Energy Efficient, Real-time and Reliable Task Deployment on NoC-based Multicores with DVFS

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Abstract—Task deployment plays an important role in the overall system performance, especially for complex architectures, including several cores with Dynamic Voltage and Frequency Scaling (DVFS) and Network-on-Chips (NoC). Task deployment affects not only the energy consumption but also the real-time response and reliability of the system. In this work, a task deployment approach is proposed to optimize the overall system energy consumption, including computation of the cores and communication of the NoC, under task reliability and real-time constraints. More precisely, the task deployment approach combines task allocation and scheduling, frequency assignment, task duplication, and multi-path data routing. The task deployment problem is formulated using mixed-integer non-linear programming. To find the optimal solution, the original problem is equivalently transformed to mixed-integer linear programming, and solved by state-of-the-art solvers. Furthermore, a decomposition-based heuristic, with low computational complexity, is proposed to deal with scalability. Finally, extended simulations evaluate the proposed methods.

I. INTRODUCTION

Multicore architectures integrate multiple processors on a single chip, leading to platforms with low supply frequency, high data throughput and better energy efficiency [1]. With the development of nanoscale technologies, various processors communicate via the Network-on-Chips (NoC), instead of traditional, non-scalable, data buses [2]. The NoC uses its underlying micro-network components, i.e., routers, for the communication among the processors. The routers are usually connected by a mesh network, one of the most effective NoC topologies, due to its regularity, high bandwidth and short interconnections [3].

The inter-processor communication cost (time and energy) over NoC is not negligible compared to the cost of computation, occurring at the processors [4]. Furthermore, the communication cost depends on both task mapping and routing path decision. When dependent tasks are allocated and executed on different processors, data must be transmitted. Furthermore, multiple routing paths for the data transmission can exist in NoC, such as in the mesh network [2]. To improve the overall system performance, it is necessary to consider inter-processor communication, task mapping and routing path selection as an integral task deployment process.

Meanwhile, critical applications have the real-time and reliability constraints [5], whereas system energy consumption is essential. Although energy efficiency, real-time and reliable task execution are both important design objectives, they are usually conflicting. Enhancing real-time execution and reliability often requires more energy consumption. Dynamic Voltage and Frequency Scaling (DVFS) [6] has been introduced into modern multicore platforms to improve the energy efficiency, as it adjusts the time and the energy required to execute the tasks. However, DVFS has a negative impact on task execution and reliability. Lower frequencies lead to longer execution times and increased transient fault rates [7]. To increase the reliability, task duplication is applied [8]. However, task duplication has a significant impact both on energy and time; more tasks are executed, thus, more energy and time is required for the task computation and their communication over the NoC. Therefore, task duplication and frequency assignment should be also considered during the deployment process [9].

The task deployment problem has already been studied in embedded systems. Table I categorizes representative papers from the literature, performing task allocation (All.), scheduling (Sch.) and duplication (Dup.) on multicores with DVFS (VF.), considering multi-path routing (MP.), task reliability (Reli.) and communication cost (Com.). The solutions are given by optimal (Opt.) and heuristic (Heur.) algorithms. Several approaches exist to map dependent/independent tasks on the multi-core/single-core embedded platforms under multiple constraints, such as energy, real-time, and reliability [6], [8], [10], [11]. These works consider processors typically connected with a high-speed data bus. Thus, the communication cost between any two processors is usually ignored, as it’s much smaller compared to task execution cost. However, for the platforms based on NoC, the communication cost becomes important. To reduce the communication cost on NoC-based platforms, the common methods include mapping tasks to processors [4], [12] and adjusting the operating voltage of the routers [3], [13]. However, task reliability is not taken into account, especially when DVFS is available. Existing approaches, to enhance NoC reliability,
include spare processors \([2]\) and task duplication \([5], [14]\). However, no DVFS is considered \([5], [14]\). Compared with the state-of-the-art, we propose a novel task deployment process that includes simultaneous optimization of task allocation and scheduling, frequency assignment, task duplication and path selection, in order to balance the energy consumption of NoC-based multicore platforms, while meeting the system requirements regarding real-time execution and reliability. The main contributions of this work are:

1) An MINLP formulation for energy efficient task deployment problem on NoC-based multicore. The original problem is equivalently converted to an MILP problem, by adding auxiliary variables and constraints, to be optimally solved.

2) A decomposition-based heuristic to solve the above problem, which divides the original problem into three subproblems, having a simpler structure with less constraints and variables.

3) Extensive experimental results to demonstrate the advantages of the proposed approach, and evaluate the impact of parameters on task deployment. Compared with the optimal method, the proposed heuristic has negligible computation time, with an average cost of 26.5% in energy savings.

Next, Section II introduces the system model and the problem formulation. Section III designs the heuristic method. Section IV presents the evaluation and Section V the conclusion.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

1) Task Set: The task set consists of \(M\) periodic tasks \(\{\tau_1, \ldots, \tau_M\}\), released at time 0, sharing a common scheduling horizon \(H\). Each task \(\tau_i\) is described by a tuple \(\{C_i, D_i, p_{ij}, s_{ij}\}\), where \(C_i\) is the Worst Case Execution Cycle (WCET), \(D_i\) is the relative deadline, and \(p_{ij}\) is the \((i, j)^{th}\) element of task dependency matrix \(p = [p_{ij}]_{M \times M}\). If tasks \(\tau_i\) and \(\tau_j\) are dependent, and \(\tau_i\) is a predecessor of \(\tau_j\), \(p_{ij} = 1\), else, \(p_{ij} = 0\). When \(\tau_i\) finishes, it will generate a set of data with sizes \(s_{ij}\) for its successor \(\tau_j\) (\(p_{ij} = 1\)).

2) Platform: The target platform consists of \(N\) processors \(\{\theta_1, \ldots, \theta_N\}\) and \(N\) routers (R), connected through a 2D-mesh network, as a \(2 \times 2\) example shown in Fig. 1(a). Each router communicate with the neighbor routers through a pair of links. Data can be transmitted through multiple paths.

The processors support DVFS and have the same Instruction Set Architecture (ISA). A processor has \(L\) different Voltage/Frequency (V/F) levels \(\{(v_1, f_1), \ldots, (v_L, f_L)\}\). A typical power model \([13]\) is considered: the processor power with \((v_1, f_1)\) is \(P_1 = P_{st} + P_{st}^d\). The static power is \(P_{st} = L_g(v_1 K_1 e^{K_2 v_1} e^{K_3 v_1} + |v_1| I_0)\). The dynamic power is \(P_{st}^d = C_e v_1^2 f_1\). \(L_g\) is the average switched capacitance. \(I_0\) is the number of logic gates. \(K_1, K_2\) and \(K_3\) are parameters depending on the processor type. \(v_1\) and \(I_0\) are the body-bias voltage and body junction leakage current. The computation energy of task \(\tau_i\) is \(e_{comp}^{\tau_i} = P_{st}^d t_{comp}^{\tau_i}\), where \(t_{comp}^{\tau_i}\) its computation time.

The NoC topology is described by a directed graph \(G(V, E)\), where the vertexes represent each processor \(\theta_k \in V\), while the edge \(e_{ij} \in E\) represents a direct communication link between the routers of processors \(\theta_i\) and \(\theta_j\). Based on the NoC communication model and the Manhattan distance between

the source and destination processors, a positive weight \(w_{ij}\) is associated with the edge \(e_{ij}\). The goal of the task deployment is energy reduction under real-time constraints, we consider both energy-oriented and time-oriented paths as available options to transmit data, as shown in Fig. 1(b). Note that, the path with minimal energy can be different from the path with minimal latency \([4]\). Our approach explores these different paths.

For the energy (time)-oriented path, the weight \(w_{ij}\) represents the energy (time) required for transmitting and receiving a unit of data between processors \(\theta_i\) and \(\theta_j\). Hence, the aim of energy (time)-oriented routing is to find the shortest path, e.g., according to Dijkstra’s algorithm. Based on the graph \(G(V, E)\), we obtain an energy matrix \(e = [e_{ij}]_{N \times N \times P}\) and a time matrix \(t = [t_{ij}]_{N \times N \times P}\), where \(e_{ij}\) represents the energy consumed at processor \(\theta_i\), if a unit of data is routed from \(\theta_j\) to \(\theta_i\) through the \(\rho\)th path, while \(t_{ij}\) denotes the time required to transmit a unit of data from \(\theta_j\) to \(\theta_i\) through the \(\rho\)th path.

When two dependent tasks are mapped on the same processor, the communication cost (time and energy) is zero \([12]\). The communication energy of a router, including the communications between this router and its neighbor routers and associated processor, is incorporated into the energy consumption of the processor for convenience.

3) Reliability: This work focuses on transient faults and adopts the Poisson fault probability model \([8]\). If a processor uses \((v_1, f_1)\) to execute the task \(\tau_i\) with \(C_i\) cycles, the task reliability is \(R_{il} = e^{-\lambda \times d_{max} \times (f_{max} - f_i)} \times C_i\), where \(\lambda\) is the maximum failure, \(d\) is a constant that indicates the sensitivity of the failure rate corresponding to frequency scaling, \(f_{max} = \max\{f_1\}\) and \(f_{min} = \min\{f_1\}\). When the reliability of task \(\tau_i\) is lower than its threshold \(R_{il}\), to enhance the task reliability, task \(\tau_j\) is duplicated (see \((4)\) and \((5)\)), considering that it is unlikely to have faults occurring concurrently in both copies \([7]\).

Note that the task duplication affects the task model, and thus, the computation and communication cost. For instance, tasks \(\tau_1, \tau_2\) and \(\tau_3\) are the original tasks, and tasks \(\tau_4, \tau_5\) and \(\tau_6\) are their copies in Fig. 1(c). By task duplication, the task dependencies change, e.g., due to the dependency of \(\tau_1\) and \(\tau_2\), \(\tau_4\) and \(\tau_5\) become dependent and \(\tau_1\) generates data to \(\tau_2\).

B. Problem Formulation

The goal is to deploy tasks to balance the energy consumption of the overall system under real-time and reliability constraints. To achieve that, the following decisions are taken: 1) task frequency assignment, 2) task duplication, 3) path selection, 4) task allocation and 5) task scheduling. To formulate the task deployment problem, we introduce the following variables: 1) binary variable \(y_{il}\) if task \(\tau_i\) is executed with frequency
Let $t_i^s$ and $t_i^e$ denote the start time and the end time of task $\tau_i$, respectively, where $0 \leq t_i^s \leq t_i^e \leq H$. The task execution time $t_i^{\text{comp}} = t_i^e - t_i^s = \sum_j yil_i c_{ij}$. For the dependent tasks $\tau_i$ and $\tau_j$, their start time and end time are bounded by

$$t_j^s + (1 - p_{ij})H \geq t_i^s + p_{ij}c_{ij} + t_{ij}^{\text{comm}}, \forall i \neq j \in \mathcal{M}. \ (6)$$

If $p_{ij} = 1$, $\tau_i$ precedes $\tau_j$ and $\tau_j$ is the closest task of $\tau_i$, we get $t_i^s \geq t_j^s + t_{ij}^{\text{comp}}$, else, (6) is always satisfied.

6) Task Non-Overlapping Constraint: When independent tasks $\tau_i$ and $\tau_j$ (i.e., $p_{ij} = 0$), are allocated to the same processor, their execution sequence must be determined, since the processor executes only one task at a time instance:

$$t_i^s \leq t_j^s + (2 - x_{ik} - x_{jk})H + (1 - u_{ij})H, \forall i \neq j \in \mathcal{M}', \forall k \in \mathcal{N}. \ (7)$$

If $\tau_i$ and $\tau_j$ are assigned to the same processor (e.g., $x_{ik} = x_{jk} = 1$), (7) is meaningful, else, (7) is always true. With $x_{ik} = x_{jk} = 1$, if $u_{ij} = 1$ (i.e., $\tau_i$ precedes $\tau_j$), we have $t_i^s \leq t_j^s$ else (i.e., $u_{ij} = 0$), (7) is always satisfied.

7) Real-Time Constraints: Since task $\tau_i$ should be finished within the scheduling horizon $H$ and its execution time should be smaller than the relative deadline $D_i$, we have

$$t_i^e \leq D_i, \forall i \in \mathcal{M}', \ (8)$$

$$t_i^e \leq H, \forall i \in \mathcal{M}'. \ (9)$$

8) Objective Function: Regarding the communication energy, if dependent tasks $\tau_i$ and $\tau_j$ are allocated to different processors, e.g., $\theta_i$ and $\theta_j$, the energy consumed on processor $\theta_k$ to transmit task data, with size $s_{ij}$ from $\theta_i$ to $\theta_j$, through the $\rho^{th}$ path, is $c_{ij}^{\text{comm}}$. On this basis, taking task duplication $h_i$ into account, the communication energy consumed by processor $\theta_k$ is $E_k^{\text{comm}} = \sum_i \sum_j \gamma_i \sum_{\rho} h_i c_{ij}^{\text{comm}}$. Considering the computation energy, to execute task $\tau_i$ with $\rho(x, y, f_1)$, the required energy is $c_i^{\text{comp}} = h_i \sum yil_i p_{il}$. Taking task allocation $x_{ik}$ into account, the computational energy consumed by processor $\theta_k$ is $E_k^{\text{comp}} = \sum c_{ik}$. To balance the energy consumption of the processors [15], the task deployment problem is formulated as follows:

$$\begin{align*}
\mathbf{P1:} \quad & \min_{x, y, h_i, c_{ij}, u_{ij}} \left( \max_{k} \left( E_k^{\text{comp}} + E_k^{\text{comm}} \right) \right) \\
\text{s.t.} \quad & (1)-(8).
\end{align*}$$

9) Problem Linearization: Since the nonlinear items $h_i y_{il}$, $x_{ik} h_i y_{il}$ and $h_i x_{ik} x_{ij} x_{jk}$ are included in the constraints (5)–(8), problem (10) is a MINLP, which is difficult to solve directly. To simplify the structure of the problem, we propose a linearization method to deal with nonlinear items.

Lemma 2.2: Assume that $x$, $y$ and $z$ are the binary variables. The nonlinear items $z = x y$ can be replaced by the following constraints: $z \leq x \leq 0$, $z \leq y \leq 0$ and $x + y - z \leq 1$.

The objective function with the constraints completes the MILP formulation, which can be optimally solved by the existing methods, such as branch-and-bound or Gurobi solver. However, significantly large amount of CPU time and resources is required for the optimal solution, especially with large problem sizes. This limitation reduces the applicability of complex, but more realistic, task deployments approaches in real systems.
Algorithm 1 Frequency Assignment and Task Duplication

1: Input: \((u, f_i)\) (\(\forall i \in L\), \(C_i\), \(D_i\) (\(\forall i \in M\))
2: Output: \(y_{il}\) and \(h_i\)
3: Initialize: \(S[i] = -1\) (\(\forall i \in M\)), \(h_i = 1\), \(h_{i+M} = -1\) (\(\forall i \in M\))
4: for \(\forall i \in M\) do
5: \(eMin\text{MaxComp} = \infty\)
6: for \(\forall f \in L\) do
7: if \(\frac{E_{\text{MaxComp}}}{D_i} > D_i\) then
8: Continue;
9: else
10: \(eMaxComp = \max\{\frac{E_{\text{MaxComp}}}{D_i}, P_{S[i]}\}\) (\(S[i] \neq -1\));
11: if \(eMaxComp < eMin\text{MaxComp}\) then
12: \(eMin\text{MaxComp} = eMaxComp\);
13: \(S[i] = l\);
14: else
15: Continue;
16: end if
17: end if
18: end for
19: Calculate \(y_{il}\) according to \(S[i] = l\);
20: Calculate \(h_{i+M}\) according to (4);
21: Calculate \(y_{i(M+1)}\) according to (5);
22: end for

Algorithm 2 Task Allocation and Scheduling

1: Input: \(u_{il}\) and \(h_i\)
2: Output: \(x_{ik}, u_{ij}\) and \(t_i^k\)
3: Initialize: \(O[i] = -1\) (\(\forall i \in M\))
4: Sort tasks according to their in-degree and out-degree:
5: for \(\forall i \in M\) do
6: \(\text{MinMaxEng} = \infty\)
7: for \(\forall v \in N^\prime\) do
8: Calculate \(E^\text{comm}_{k}^v\) and \(E^\text{comp}_{k}^v\);
9: \(\text{MaxEng} = \max\{E^\text{comm}_{k}^v + E^\text{comp}_{k}^v\}\)
10: if \(\text{MaxEng} < \text{MinMaxEng}\) then
11: \(\text{MinMaxEng} = \text{MaxEng}\)
12: \(O[i] = k\);
13: else
14: Continue;
15: end if
16: end for
17: Calculate \(x_{ik}\) according to \(O[i] = k\);
18: Calculate \(u_{ij}\) and \(t_i^k\) according to \(x_{ik}\), \(t_i^m\) and \(t_i^c\);
19: end for

III. HEURISTIC ALGORITHM

Therefore, to improve the scalability of the proposed task deployment approach, we propose a novel heuristic to efficiently solve problem (10), which contains the following three phases.

1) Frequency Assignment and Task Duplication: The processors have the same ISA and V/F levels. Therefore, if a frequency is assigned to each task, and then, the tasks are allocated to the processors or different paths are selected for transmission, the decision regarding the frequency assignment is still valid. In addition, as task duplication \(h_i\) is determined by frequency assignment \(y_{il}\), according to (4), \(y_{il}\) and \(h_i\) should be still jointly optimized. Since \(y_{il}\) and \(h_i\) mainly influence the time \(t_i^\text{comp}\) and the energy \(e_i^\text{comp}\) of task computation, to balance the computation energy, the frequency assignment and task duplication problem is formulated as:

\[
P_2: \min_{y_{il}, h_i} \max_{\forall i} \{e_i^\text{comp}\} \tag{11}
\]

\[
\text{s.t. (3), (4), (5), (8)}.
\]

Minimizing the maximum energy consumption of each task execution helps to balance the energy consumption of the processors during task allocation occurring in phase 2. Since task allocation \(x_{ik}\) and path selection \(c_{\beta\gamma\rho}\) are currently unknown, the communication cost (time and energy) is not considered in (11). Note that P2 is an INLP problem, as the binary variables \(y_{il}\) and \(h_i\) are coupled nonlinearly in (5) and (8). To solve this problem, a heuristic is proposed (described in Algorithm 1) based on the Greedy Algorithm (GA) [16]. The steps are:

a. An index \(S[i]\) is introduced for frequency assignment per task \(\tau_i\) (\(\forall i \in M\)), and it is initialized as \(S[i] = -1\) (Line 3).

b. If \(\{u, f_i\}\) is used to execute task \(\tau_i\), then \(S[i] = l\).

c. Algorithm 1 follows the sequence \(\{\tau_1, \ldots, \tau_M\}\) to iteratively assign the frequencies \(\{f_1, \ldots, f_L\}\) for each task \(\tau_i\), with the aim to minimize the increase of energy consumption among the tasks that have already been assigned a frequency, i.e., \(\min\{\max_{\forall i} \{e_i^\text{comp}\}\}\) (Line 10). If the real-time constraint (8) cannot be satisfied, the frequency assignment \(y_{il}\) is excluded (Line 7).

d. When the frequency assignment \(y_{il}\) regarding the original task \(\tau_i\) is known, the existence of the duplicated task \(h_{i+M}\)

\[\text{can be computed through (4). A similar method is used to assign a frequency to the duplicated tasks. The main difference is that, when assigning frequency to the duplicated tasks, the selected frequency should satisfy the reliability constraint (5) while providing the minimum energy increase.}

2) Task Allocation and Scheduling: With the frequency assignment \(y_{il}\) and task duplication \(h_i\), the computation time and energy of task \(\tau_i\) are \(t_i^\text{comp} = h_i \sum_j y_{il} C_{ij}\) and \(e_i^\text{comp} = h_i \sum_j y_{il} P_{ij}\), respectively. The next step is to determine the task allocation \(x_{ik}\), task sequence \(u_{ij}\), and task start time \(t_i^k\).

To balance the energy consumption of the processors under the task sequence and the task non-overlapping constraints, the task allocation and scheduling problem is given by:

\[
P_3: \min_{x, u, t_i^k} \{\max_{v, k} \{E^\text{comm}_{k}^v + E^\text{comp}_{k}^v\}\} \tag{12}
\]

\[\text{s.t. (1), (6), (7).}\]

Note that the communication energy \(E^\text{comm}_{k}^v\) and communication time \(t_i^\text{comm}\) are influenced by the path selection \(c_{\beta\gamma\rho}\). However, \(c_{\beta\gamma\rho}\) is unknown at the current step. To formulate the problem (12), we fix the values of \(E^\text{comm}_{k}^v\) and \(t_i^\text{comm}\) to the average communication time of task \(\tau_i\) and average communication energy of processor \(\theta_k\), respectively, i.e., \(t_i^\text{comm} = M_1 (\max_{c_{\beta\gamma\rho}} \{c_{\beta\gamma\rho}\} + \min_{c_{\beta\gamma\rho}} \{c_{\beta\gamma\rho}\})/2\) and \(E^\text{comm}_{k} = M_2 (\max_{\forall j, k} \{e_{j\beta\gamma\rho k}\} + \min_{\forall j, k} \{e_{j\beta\gamma\rho k}\})/2\). \(M_1\) is the number of predecessors of \(\tau_i\), while \(M_2\) is the number of original and duplicated tasks. Once the path selection \(c_{\beta\gamma\rho}\) is determined, the value of \(t_i^\text{comm}\) and \(E^\text{comm}_{k}^v\) is updated accordingly. Based on the structure of MINLP problem (12), we design Algorithm 2:

a. A task allocation index \(O[i]\) is introduced for each task \(\tau_i\) (\(h_i = 1\)) and it is initialized as \(O[i] = -1\). If task \(\tau_i\) is allocated to processor \(\theta_k\), we have \(O[i] = k\).

b. The in- and out-degrees of all tasks are calculated and the tasks are divided into layers. For instance, in Fig. 1(c), tasks \(\{\tau_1, \tau_1\}, \{\tau_2, \tau_5\}\) and \(\{\tau_2, \tau_6\}\) are assigned to the first (L1), the second (L2) and the third (L3) layers, respectively. Tasks in the same layer are sorted in a descending order based on their execution cycles. If the tasks in same layer have same execution cycles, they are ordered randomly.

c. Algorithm 2 follows the sequence provided in the previous step to perform task allocation. With this sequence,
Algorithm 3 Path selection

1: Input: $y_1, b_k, x_{ik}, y_{ik}$ and $t_i^c$;
2: Output: $c_{\beta\gamma \rho}$ and $t_i^c$;
3: Initialize: $Q[\beta][\gamma] = -1$ ($\forall \beta, \gamma \in N$);
4: for $\forall (\beta, \gamma) \in N$ do
5: \hspace{1cm} $\text{MinMaxCost} = \infty$;
6: \hspace{1cm} for $\forall \beta \in P$ do
7: \hspace{2cm} $Q[\beta][\gamma] = \beta$;
8: \hspace{2cm} Calculate $t_i^c, t_i^{comm}$ and $t_i^e$ ($x_{i\gamma} = 1$);
9: \hspace{2cm} $tMax = \max_{\forall i} (t_i^e)$;
10: \hspace{2cm} if $tMax > H$ then
11: \hspace{3cm} Continue;
12: \hspace{2cm} else
13: \hspace{3cm} Calculate $E_{k}^{comm}$;
14: \hspace{3cm} $\text{MinMaxCost} = \max_{\forall i} (E_{k}^{comm} + E_{k}^{comp})$;
15: \hspace{2cm} if $\text{MinMaxCost} < \text{MinMaxCost}$ then
16: \hspace{3cm} $\text{MinMaxCost} = \text{MaxCost};$
17: \hspace{2cm} $\text{flag} = \rho$;
18: \hspace{2cm} else
19: \hspace{3cm} Continue;
20: \hspace{1cm} end if
21: \hspace{1cm} end if
22: \hspace{1cm} end for
23: $Q[\beta][\gamma] = \text{flag}$;
24: end for

where $C$ is the set of tasks belonging to the critical path. $t_i^{ave} = \frac{\max_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho}) + \min_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho})}{2}$ and $t_i^{comm} = M_1 (\max_{\forall \beta, \gamma, \rho} (t_\gamma^p)) + \min_{\forall \beta, \gamma, \rho} (t_\gamma^p))$ are the average computation time and communication time of task $\tau_i$, respectively.

Fig. 2(a) shows that with small $\alpha$, e.g., $\alpha = 0.1$ or $\alpha = 0.2$, the problem is infeasible, since the constraints are hard to satisfy. The problem feasibility increases with $\alpha$; the larger the value of $\alpha$, the smaller the energy consumption. This is because the feasibility region of the problem enlarges with $\alpha$, and the task deployment is a minimization problem. Fig. 2(a) also shows that under the same value of $\alpha$, multi-path routing has a higher problem feasibility than single-path routing. Multi-path routing achieves a lower energy consumption because the path selection $c_{\beta\gamma \rho}$ is considered in the optimization. Thus, it can find a better path selection, further improving the energy efficiency, compared with single-path routing.

Fig. 2(b) shows the influence of processor parameters on task allocation decision $x_{ik}$. We introduce $M_{\max} = \max_{\forall k} (M_k)$, where $M_k$ is the number of tasks allocated to processor $\theta_k$, and $\mu = \frac{e_{\text{comp}}}{e_{\text{e}}}$. When $\mu$ increases with $\mu$; when tasks have a large communication energy, the dependent tasks are allocated to the same processor to reduce the cost.

Fig. 2(c) explores the influence of processor parameters on task duplication decision $x_{ik}$, where $M_k$ represents the number of duplicated tasks for $M_k$ original tasks, and $\epsilon = \frac{\max_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho}) + \min_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho})}{2}$ is an index that represents the gap regarding task execution energy. Note that $t_i^{\text{comm}} = \sum_{\forall \beta \in P} (\sum_{\forall \rho} C_{\beta\gamma \rho})$ is the energy required to execute task $\tau_i$. The larger the value of $\epsilon$, the more the energy is consumed because of task execution with high frequency, compared to task execution with low frequency. Fig. 2(c) shows that $M_{\max}$ increases with $\epsilon$. When $\epsilon$ is small, the execution of one task (original task) with high frequency is more energy efficient than executing two tasks (original and duplicated tasks) with low frequency. With $\epsilon$ increasing, executing two tasks with low frequency becomes more efficient than executing one task with high frequency.

Fig. 2(d) and Fig. 2(e) compare the energy consumption of the proposed task deployment scheme, with the goal of Balancing the Energy consumption (BE), and the task deployment scheme with the goal of Minimizing the Energy consumption (ME), i.e., $\min_{\forall \beta \in P} E_{\text{all}k}^{\text{comm}} + E_{\text{comp}}^{\text{comp}}$ is the total energy of processor $\theta_k$. To evaluate the performances of these schemes, we introduce an index $\phi = \frac{\sum_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho})}{\min_{\forall \beta \in P} (\sum_{\gamma} C_{\beta\gamma \rho})}$, where $E_{\text{all}k}^{\text{comm}} \neq 0$. The smaller the value of $\phi$, the more balance is achieved regarding energy consumption of all processors. Fig. 2(d) and Fig. 2(e) show that the total energy consumption of ME is lower than BE (average 13.62%). However, the value of $\phi$ for BE is smaller than ME. This is because ME allocates the tasks to the same processors to reduce communication energy. Therefore, some processors will consume more energy than others. However, with BE this trend can be avoided in order to achieve energy balance.

Fig. 2(f) and Fig. 2(g) compare the solutions of problem (10)
achieved by the proposed heuristic and the optimal solution, obtained by the Gurobi solver. From Fig. 2(f), we observe that the algorithm computation time increases with task number \( M \), as more variables and constraints are involved. On the contrary, the proposed heuristic has a negligible computation time, since it divides the problem into three subproblems, i.e., P2, P3 and P4, which are solved in sequence. From Fig. 2(g), we observe that the solution of the heuristic has a higher, but still acceptable, energy consumption (average 26.05\%) than the optimal solution, since it only provides a feasible solution.

Fig. 2(h) shows the feasibility in solving the task deployment problem (10) for the optimal and the heuristic methods. The experiments have been repeated \( n_s = 30 \) times with different task graphs. The used metric is the problem feasible ratio \( \delta \) for a task graph. The constraints are relaxed with \( \alpha \), thus the feasible region of problem is enlarged. The optimal feasibility is higher than the heuristic, since it optimizes the variables concurrently, whereas the heuristic optimizes the variables step by step.

V. CONCLUSION

This work proposes a task deployment process for NoC-based multicore platforms with DVFS, that balances the overall energy consumption, under reliability and real-time constraints. The deployment process is formulated as an MINLP problem and equivalently transformed to an MILP problem. Our formulation jointly optimizes frequency assignment, task allocation, task scheduling, task duplication and path selection. Moreover, a novel heuristic method is proposed to enhance scalability, achieving good solutions with low computation time.

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