time unit can be formulated as [16]:

$$dT(t) = \frac{P(t) - T(t)}{RC} dt .$$

where $T(t)$ and $P(t)$ are the temperature and total power consumption of a specific node at time $t$; $R$ and $C$ are the effective thermal resistance and thermal capacitance toward the ambient, respectively. To simplify the equation, we rewrite (1) as,

$$\frac{dT(t)}{dt} = a \cdot P(t) - b \cdot T(t) ,$$

where $a$ (i.e., it is equal to $1/C$) and $b$ (i.e., it is equal to $1/RC$) are the physic constant, which depends on the material of employed technology. To solve the linear differential equation, we can set the boundary condition, which the initial temperature at $t_0$ is set as $T_0$ (i.e., $T(t_0) = T_0$). Therefore, the (2) can be solved as

$$T(t) = \int_{t_0}^{t} a \ P(\tau) e^{-b(t-\tau)} d\tau + T_0 \cdot e^{-b(t-t_0)} .$$

In this work, we consider the worst case to mitigate the system impact caused by the thermal problem and assume the 3D NoC system is near saturation throughput (i.e., quasi-stationary system). Because the $P(t)$ in (3) linearly depends on the clock frequency, we assume the clock frequency of every one specific node of NoC is identical in a time interval $[t_0, t]$ for a quasi-stationary system. Consequently, the temperature will approximate to a steady-state temperature in long-term running (i.e., $T(t) = T_{ss}$ when $t = \infty$), and the (3) can be derived to

$$T(t) = T_{ss} - (T_{ss} - T_0) \cdot e^{-bt} .$$

3.1.2 Low-Cost RC Product Derivation

In (4), the physic constant $b$ is equal to the reciprocal of RC product. Obviously, the precision of the temperature estimation highly depends on the RC product. However, it is difficult to find the precise RC product because of the complex thermal coupling in the 3D NoC systems. In [5], the effective RC product is extracted through running several benchmarks. However, by this way, the RC product would become application dependency. In [10], Ayoub et al. proposed to use the analogous electric RC network and the one dimensional (1D) heat transference (i.e., the heat flow is dissipated through the vertical direction) to find the effective RC product. We use Fig. 4b as an example. If a 3D NoC system contains $N$ silicon layers, the effective RC product is

$$RC = [(N-1) \cdot R_{\text{inter}} + R_{\text{hs}} + R_{\text{sink}}] \cdot [(N-1) \cdot C_{\text{inter}} + C_{\text{hs}}] .$$

Although the effective thermal RC product can be easily found through analogous electric RC network, this method does not consider the thermal coupling. Because the heterogeneous thermal conductance in different silicon layer of 3D NoC system, the thermal resistance $R$ and thermal capacitance $C$ are varing in different silicon layer of the system. Therefore, it is not a feasible way to use identical $R$ and $C$.

As shown in [22], the $R$ has a relationship between the thermal conductivity $K$, the cross area of the heat flow $A$, and the thickness of the direction of the heat flow $L$, which can be shown as

$$R = \frac{L}{K A} .$$

For the comparison between the $R$ among horizontally adjacent nodes (i.e., $R_{\text{intra}}$) and the one among vertically nodes (i.e., $R_{\text{inter}}$), the $R_{\text{intra}}$ is larger than the $R_{\text{inter}}$ because the $A$ among the horizontally adjacent nodes is smaller than the one among the vertically adjacent nodes. Therefore, the most heat is dissipated through the vertical direction, as shown in Fig. 4a. On the other hand, the author in [30] also showed that almost 90 percent heat quantity transfer from silicon to heat sink. To approximate the RC product, the popular academic approach is to apply the property of 1D heat transference [10]. By this reason, in this work, the
The discipline of 1D heat transference is adopted to extract the RC product with thermal coupling consideration. By (6), the Fourier's Law can be rewritten as

\[ Q = -kA \frac{dT}{dt} = - \frac{T_{down} - T_{up}}{R}, \tag{7} \]

where \( Q \) is the heat flux, and the minus sign means that the heat is propagated out of the system. The \( T_{up} \) and \( T_{down} \) are the temperature at the two sides of the 3D NoC system, as shown in Fig. 4a. The dissipation of \( Q \) can help to decrease the temperature per time interval, and the temperature difference is \( \Delta T \) (i.e., \( \Delta T = Q/C \)). Hence, we can rewrite (7) as

\[ Q = \Delta T \cdot C = - \frac{T_{down} - T_{up}}{R}. \tag{8} \]

Finally, we can rearrange the (8) to obtain the effective RC product of the 3D NoC system as

\[ RC = - \frac{T_{down} - T_{up}}{\Delta T}. \tag{9} \]

In this work, we can set the \( T_{down} \) to the ambient temperature and \( T_{up} \) to around the specific thermal limit (i.e., 100°C in this work). The effective \( b \) value of (4) can be extracted by observing the change of the temperature \( \Delta T \) per time interval (i.e., one thermal sensing period). In this paper, we set the \( b \) value to 1.98.

### 3.2 Thermal RC-Based Thermal Prediction (RCTP) Model

To control each NoC node’s temperature before thermal emergency, the embedded PTMU needs to early predict the future temperature of local node. In this work, we present a temperature prediction scheme using Thermal RC model in this section. Based on the temperature trend between the current temperature and the one in the history, there are two kinds of prediction modes:

- **Increasing mode.** In normal operation, the change of temperature is usually an exhaustive increasing trend (as shown in Fig. 5a) because of worst case consideration. The future temperature can be predicted through a linear approximation, which will be introduced in Section 3.2.1.

- **Decreasing mode.** For the temperature-controlled operation (i.e., the operation period when the DTM is triggered), the temperature difference between the current temperature and the one in the history would be a negative trend, as shown in Fig. 5b. The prediction model should be enhanced, which will be described in Section 3.2.2.

#### 3.2.1 Baseline Thermal RC-Based Thermal Prediction Model

For arbitrary thermal-aware multicore system, embedded thermal sensor for each node is a popular practical method [17], [18]. Based on the present voltage and current, the thermal sensor can provide a result of temperature periodically [19]. We assume the embedded thermal sensor provides an information of temperature every thermal sensing period \( \Delta t_s \). Our goal is to predict the temperature at the time after \( k\Delta t_s \) (as shown in Fig. 5a), and \( k \) is the thermal prediction distance (i.e., the thermal sensing time far away from the current time). Obviously, the temperature of a specific node at the time after \( k\Delta t_s \) is

\[ T(t + k\Delta t_s) = T^*(t) + \Delta T, \tag{10} \]

where \( T^*(t) \) represents the current temperature at time \( t \), which is provided by the embedded thermal sensor. In this work, we use the superscript, star, to represent that this temperature is measured temperature, which is resulted from the thermal sensor.

To predict the \( \Delta T \), we adopt the derivative analysis to extract the temperature difference in a thermal sensing period \( \Delta t_s \). Therefore, the first derivative of (4) can be derived to

\[ \frac{dT(t)}{dt} = b \cdot (T_{ss} - T_0) \cdot e^{bt}, \tag{11} \]

which is the temperature slope between the temperature at current time \( t \) and the one at the previous thermal sensing time \( t - \Delta t_s \). With (11), we can predict the temperature slope between the temperature at time \( t + k\Delta t_s \) and \( t + k\Delta t_s - \Delta t_s \) by using the following recursive equation:

\[ \frac{dT(t + k\Delta t_s)}{dt} = \frac{dT(t)}{dt} \cdot e^{-b \Delta t_s}. \tag{12} \]

To simplify the symbols, we use \( \Delta T_k \) to represent the temperature difference between the temperature at time \( t + k\Delta t_s \) and \( t + k\Delta t_s - \Delta t_s \) (i.e., \( \Delta T(t) = T^*(t) - T^*(t - \Delta t_s) \)), and it can be derived as

\[ \Delta T_k = \Delta T^*(t) \cdot e^{-b \Delta t_s}. \tag{13} \]

With (13), the \( \Delta T \) in (10) is the accumulation of each change of temperature in each sensing time period from the time \( t \) to the time \( t + k\Delta t_s \), which can be derived as

\[ \Delta T = \sum_{i=1}^{k} \Delta T_i = \Delta T^*(t) \cdot \frac{e^{-b \Delta t_s} \cdot (1 - e^{-b \Delta t_s})}{1 - e^{-b \Delta t_s}}. \tag{14} \]

which is shown in Fig. 5a. With (10) and (14), the temperature at the time after \( k\Delta t_s \) can be predicted as

\[ T(t + k\Delta t_s) = T^*(t) + \Delta T \]

\[ = T^*(t) + \Delta T^*(t) \cdot \frac{e^{-b \Delta t_s} \cdot (1 - e^{-b \Delta t_s})}{1 - e^{-b \Delta t_s}}, \tag{15} \]
As the thermal prediction distance \( k \) is determined, the term of \( e^{-\frac{C_0}{k} \cdot \Delta t_s} \) in (15) will be a constant. Hence, the computational overhead is negligible because the computational complexity of the proposed thermal prediction model is \( O(1) \).

### 3.2.2 Enhanced Thermal RC-Based Thermal Prediction Model

For the temperature trend in a thermal-aware NoC system, it is not an exhaustive increasing trend because the DTM will control the temperature of the thermal-emergent nodes. Therefore, the \( \Delta T^e(t) \) in (15) would be a negative value, if the DTM starts to control the temperature. Fig. 5b illustrates an example. If the triggering temperature of the DTM policy is \( T_{limit} \), the DTM starts to control the temperature at time \((t - \Delta t_s)\) because the temperature \( T \ast (t - \Delta t_s) \) exceeds the \( T_{limit} \). Therefore, the sensing temperature might decrease at time \( t \) and leads to the negative temperature trend. By following the baseline \( RCTP \) model in (15), the \( \Delta T^e(t) \) becomes a negative value and results in smaller predictive temperature at time \((t + k \Delta t_s)\), which results in large prediction error by using the baseline \( RCTP \) model. The large prediction error affects the DTM policy and leads to significant performance impact. Therefore, it is necessary to enhance the \( RCTP \) model in (15) for the negative temperature trend.

As shown in (4), in a quasi-stationary system, the temperature trend without DTM influence follows an approximated exponential function (i.e., the total power consumption is identical in every thermal sensing period). For the predictive temperature, the inherent prediction error is occurred because of the \( b \) value in (15). As mentioned before, the \( b \) value is the reciprocal of effective thermal RC product. However, the thermal RC product is temperature-dependent, and it leads to the modeling error in our thermal model. We use the Fig. 5b to derive the enhanced \( RCTP \) model for the negative temperature trend. Assume the \( T'_k \) and \( T''_k \) are the predictive temperature without DTM influence at time \( t \) and time \((t + k \Delta t_s)\), and they have an inherent modeling error \( \epsilon'_k \) and \( \epsilon''_k \) associated with the measured temperature (i.e., the temperature resulted from the embedded thermal sensor) \( T^*_k \) and \( T^*_k \), respectively. As shown in Fig. 5b, we can know that the \( \epsilon'_k \) is equal to \( \Delta T'_e \). After the DTM triggering, to consider the worst case, our goal is to predict the temperature at time \((t + k \Delta t_s)\) (i.e., the projective temperature is \( T'_k \)) without DTM influence, and there is an inherent modeling error \( \epsilon''_k \) associated with the measured temperature \( T''_k \). With the result of (4), we can derive the following two equations:

\[
T'_k = T^*_k + \epsilon'_k = T_{ss} - (T_{ss} - T^*_k) \cdot e^{-b \cdot \Delta t_s},
\]

(16)

and

\[
T''_k = T_{ss} - (T_{ss} - T'_k) \cdot e^{-b \cdot \Delta t_s} = T_{ss} - (T_{ss} - (T^*_k + \epsilon'_k)) \cdot e^{-b \cdot \Delta t_s}.
\]

(17)

By subtraction of (16) and (17), the relationship between \( \Delta T'_e \) and \( \Delta T''_e \) can be extracted as

\[
(T'_k - T''_k - \epsilon'_k) = (T^*_k - T'_k) \cdot e^{-b \cdot \Delta t_s} \Rightarrow \Delta T'_e = \Delta T''_e \cdot e^{-b \cdot \Delta t_s}.
\]

(18)

Therefore, as shown in Fig. 5b, we can predict the temperature at time \((t + k \Delta t_s)\) by following equation:

\[
T(t + k \Delta t_s) = T_k = T'_k = \Delta T'_e = (T^*_k + \epsilon'_k) - (T^*_k - T_k + \epsilon'_k - \epsilon'k) = T^*_k + \epsilon'_k - \epsilon''_k.
\]

(19)

Obviously, the prediction error only associates with the current sensing temperature (i.e., there is no accumulated error). Hence, the \( RCTP \) model for the temperature-controlled operation period becomes

\[
T(t + k \Delta t_s) = T(t) + \Delta T(t) = \sum_{j=1}^{k} e^{-b \cdot \Delta t_s} - \Delta T'_e,
\]

(20)

where the \( T(t)' \) is the predictive temperature without DTM influence at time \( t \) and the \( \Delta T(t)' \) is the temperature difference between \( T(t)' \) and \( T(t) \). Similar to (15), the computational complexity of the proposed enhanced prediction model is \( O(1) \).

### 3.3 Precision Analysis of the Proposed Prediction Model in a 3D NoC System

To analyze the prediction error of the proposed approaches, a cycle-accurate traffic-thermal co-simulator is realized [15]. To simulate the distributive thermal sensor, the Hotspot [21] is integrated to our simulator. The tile geometry and power model of Intel’s TeraFlops 80-core processor [1] is adopted, as shown in Fig. 6. Besides, we use the default parameters of Hotspot about thickness and the thermal conductance of each silicon layers. To consider the thermal conductance between each vertical silicon layer, similar to the approach in [33], we use union isolator layer to approximate the TSV layer, which contains isolative TSVs. For the simulation of 3D NoC platform, the Naxim [20] is involved in our simulator. For each router, the channel depth of the input buffer is 4 flits without virtual channel, and the wormhole flow control scheme is employed.

For all the following experiments, we use the following setting, which are defaults in Hotspot [21]. The heat sink is assumed to be copper with a thermal conductance of 400 W/mK, and the ambient temperature is set to 25°C. To reduce the simulation time, the initial temperature is set to 80°C. Due to the limited accuracy of temperature sensing, the thermal sampling interval of Hotspot is set to 10 ms [13].
An 8×8×4 mesh-based 3D NoC is set as a design example. Besides, the packet length is 8 flits. To simplify the problem, the XYZ routing algorithm is adopted in this work.

Fig. 7a compares the peak temperature, resulted from Hotspot [21], and the predictive peak temperature of one particular hotspot node, while the prediction distance is equal to one (PD(1)). In this case, we apply the random traffic pattern with a time-varying random seed. Therefore, the power consumption of each node is not identical, which leads to time-varying power map. The comparison of the predictive thermal map and the thermal map, which is resulted from Hotspot [21], of a 3D NoC system at 0.9 second is shown in Fig. 8. Obviously, the proposed temperature prediction model can result similar thermal map to the one, reported by Hotspot [21]. To analyze the prediction error over different prediction distance, Fig. 7b shows the prediction Mean Absolute Error (AE) and Maximum Absolute Error. Obviously, the prediction error increases with respect to the prediction distance, which can be observed in Fig. 8. Because the prediction error affects the efficiency of DTM, we set the tolerated average prediction error as 0.2°C as a design example in this work. Therefore, the biggest prediction distance in this work is set to five (i.e., PD(5)). For other applications, the designers can select the constrain of feasible prediction error based on the design specification.

4 PROPOSED THROTTLE-BASED PROACTIVE DYNAMIC THERMAL MANAGEMENT

As shown in Fig. 2, the framework of the proposed T-PDTM is controlled by an embedded Proactive Thermal Management Unit. The PTMU determines the policy of the involved thermal management (i.e., GT [6], DT [7], and VT [4]) based on the sensing results of thermal sensor. As mentioned in Section 3.2.1, the embedded thermal sensor is a popular practical method [17], [18]. Therefore, we assume the PTMU can be integrated in each node of the NoC system. The framework of the T-PDTM scheme contains:

1) Thermal prediction phase. Based on the Thermal RC model, the future temperature \( T_{\text{predict}} \) can be predicted through the proposed RCTP model, which was introduced in Section 3.2.

2) Thermal management phase. Based on the \( T_{\text{predict}} \) and the current one \( T_{\text{current}} \), the embedded PTMU will determine the percentage of local node’s activity and control the temperature of local node, which will be introduced in Section 4.2.

In Section 4.1, the problem of frequency assignment is described. In Section 4.2, we will introduce a method of frequency assignment for each node of NoC systems with low computational complexity. Besides, a framework of the proposed T-PDTM scheme and the operation flow will be introduced in this section. At last, the cooling efficiency and system performance is analyzed in Section 4.3.

4.1 Problem Description

By the First Law of Thermodynamics [22], the total power consumption (i.e., electric energy) in a time interval is transferred to thermal energy, which is shown in the first term of (1). Because the power consumption depends linearly on the clock frequency [8], [12], we will reduce the thermal energy through frequency scaling (i.e., DFS is applied) in this paper. In this section, we will describe the problem formulation of frequency (i.e., throttled ratio) assignment in a 3D NoC system.

Because of the pessimistic consideration of the conventional reactive DTMs, the thermal-emergent node is usually shut down (i.e., power gating) for emergent cooling. To consider the switching power consumption, the policy of full throttling scheme can eliminate the generated thermal energy. Therefore, the (1) can be written as

\[
\frac{dT(t)}{dt} = -\frac{T(t)}{RC}. \tag{21}
\]

Obviously, the temperature will decrease because of the thermal conductance. To reduce the performance impact due to the fully throttling scheme, a partially throttling scheme (i.e., non-full throttling) is proposed in this paper.
With the Fourier’s Law in (1), in addition to the current temperature, the change of temperature depends on the current total power consumption of the node. As mentioned before, we adopt the DFS to perform the throttling scheme to control the current power consumption in this work.

In Fig. 4b, the temperature of node at \((x, y, z)\) is \(T_{x,y,z}\) and the corresponding power consumption is \(P_{x,y,z}\). For an X-by-Y-by-Z 3D NoC system, the entire temperature profile \(T(t)\) and the entire power profile \(P(t)\) of each node at time \(t\) can be represented as

\[
T(t) = \begin{bmatrix}
T_{1,1,k}(t) & \cdots & T_{X,1,k}(t) \\
\vdots & \ddots & \vdots \\
T_{1,Y,k}(t) & \cdots & T_{X,Y,k}(t)
\end{bmatrix}_k,
\]

and

\[
P(t) = \begin{bmatrix}
P_{1,1,k}(t) & \cdots & P_{X,1,k}(t) \\
\vdots & \ddots & \vdots \\
P_{1,Y,k}(t) & \cdots & P_{X,Y,k}(t)
\end{bmatrix}_k,
\]

where \(k\), which is from 1 to \(Z\), indicates a specific silicon layer of the 3D NoC. Note that the \(P(t)\) depends on the network activity, which relies on the adopted application. As mentioned in [3], the power consumption depends linearly on the clock frequency. Consequently, the (23) can be written as

\[
P(t) = \frac{P_{\text{max}}}{f_{\text{max}}} \begin{bmatrix}
\sum_{i=1}^{X} \sum_{j=1}^{Y} \sum_{k=1}^{Z} P_{i,j,k}(t)
\end{bmatrix},
\]

where the \(f_{\text{assign}}(t)\) is the assigned clock frequency for the node at \((x, y, z)\) at time \(t\). Besides, the \(P_{\text{max}}\) is the power consumption of each node of the 3D NoC system with the maximum clock frequency \(f_{\text{max}}\). According to (1), the entire temperature profile at \((t + \Delta t_s), T(t + \Delta t_s)\), depends on the total power consumption \(W\) from time \(t\) to time \(t + \Delta t_s\) (i.e., \(W = \int_{t}^{t+\Delta t_s} P(t)dt\)) and current temperature \(T(t)\). By the first law of thermodynamics, the \(W\) will transfer to the heat \(Q(\Delta t_s)\). Hence, the \(T(t + \Delta t_s)\) can be written as

\[
T(t + \Delta t_s) = T(t) + \frac{Q(\Delta t_s)}{C} - \frac{T(t)}{RC} = \frac{1}{RC} \int_{t}^{t+\Delta t_s} P(t)dt - \frac{1}{RC} \cdot T(t)
\]

\[
= \begin{bmatrix}
T_{1,1,k}(t) + \frac{1}{C} \int_{t}^{t+\Delta t_s} P_{\text{max}} f_{\text{assign}}(t) dt - T_{1,1,k}(t) \\
\vdots \\
T_{1,Y,k}(t) + \frac{1}{C} \int_{t}^{t+\Delta t_s} P_{\text{max}} f_{\text{assign}}(t) dt - T_{1,Y,k}(t) \\
\vdots \\
T_{X,1,k}(t) + \frac{1}{C} \int_{t}^{t+\Delta t_s} P_{\text{max}} f_{\text{assign}}(t) dt - T_{X,1,k}(t) \\
\vdots \\
T_{X,Y,k}(t) + \frac{1}{C} \int_{t}^{t+\Delta t_s} P_{\text{max}} f_{\text{assign}}(t) dt - T_{X,Y,k}(t)
\end{bmatrix}_k.
\]

We can observe that we can appropriately scale the frequency of each node to control the temperature. Hence, our goal is to find a feasible frequency assignment matrix \(F\) at time \(t\)

\[
\left(\text{i.e., } F(t) = \begin{bmatrix}
f_{\text{assign}}(t) & \cdots & f_{\text{assign}}(t) \\
\vdots & \ddots & \vdots \\
f_{\text{assign}}(t) & \cdots & f_{\text{assign}}(t)
\end{bmatrix}
\right)
\]

to maximize the system throughput under a certain thermal limit \(T_L\), which can be modeled as

\[
\exists \mathcal{F} : \max \left(\sum_{i=1}^{X} \sum_{j=1}^{Y} \sum_{k=1}^{Z} P_{i,j,k}(t)\right)
\]

In general, the problem cannot be solved in polynomial time. In [23], Murali et al. reduced the problem of frequency assignment to an approximated convex optimization problem by 2-phase iterative algorithm. Therefore, the problem of clock frequency assignment under a thermal constraint is an \(NP\)-hard problem, and it is difficult to find an optimal solution for a real-time system due to high computational complexity. In this work, we propose a method to assign the feasible clock frequency with low computational overhead, and it will be introduced later.

### 4.2 Clock Frequency Assignment Based on Power Budget Distribution

For an NoC operation period, we assume one node becomes thermal emergent at time \(t\), and it will become thermal safety after \((j\Delta t_s)\) (i.e., the time at \((t + j\Delta t_s)\)). Besides, we assume that the thermal emergency is predicted before \(k\Delta t_s\) (i.e., the time at \((t - j\Delta t_s)\)). As mentioned before, the total power consumption in a time interval affects the change of temperature. To derive the proposed method of frequency assignment, we first analyze the total power consumption in the time interval, which is from \((t - j\Delta t_s)\) to \((t + j\Delta t_s)\), based on the previous assumptions.

To perform the emergent cooling, the conventional reactive DTM (i.e., the prediction distance is zero) will fully throttle the thermal emergent nodes. As mentioned before, we consider the worst case to mitigate the system impact caused by the thermal problem and assume the throughput of the 3D NoC system is quasi-stationary. Therefore, each isolated node of the 3D NoC system usually operates at full speed in normal operation, which makes the total power consumption at each thermal sensing period is the same as \(P_{\text{max}}\). Because the node is fully throttled from the time \(t\) to the time \((t + j\Delta t_s)\), the total power consumption from the time \((t - k\Delta t_s)\) to time \((t + j\Delta t_s)\) is

\[
P[(t - k\Delta t_s), (t + j\Delta t_s)] = \int_{t-k\Delta t_s}^{t+j\Delta t_s} P(t)dt = P_{\text{max}} \cdot k\Delta t_s.
\]

Therefore, we can summarize the following Deduction:

**Deduction 1.** A particular node of the 3D NoC system will be thermal-emergent at time \(t\) and be thermal-safety at time \((t + j\Delta t_s)\). Besides, the situation of thermal emergency has been predicted at time \((t - k\Delta t_s)\). By following the First Law of Thermodynamics and (27), the node will be thermal safety, if the total power consumption from the time \((t - k\Delta t_s)\) to \((t + j\Delta t_s)\) is the same as the one from the time \((t - k\Delta t_s)\) to \(t\), when is in normal operation.

According to (27), the slack power budget is \(P_{\text{max}} \cdot k\Delta t_s\) (e.g., the node will be fully throttled, if the total power consumption from \((t - k\Delta t_s)\) to \(t\) exceeds \(P_{\text{max}} \cdot k\Delta t_s\).
as the thermal emergency at time $t$ is predicted before $k\Delta t_s$ (i.e., the time at $(t-k\Delta t_s)$). Based on the Deduction 1, to simplify the control mechanism of DFS, we evenly distribute the power budget between each thermal sensing period $\Delta t_s$ from time $(t-k\Delta t_s)$ to time $(t+j\Delta t_s)$ in this paper. Because the power consumption depends linearly on the clock frequency, the clock frequency of the node, which is predicted as a thermal-emergent node at time $(t-k\Delta t_s)$, can be reduced to $f_{\text{max}}/(k+j)$. As mentioned before, lower clock frequency leads to lower energy as delivering a packet. Hence, by observing (25), the temperature of the thermal-emergent node can be controlled. To reduce the performance impact caused by the DFS, we consider the ideal situation that the thermal-emergent node is thermal-safety at $(t+\Delta t_s)$ (i.e., the $j$ is equal to 1). Therefore, we can obtain the following Lemma:

**Lemma 1.** For a node of a 3D NoC system, the clock frequency is decreased by $\frac{1}{k+j}$ if the node is expected as a thermal-emergent node before $k\Delta t_s$, where $k$ is the prediction distance and $k \geq 0$.

Fig. 9 illustrates an example. For a specific node of the 3D NoC system, it will be thermal-emergent at time 2, as shown in Fig. 9a. As the conventional reactive throttle-based DTM is employed, the system will becomes thermal-safety at time 3, as shown in Fig. 9b.

Obviously, there is no power consumption in the time interval between time 2 and 3, and the total power consumption (i.e., power budget) from time 1 to 3 is $P_{\text{max}}$. On the other hand, if the time of thermal emergency can be predicted at time 1, the power budget can be distributed evenly between each time interval by employing the proposed method. Therefore, the power consumption in each time interval is $P_{\text{max}}/2$ from time 1 to 3, which makes the total power consumption from time 1 to 3 the same as $P_{\text{max}}$, as shown in Fig. 9c.

In the usual practical system, the levels of employed DFS are restricted. For a DFS scheme with $L$ frequency levels as $1 \leq L \leq (k+1)$, Fig. 10 shows the operation flow of the proposed T-PDTM scheme, which is operated by each distributive embedded PTMU. In the Thermal Prediction Phase, based on the information of sensing temperature, the future temperature is predicted by using the proposed RCTP model. In Thermal Management Phase, the throttled ratio is determined based on the predictive temperature and the current sensing temperature. The upper boundary level of the DFS, fully throttling scheme (i.e., the throttled ratio is 100 percent), will be triggered for the consideration of emergent cooling, if the current temperature exceeds the triggering temperature $T_{\text{limit}}$. On the other hand, if the predictive temperature exceeds the triggering temperature $T_{\text{limit}}$, the partially throttling scheme is performed to consider both thermal dissipation and performance maintenance. The lower boundary of the DFS level (i.e., the throttled ratio is $(100/L)\%$) is set, while the request throttled ratio from the PTMU is lower than the lower boundary level of the employed DFS. Because the throttled ratio is decided without any computational overhead, the proposed T-PDTM scheme has the benefit of short response time.

### 4.3 Experimental Results of the Proposed T-PDTM Scheme

In this section, we apply the proposed T-PDTM scheme to the state-of-the-art throttling schemes: (i) Global Throttling [6], (ii) Distributive Throttling [7], and (iii) Vertical Throttling [4]. We compare the system performance and the cooling efficiency of the 3D NoC system by using the three reactive throttling schemes and the proposed T-PDTM scheme with prediction distance $k$ (i.e., $GT_{\text{PD}}(k)$, $DT_{\text{PD}}(k)$, and $VT_{\text{PD}}(k)$). To simplify the problem, the XYZ routing is involved in this work. To prevent the packets from blocking in the fully throttled node, similar to the approach in [13], we restrict the injection of the undeliverable packets (i.e., the packets cannot be delivered to the destination and be stored in the local buffer of source node due to the fully throttled nodes in the routing path), which reduces the packet injection rate of the node. By this way, the deadlock and livelock can be avoided.

To keep the representation of performance indices and fair comparison, we consider the following two indices to measure the cooling efficiency and system performance by applying each DTM scheme:

- **Number of thermal-emergent node.** The thermal-emergent node represents that the temperature of this node exceeds the triggering temperature $T_{\text{limit}}$. This index measures the availability of a thermal-aware system.
- **System throughput.** The system throughput depends on the availability of the system. The definition of the system throughput is the total number of received flits per cycle.

To prevent the transient temperature of the 3D NoC system from exceeding the hard thermal limit (i.e., 100°C), Table 2 shows the triggering temperature of each reactive throttling scheme and the proposed T-PDTM with prediction distance $k_{PD}(k)$. Because the tolerated average prediction error is set as 0.2°C in this work, the $k$ is less than 5. Besides, we assume the employed DFS has two frequency levels.
levels (i.e., \( L = 2 \)) as a design example. For other applications, the designers can select the feasible numbers of frequency levels for the employed DFS scheme. Because the GT scheme has the best cooling efficiency, the triggering temperature can be higher than the other two throttling schemes. The triggering temperature is obtained under the saturation point as the entire system workload close to the maximal throughout (i.e., the Packet Injection Rate (PIR) is 0.025). Because of the early temperature control, the triggering temperature of the proposed T-PDTM schemes is higher than the reactive ones. For all the following experiments, if there is no special description, we set the PIR to 0.025.

### 4.3.1 Analysis of Performance Evaluation and Cooling Efficiency Using Synthetic Traffic Pattern

In this section, we first apply the proposed T-PDTM scheme to the VT scheme to demonstrate the benefit of the proposed T-PDTM scheme. Then, the similar results, as applying the T-PDTM to other throttling schemes, will be shown in the Tables 3 and 4. Figs. 11a and 11b show the maximum transient temperature of the system, which is resulted from Hotspot [21], from 0.4 second to 0.9 second when the VT, VT_PD(1), VT_PD(2), VT_PD(3), VT_PD(4), and VT_PD(5) under the random and transpose-1 traffic patterns, respectively. Because every node of NoC system sends packets to a fixed destination as applying transpose-1 traffic pattern, the traffic load is lower than the one by applying random traffic pattern. Hence, system temperature as applying transpose-1 traffic pattern is lower than the one as applying random traffic pattern. Obviously, all the VT and VT_PD(k) schemes can control the peak temperature under the hard thermal limit (i.e., 100°C). Because the pessimistic consideration of the reactive VT scheme, it should leave more design margins (i.e., lower triggering temperature) to perform emergent cooling. Therefore, the reactive VT scheme is easily triggered than the proposed T-PDTM scheme. Lower triggering temperature means more cooling time is required for temperature decreasing. As shown in Fig. 11, the proposed T-PDTM scheme applied to the VT can utilize the heat sink better because the peak transient temperature stays close to the hard thermal limit.

Fig. 12 shows the transient numbers of thermal-emergent nodes within 1 second as adopting (a) VT, (b) VT_PD(1), (c) VT_PD(2), (d) VT_PD(3), (e) VT_PD(4), and (f) VT_PD(5) under random traffic pattern. The number of thermal-emergent nodes affects the system availability, which can be measured through analyzing the latency of each packet delivery. In this experiment,

<table>
<thead>
<tr>
<th>TABLE 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Triggering Temperature of Each Throttling Scheme</strong></td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Reactive</td>
</tr>
<tr>
<td>PD(1)</td>
</tr>
<tr>
<td>PD(2)</td>
</tr>
<tr>
<td>PD(3)</td>
</tr>
<tr>
<td>PD(4)</td>
</tr>
<tr>
<td>PD(5)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Comparison of Each DTM under Random Traffic</strong></td>
</tr>
<tr>
<td>( \text{# TEN} )</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Throughput</td>
</tr>
<tr>
<td>DT [7]</td>
</tr>
<tr>
<td>( \text{# TEN} )</td>
</tr>
<tr>
<td>Throughput</td>
</tr>
<tr>
<td>VT [4]</td>
</tr>
<tr>
<td>( \text{# TEN} )</td>
</tr>
<tr>
<td>Throughput</td>
</tr>
</tbody>
</table>

* \( \text{# TEN} \): Numbers of thermal-emergent node, Throughput: (flits/cycle)
Fig. 13. The numbers of thermal-emergent nodes within 1 second as adopting (a) VT, (b) VT_PD(1), (c) VT_PD(2), (d) VT_PD(3), (e) VT_PD(4), and (f) VT_PD(5) under transpose-1 traffic pattern.

Fig. 14. Latency distribution of each packet during the simulation time (i.e., 1 second) under the random traffic pattern and transpose-1 traffic pattern when the VT, VT_PD(1), VT_PD(2), VT_PD(3), VT_PD(4), and VT_PD(5) are applied. Obviously, the most of packets in the network belong to Pkt_{HL} as adopting reactive VT scheme. The reason is that the non-routable packets (i.e., the packet cannot be delivered to the destination due to the fully throttled nodes) will be blocked in the the local node until there is no fully throttled node on the routing path. As applying the proposed T-PDTM scheme, it can help to reduce 5.0~19.2 percent Pkt_{HL} and increase the numbers of Pkt_{LL} and Pkt_{ML}.

Tables 3 and 4 show the detail comparison of system performance and the total numbers of thermal-emergent node between the reactive DTM and the proposed T-PDTM scheme with different prediction distances under random traffic and transpose-1 traffic patterns during the simulation time (i.e., 1 second), respectively. The throughput improvement as applying the T-PDTM to the GT is almost identical because the control granularity of GT is whole network system. Therefore, the entire system will be fully throttled or partially throttled as the T-PDTM is triggered, which results in larger performance impact and reduces the benefits of early temperature control. For different applications, the designers can select the feasible prediction distance based on the constraints of prediction error and system throughput. Compared with the conventional reactive DTM scheme, in this case, the proposed T-PDTM scheme can improve the system performance by around 10.1~83.9 percent due to less thermal-emergent nodes.

Fig. 15. The representation of a (10, 5) LDPC code in (a) H matrix, (b) Bipartite graph.

4.4 Case Study of Real-Traffic Data

To evaluate the proposed T-PDTM scheme in the real applications, we first refer to the Low-Density Parity-Check (LDPC) codes. In general, the LDPC decoding algorithm can be represents as a parity H matrix or a bipartite graph, as shown in Fig. 15. To increase the efficiency of the hardware implementation, an NoC-based LDPC was proposed to realize the flexible LDPC decoder because of the characteristics of regularity and scalability [26], [27].

Similar to the method in [26] and [27], we evaluate the proposed T-PDTM scheme with the data flow of the (1944, 972) LDPC codes, which is defined in IEEE 802.11n [24], and the (960, 480) LDPC codes, which is defined in IEEE 802.16e [25]. To simplify the problem, the mapping of BNUs and CNUs onto PEs is done by:

\[
\text{Mapped Node Number} = (\text{The BNU(or CNU) number}) \mod (\text{The total number of NoC nodes}).
\]  

Table 5 shows an example of mapping results, which map a (10, 5) LDPC code of Fig. 15 on a 3×3 NoC platform. Because the (column, row) of the pairs of \((B_0, C_0)\) in the H matrix is (9, 1), and there are nine nodes in this NoC platform, the node number of mapping destination is \((N_{in}, N_0)\) by following (28). With the similar method, the (10, 5) LDPC code can be fully mapped to a 3×3 NoC platform. The comparison of system throughput in a real data flow of LDPC between the proposed T-PDTM scheme and previous related works [4], [6], [7] are shown in Tables 6 and 7. Compared with the previous works, the proposed T-PDTM scheme can reduce 11.4~47.1 percent thermal-emergent nodes, which help to improve the system performance by around 1.6~118.6 percent.

![Fig. 14. Latency distribution as adopting VT, VT_PD(1), VT_PD(2), VT_PD(3), VT_PD(4), and VT_PD(5) under (a) random traffic pattern and (b) transpose 1 traffic pattern, respectively.](image-url)
In addition to LDPC code, we refer to the FFT benchmark in SPLASH-2 [28] and CANNEAL benchmark in SPAREC [31] to evaluate the proposed T-PDTM scheme. By following the proposed mapping algorithm in [29], the 64 k-point FFT of SPLASH-2 can be mapped to our 8/C2 8/C2 4 3D NoC platform. Table 8 shows the comparison between the previous works and the proposed T-PDTM scheme. Compared with the previous works, the proposed T-PDTM scheme can improve the system performance by around 6.6/C2 4 21.8 percent due to less thermal-emergent nodes. On the other hand, compared with the previous works, Table 9 shows that the proposed T-PDTM scheme can reduce 29.2/C2 75.2 percent thermal-emergent nodes and improve the system performance by around 1.5/C2 22.3 percent as applying the CANNEAL benchmark.

**TABLE 5**
The Mapping Results of a (10, 5) LDPC Code in Fig. 15 for a 3 × 3 NoC

<table>
<thead>
<tr>
<th>Node</th>
<th>Mapping Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>N0</td>
<td>B0, B9, C0</td>
</tr>
<tr>
<td>N1</td>
<td>B1, C1</td>
</tr>
<tr>
<td>N2</td>
<td>B2, C2</td>
</tr>
</tbody>
</table>

**TABLE 6**
Comparison of Each DTM under (1944, 972) LDPC Code in 802.11n Standard [23]

<table>
<thead>
<tr>
<th>T-PDTM</th>
<th>GT(0)</th>
<th>GT_PDI(0)</th>
<th>GT_PDI(2)</th>
<th>GT_PDI(4)</th>
<th>GT_PDI(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT(4)</td>
<td>+4.05%</td>
<td>-11.75%</td>
<td>-7.05%</td>
<td>+1.35%</td>
<td>+3.05%</td>
</tr>
</tbody>
</table>

**TABLE 7**
Comparison of Each DTM under (960, 480) LDPC Code in 802.16e Standard [24]

<table>
<thead>
<tr>
<th>T-PDTM</th>
<th>GT(0)</th>
<th>GT_PDI(0)</th>
<th>GT_PDI(2)</th>
<th>GT_PDI(4)</th>
<th>GT_PDI(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT(4)</td>
<td>+4.05%</td>
<td>-11.75%</td>
<td>-7.05%</td>
<td>+1.35%</td>
<td>+3.05%</td>
</tr>
</tbody>
</table>

**TABLE 8**
Comparison of Each DTM as Applying to SPLASH-2 Benchmark of FFT

<table>
<thead>
<tr>
<th>T-PDTM</th>
<th>GT(0)</th>
<th>GT_PDI(0)</th>
<th>GT_PDI(2)</th>
<th>GT_PDI(4)</th>
<th>GT_PDI(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT(4)</td>
<td>+4.05%</td>
<td>-11.75%</td>
<td>-7.05%</td>
<td>+1.35%</td>
<td>+3.05%</td>
</tr>
</tbody>
</table>

**TABLE 9**
Comparison of Each DTM as Applying to SPAREC Benchmark of CANNEAL

<table>
<thead>
<tr>
<th>T-PDTM</th>
<th>GT(0)</th>
<th>GT_PDI(0)</th>
<th>GT_PDI(2)</th>
<th>GT_PDI(4)</th>
<th>GT_PDI(6)</th>
</tr>
</thead>
<tbody>
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<td>+4.05%</td>
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<td>-7.05%</td>
<td>+1.35%</td>
<td>+3.05%</td>
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</tbody>
</table>

In addition to LDPC code, we refer to the FFT benchmark in SPLASH-2 [28] and CANNEAL benchmark in SPAREC [31] to evaluate the proposed T-PDTM scheme. By following the proposed mapping algorithm in [29], the 64 k-points FFT of SPLASH-2 can be mapped to our 8 × 8 × 4 3D NoC platform. Table 8 shows the comparison between the previous works and the proposed T-PDTM scheme. Compared with the previous works, the proposed T-PDTM scheme can improve the system performance by around 6.6–21.8 percent due to less thermal-emergent nodes. On the other hand, compared with the previous works, Table 9 shows that the proposed T-PDTM scheme can reduce 29.2–75.2 percent thermal-emergent nodes and improve the system performance by around 1.5–22.3 percent as applying the CANNEAL benchmark.

5 Conclusions

For a thermal-aware 3D NoC system, the traditional reactive throttle-based DTMs usually use fully throttling scheme for emergent cooling, which leads to significant performance impact. In this paper, we proposed a T-PDTM scheme to regulate the temperature of a 3D NoC system. Based on the proposed RCTP model, the T-PDTM can predict the future temperature and early control the thermal-emergent node through partially throttling scheme. Compared with the conventional reactive DTMs, the proposed T-PDTM can help to reduce 11.4–80.3 percent thermal-emergent nodes and improves the system performance by around 1.5–21.8 percent.

Acknowledgments

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References

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