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Abstract Minimizing energy consumption, as well as meeting real-time and reliability constraints, are major goals during system deployment. When complex platforms, such as multicore architectures with DVFS, and parallel applications are considered, these goals are significantly impacted by task mapping. To minimize energy consumption, while meeting real-time and reliability constraints, this work proposes a task mapping approach to jointly solve the problem of task allocation, task scheduling, frequency assignment, and task duplication. A novel heuristic algorithm is proposed to cope with this NP-hard problem, consisting of a pruning phase, which maintains only the task configurations that satisfy reliability constraints, and a mapping phase, which minimizes total energy consumption under real-time and precedence constraints. The obtained results show that the proposed heuristic obtains near-optimal results, with low computation time, compared to optimal solvers, while it achieves better energy consumption and finds more solutions compared to other heuristic approaches.

Keywords Fault tolerant · Task mapping · DVFS · Real-time execution · Reliability · Energy minimization

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1 Introduction

1.1 Context

The execution of embedded real-time parallel applications on multicore platforms require guarantees for real-time execution [1–3] and reliability [1,4]. Due to technology size reduction, multicore platforms are susceptible to transient faults [1]. Reliability is defined as the probability of executing a task without faults. Typical techniques to increase reliability are the execution of tasks with high frequency [5] and task replication [1,4]. However, both techniques can lead to large energy consumption. Dynamic Voltage and Frequency Scaling (DVFS) is a well-known energy management technique, which optimizes energy consumption by scaling down the processor supply voltage and frequency [1, 4]. However, this has a negative impact on reliability, since more transient faults occur at a low voltage and frequency level [1, 4]. Therefore, during the task mapping not only task allocation and scheduling, but also frequency assignment and task replication should be incorporated in the optimisation process to achieve energy efficiency, while meeting real-time and reliability constraints.

1.2 Related work and motivation

Table 1 summarises representative State-of-the-Art (SoA) task mapping approaches that minimize energy consumption considering DVFS, under Real-Time (RT) and Reliability (R) constraints. The platform consists of Homogeneous (HO), Heterogeneous (HE) or Single (S) processor. The applied fault tolerance policy can be task Recovery (Rec.) or task Replication (Rep.). A task is executed successfully, if at least one replica is executed without faults [1]. Last, the proposed solving method can Optimal (O) or Heuristic (H).

Approaches exist without applying a fault tolerance policy, e.g., the task mapping problem is decomposed into a sub-problem that satisfies the reliability constraint and another that minimizes resources [5] and a whale optimization algorithm is proposed [6]. In [7], the scheduling algorithm for dependent multi-version tasks is studied based on Forward List Scheduling with the goal of minimise the total energy consumption under real-time constraint. Approaches execute a recovery task, e.g., individual [8] or shared [2, 9], or both [10], with maximum frequency, exploring available time slack to meet the reliability constraint. Last, approaches apply task replication. Some works decide the required number of replicas per task to always meet the reliability constraint, e.g., for independent tasks on homogeneous platform [1] and dependent tasks on heterogeneous platforms [4]. In [1], all replicas of a task are executed at same frequency, whereas in [4] no real-time constraints are taken into account. In [11] the number of replicas per task is given. In the first phase, half-plus-one copies per task are executed. If a fault occurs, the second phase is applied to execute the remaining number of copies. Other works decide among different reliability mechanisms for each task. In [12], a

Table 1: Comparison with representative SoA approaches

Ref.	Task model		Fault tol.		Platform			Constraints		Solution	
	I.	D.	Rec.	Rep.	HO	HE	S	RT	R	O	H
[1]	√			√	√			√	√		√
[4]		√		√		√			√		√
[5]		√				√			√		√
[6]		√				√		√	√		√
[7]		√				√		√			√
[2, 8, 10]		√	√			√		√	√		√
[9]		√	√				√	√	√		√
[3]		√	√	√	√			√			√
[13]	√			√	√			√	√	√	
[12]		√		√	√			(√)	(√)		√
[11]		√		√	√			√	√		√
[14]		√		√	√			√	√	√	
Prop.		√		√	√			√	√		√

heuristic explores among three reliability mechanisms in sequence to decide single task execution, task duplication and task triplication, without the requirements of always meeting the real-time and reliability constraints. In [3], a heuristic determines which tasks to be duplicated, removing the need of a recovery task for all tasks. An optimal approach decides which task to duplicate, taking into account reliability and real-time constraints for independent [13] and independent tasks [14].

Overall, optimal approaches are applicable only for small problem sizes and existing heuristics, either do not fully guarantee real-time or reliability constraints, or use a high number of replicas, leading to large energy consumption with a negative impact on execution time, and thus, potentially no feasible solution.

1.3 Contributions

This work addresses the task mapping problem of parallel applications on homogeneous multicore platforms with DVFS, with the goal of minimizing total energy consumption, under real-time and reliability constraints. An effective heuristic is proposed, considering multiple non-functional properties of execution time, energy and reliability, that combines task allocation, task scheduling, frequency assignment and selective task duplication. Unlike the majority of SoA techniques, original and duplicated tasks can have different operating frequencies, being more suitable for real-world systems [15]. A pruning phase maintains only the task configurations that satisfy reliability constraints. A mapping phase minimizes total energy consumption under real-time and precedence constraints. Last, but not least, the proposed method is evaluated both with task graphs from real applications and randomly generated graphs. The experiment results show that our approach provides near-optimal energy sav-

Notations	Definitions
τ_i^o/τ_i^d	the original/duplicated copy of task τ_i
(v_l, f_l)	the l^{th} voltage/frequency level
W_i	WCEC of task τ_i
D	the global deadline
R_i^{th}	reliability threshold of task τ_i
SL	schedule length of DAG G
EST_i	earliest start time of task τ_i
LFT_i	latest finish time of task τ_i
st_i	actual start time of task τ_i
ft_i	actual finish time of task τ_i
et_i	execution time of task τ_i
$slack_i$	time slack of task τ_i
$Pred\{\tau_i\}$	all immediate predecessors of task τ_i
$Succ\{\tau_i\}$	all immediate successors of task τ_i
$proc\{m\}$	task set that are allocated on processor θ_m
SC_i	Selected configuration of task τ_i in current task mapping
NC_i	New checked configuration of task τ_i

Table 2: Main Notations and their definitions

ings, with low computation time compared to optimal solvers, while it has better energy consumption and feasibility compared to other heuristics.

The rest of the paper is organized as follows. Section 2 introduces the system model. Section 3 presents the formulation of the proposed approaches. Section 4 presents the evaluation results. Finally, Section 5 concludes this study.

2 System Model

Table 2 shows the main notations. For the sake of paper presentation, when original and duplicated tasks must be distinguished in mathematical formulations, the subscript $k \in \{o, d\}$ indicates the original task (^{o}) or the duplicated task (^{d}). If no subscript exists, the mathematical formulation is valid for both.

2.1 Task Model

This work considers a real-time application modelled as a Directed Acyclic Graph (DAG) $G(\mathbb{V}, \mathbb{E})$, where $\mathbb{V}$ denotes the set of N frame-based, non-preemptive, dependent tasks $\{\tau_0^o, \ldots, \tau_{N-1}^o\}$, while $\mathbb{E}$ represents the edges, corresponding to the tasks' precedence constraints. Tasks are released at time 0 and have a global deadline D, given by the application frame. If a task has no predecessors (successors), it is an entry task τ_{entry} (exit task τ_{exit}). A task is ready for execution when all its predecessors have been completed. Each task τ_i is described by a tuple $\{W_i, R_i^{th}\}$, where W_i is the Worst Case Execution Cycles (WCEC) and R_i^{th} is its reliability threshold. Each task has

its own reliability constraint, since functions of an application exhibit distinct vulnerabilities, due to variations in the spatial and temporal vulnerabilities of different instructions [12].

2.1.1 Platform Model

The target platform has a shared-memory multicore architecture with M homogeneous processors $M = \{\theta_0, \ldots, \theta_{M-1}\}$. Each processor supports DVFS and has L pairs of frequency/voltage level $\{(f_0, v_0), \ldots, (f_{L-1}, v_{L-1})\}$. As the relationship of voltage and frequency is almost linear [4,9,11], we use the term frequency scaling to express the simultaneous change of voltage and frequency. We consider intra-task DVFS. When task τ_i is executed with frequency f_l, its execution time is $\frac{W_i}{f_l}$. The power consumption is modeled as the sum of static power P_l^{sta} and dynamic power P_l^{dyn} considering a voltage/frequency level (v_l, f_l) [1,4]. Specifically,

$$P_l = P_l^{sta} + P_l^{dyn} = P_l^{sta} + C_{eff} v_l^2 f_l, \tag{1}$$

where C_{eff} is the effective switching capacitance.

2.1.2 Fault Model and Reliability

This work addresses transient faults, having a higher occurrence than permanent faults during the useful lifetime of the system [5]. During this period, the fault model, where the fault occurrence is given by a Poisson distribution with an average fault rate $\lambda(f_l)$ at frequency f_l, is typically used [4, 5, 9, 11]. The failure rate per time unit of a processor at frequency f_l is given by

$$\lambda(f_l) = \lambda_0 \times 10^{d_0 \frac{f_{\max} - f_l}{f_{\max} - f_{\min}}}, \tag{2}$$

where $f_{\max} = \max_{\forall l}\{f_l\}$, $f_{\min} = \min_{\forall l}\{f_l\}$, λ_0 is the average failure rate of the processor corresponding to $f_{\max}$, and d_0 is a positive constant, indicating the sensitivity of failure rates to voltage scaling [4].

The reliability of task τ_i is defined as the probability of executing τ_i without any fault. Based on the exponential model in [1, 9], the reliability of a task executed at f_{τ_i} is calculated as

$$R_i(f_l) = e^{-\varphi_i(f_l)}, \tag{3}$$

where $\varphi_i(f_l) = \lambda(f_{\tau_i}) \times et_{i,l}$, and $et_{i,l}$ is the execution time of task τ_i at frequency f_l. If the reliability of original task τ_i^o is larger than its reliability threshold R_i^{th}, the execution is considered as reliable [5] and the task reliability is given by $R_i = R_i^o$. Otherwise, the task τ_i^o is duplicated and executed on a different processor, since it is unlikely that the execution of both original and duplicated tasks on different processors fail [1, 3, 4]. The duplicated task τ_i^d has the same characteristics with the original task τ_i^o. When the duplicated

task τ_i^d is executed, its reliability is R_i^d and depends on the frequency it is executed. Then, the task reliability, after duplication, is

$$R_i = 1 - (1 - R_i^o)(1 - R_i^d). \tag{4}$$

As our approach finds an offline optimal task mapping solution, with the goal of minimizing energy consumption, we consider only task duplication, i.e., a single replica per task, in order not to unnecessarily increase the number of replicas, in case no faults occur. An online mechanism can be applied to further improve the energy consumption of our solution (by not executing the duplicated task, when the first execution is correct), and to deal with the low probability cases, where both original and duplicated tasks are faulty. In this work, cores are assumed to operate below a temperature threshold, where temperature impact on reliability is low [16].

2.1.3 Problem under study

Given a DAG task graph G and M processors, the goal is to minimize the total energy consumption by deciding the: 1) task duplication, 2) assignment of frequencies to tasks, 3) allocation of tasks to processors, 4) start time of tasks, subject to reliability, real-time and task precedence constraints.

3 Proposed Approach

To solve the problem under study, we propose a *Heuristic for Reliability-aware Fault-tolerant Task Mapping (H_RAFTM)*, described in Algorithm 1. The algorithm consists of two phases:

1. `Phase A` obtains, per task, the set of possible configurations that meet the reliability constraint, ordered in decreasing energy consumption.
2. `Phase B` obtains the application mapping, by allocating tasks to processors using the least total energy consumption, under task precedence and real-time constraints.

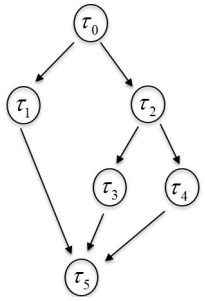
H_RAFTM is based on the following definitions:

Definition 1 (Configuration)**.** *A configuration j of a task τ_i is denoted as $C_i^j = \{f_i^o, f_i^d, et_i^o, et_i^d, E_i^o, E_i^d, R_i\}$, where f_i^o (f_i^d) is the assigned frequency, et_i^o (et_i^d) is the required execution time, E_i^o (E_i^d) is the energy consumption of the original (duplicated) task, and R_i is the reliability of the task (taking into account task duplication). If the task is not duplicated, we have $f_i^d = et_i^d = E_i^d = 0$.*

Definition 2 (Task Mapping)**.** *A mapping of a task τ_i, under the task configuration C_i^j, is denoted as $TM_i^{C_i^j} = \{\theta_i^o, \theta_i^d, st_i^o, st_i^d\}$, where θ_i^o (θ_i^d) is the allocated processor, and st_i^o (st_i^d) is the start time of the original (duplicated) task. If a task is not duplicated, then $f_i^d = 0$, and the duplicated task takes no execution time, i.e., its start time is equal with its final time, $st_i^d = ft_i^d$.*

Definition 3 (Application Mapping)**.** *The mapping of the application (AM) is given by the set of mappings of N original tasks and $S \subseteq N$ duplicated tasks. The mapping is valid if task precedence and real-time constraints are satisfied.*

The next paragraphs describe in details the two phases of the proposed approach and illustrate them using the application DAG example of Fig. 1.



Part of RTE_5* with $W_5 = 1.4728 \times 10^8$ and $R_5^{th} = 0.9994$
*Processor model based on Table 3

C_5^j	f_5^o (GHz)	f_5^d (GHz)	et_5^o (msec)	et_5^d (msec)	E_5^o (mJ)	E_5^d (mJ)	R_5
C_5^0	0.801	-	18.387	-	0.77944	-	0.9908486
C_5^1	0.8291	-	17.764	-	1.02746	-	0.9966568
C_5^2	0.8553	-	17.220	-	1.36084	-	0.9986935
C_5^3	0.8797	-	16.742	-	1.81375	-	0.9994552
C_5^4	0.9027	-	16.315	-	2.43532	-	0.9997610
C_5^5	1.0	-	14.728	-	3.29633	-	0.9999926
C_5^6	0.801	0.801	18.387	18.387	0.77944	0.77944	0.9999163
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C_5^{10}	0.801	1.0	18.387	14.728	0.77944	3.29633	~ 1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C_5^{26}	1.0	1.0	14.728	14.728	3.29633	3.29633	~ 1

Fig. 1: Illustration example: Application DAG ($N = 6$) and part of RTE_5.

3.1 Phase A: Task configurations, under reliability constraint.

`Phase A` (Lines 1-9) is applied per task. For each task (Line 1), a Reliability, execution Time, Energy consumption (RTE) table is created based on all possible configurations (Line 2). For instance, part of the RTE of task τ_5 is depicted in Fig 1. A pruning step removes the task configurations that do not satisfy the reliability constraint (Line 3).
i) Reliability Constraint: A task must be executed meeting its reliability requirement, i.e., $R_i \geq R_i^{th}$.

For instance, assuming that the reliability of τ_5 is $R_5^{th} = 0.9994$, the configurations C_5^0, C_5^1 and C_5^2 are pruned in this step. The result is the Feasible Configurations (FC) of the task. FC_i considering only the original task τ_i^o (when $f_i^d = 0$ no duplicated task exists) serve as Baseline Configurations (BC) (Line 4). In our illustration example, the BC of τ_5 are C_5^3, C_5^4 and C_5^5. The next step prunes any feasible configuration with duplicated tasks, if both the energy consumption and the execution time are larger than any defined BC_i (Lines 5-7), e.g., C_5^{10} and C_5^{26} in our illustration example of Fig 1. The result is the Possible Configurations (PC). The PC are ranked based on decreasing energy consumption (rPC_i) (Line 8).

Algorithm 1: Proposed H_RAFTM algorithm.

Require: Task graph (G) and set of processors (M).
Ensure: Application mapping (AM).

`// Phase A`

for each task τ_i in N **do**
  $RTE_i = \{C_i^j$: C_i^j is a configuration of $\tau_i\}$;
  $FC_i = RTE_i$ - $\{C_i^j$: $R_i < R_i^{th}\}$;
  $BC_i = \{FC_i$: $f_i^d = 0\}$;
  for each configuration bc in BC_i **do**
    $PC_i = FC_i$ - $\{FC_i$: $f_i^d \neq 0 \wedge \min\{et_i^o, et_i^d\} \geq et^{bc} \wedge \sum\{E_i^o, E_i^d\} > E^{bc}\}$;
  end for
  $rPC_i = \{PC_i$: PC_i decreasing energy consumption$\}$;
end for

`// Phase B`

for each task τ_i in N **do**
  Compute $rank_i$ (Eq. 8);
end for
$PL = \{N$: ordered in decreasing $rank_i\}$;
for each task τ_i in PL **do**
  $SC_i = rPC_i[0]$;
  Compute $TM_i^{SC_i}$ ($st_i = EST_i$ in Eq. 7);
end for
$AM_0 = \{TM_i^{SC_i}\}$;
Compute SL_{AM_0} (Eq. 6);
if $SL_{AM_0} > D$ **then**
  Infeasible problem, algorithm stops.
else if $SL_{AM_0} = D$ **then**
  $AM = AM_0$, algorithm stops.
else if $SL_{AM_0} < D$ **then**
  AM relaxation (Algorithm 2);
end if

3.2 Phase B: Application mapping, under precedence and real-time constraints.

`Phase B` uses `Phase A` task configurations and performs the application mapping, subject to the following constraints:

ii) Precedence constraints: Based on the dependencies defined by the task graph, a task τ_i can start execution only when all its predecessors are completed. Task predecessors include also the duplicated tasks, since our approach is applied offline, and thus, strict scheduling is considered where a task can be executed after all its predecessors are finished. Then, the Earliest Start Time

(EST) of τ_i given by

$$EST_i = \begin{cases} 0, & if\ \tau_i = \tau_{entry} \\ \max\limits_{\tau_j \in Pred\{\tau_i\}} \{EFT_j\}, & else \end{cases} \quad (5)$$

where $Pred\{\tau_i\}$ is the set of τ_i's predecessors, and $EFT_j = EST_j + et_j$ is the Earliest Finish Time (EFT) of task τ_j.

iii) Deadline constraint: The application must be finished before the deadline D. The Schedule Length, SL, of task graph G, under a given application mapping AM, is determined by the latest finish time of exit tasks:

$$SL_{AM} = \max\{ft_{\tau_{exit}}\} \leq D. \quad (6)$$

Due to precedence constraints, the start time of a task is $st_i \geq EST_i$. Our goal is to exploit the available time slack to save energy, thus, we initially consider that tasks start execution as soon as possible, i.e., $st_i = EST_i, \forall \tau_i$.

iv) Non-overlapping constraint: Only a single task should be executed on a processor at a given time instance. Taking into account the earliest available time, $avail[m]$, when processor θ_m is ready for a task execution, EST_i is modified as

$$EST_i = \begin{cases} 0, if\ \tau_i = \tau_{entry} \\ \max \left\{ \begin{matrix} \max\limits_{\tau_j \in Pred\{\tau_i\}} \{EFT_j\}, \\ avail[m], \end{matrix} \right\}, else \end{cases} \quad (7)$$

The text paragraphs describe the three steps of `Phase B` (Lines 10-26):

Step 1 (Lines 10-13): Priorities are given to tasks for task allocation based on the upward rank value [4], $rank_i$, which is common for original and duplicated tasks (Lines 10-12):

$$rank_i = \begin{cases} \overline{et}_i, & if\ \tau_i = \tau_{exit} \\ \overline{et}_i + \max\limits_{\tau_j \in Succ\{\tau_i\}} \{rank_j\}, & else \end{cases} \quad (8)$$

where $\overline{et}_i = (\sum_{l=1}^{L} W_i/f_l)/L$ is the average computation time of τ_i and $Succ\{\tau_i\}$ the immediate successors of τ_i. Then, the Priority List (PL) is ordered in decreasing rank value (Line 13).

Step 2 (Lines 14-23): The initial application mapping AM_0 is generated to check if the problem is feasible and whether time slack is available. For all task, AM_0 uses the first configuration in rPC_i as the Selected Configuration SC_i (Line 15). Setting $st_i = EST_i$ to Eq. 7, we obtain the task mapping ($TM_i^{SC_i}$) per task (Line 16). The set of all task mappings provides the AM_0 (Line 18). Then, its schedule length SL_{AM_0} is obtained (Line 19). If it is higher than the deadline, the problem is infeasible (Lines 20-21), and the algorithm stops. If it is equal to the deadline, the initial application mapping is the final mapping and the algorithm stops (Lines 22-23).

Step 3: (Lines 25-26) If the initial schedule length is less than the deadline (Line 24), time slack exists. Overall, different task configurations and different tasks that can be relaxed in order to obtain energy savings. Algorithm 2

Algorithm 2: Mapping Relaxation Algorithm.

1: $AM = AM_0$, $SL = SL_0$;
2: **while** $SL < D$ **and** $rPC_i > 1 (\forall \tau_i)$ **do**
3: **for** each task τ_i in N **do**
4: $NC_i^A = rPC_i[0]$;
5: $NC_i^B = rPC_i[j]$ with $\max \left\{ \sum_{k \in \{o,d\}} (ES^j_{\tau_i^k} / TI^j_{\tau_i^k}) \right\}$;
6: $NC_i = (E^{NC_i^A} \leq E^{NC_i^B} ? NC_i^A : NC_i^B)$;
7: Compute $TM_i^{NC_i}, i \in \boldsymbol{N}$ ($st_i = EST_i$ in Eq. 7);
8: $AM_i = \{TM_i^{NC_i}\}$;
9: Compute SL_{AM_i} (Eq. 6);
10: $SLI_i = SL_{AM_i} - SL$;
11: $Gain_i = \frac{\sum_{k \in \{o,d\}} (ES^{NC_i}_{\tau_i^k} / TI^{NC_i}_{\tau_i^k}))}{SLI_i}$;
12: **end for**
13: **for** each task τ_i in N **do**
14: Compute $slack_{AM_i}$ (Eqs. 7, 9, 10);
15: **end for**
16: $\tau_{rel} = \tau_i$ with $\arg\max_{i \in \boldsymbol{N}} (Gain_i) \wedge (TI_i^{NC_i} \leq slack_{AM_i})$;
17: $SC_{\tau_{rel}} = NC_{\tau_{rel}}$;
18: $AM = AM_{\tau_{rel}}$ and $SL = SL_{AM_{\tau_{rel}}}$;
19: **for** each configuration pc in $rPC_{\tau_{rel}}$ **do**
20: $rPC_{\tau_{rel}} = rPC_{\tau_{rel}}$ - $\{rPC_{\tau_{rel}}$: $E^{pc} \geq E^{SC_{\tau_{rel}}}\}$;
21: **end for**
22: **end while**

decides the task to be relaxed and its configuration. Initially, the current mapping (schedule length) is initialised with the initial mapping (schedule length) (Line 1). The algorithm is applied iteratively, until the schedule length reaches the deadline or all tasks reach their configuration with the least energy consumption (Line 2). First, a local search decides a new configuration per task (Lines 3-12). We combine two criteria to select a potential New Configuration (NC_i) for a task. NC_i^A explores rPC_i sequentially, by selecting always the first configuration. NC_i^B selects the j configuration in rPC_i with the highest value $(ES^j_{\tau_i^o}/TI^j_{\tau_i^o}) + (ES^j_{\tau_i^d}/TI^j_{\tau_i^d})$, where $ES^j_{\tau_i^o}$ ($ES^j_{\tau_i^d}$) is the energy savings and $TI^j_{\tau_i^o}$ ($TI^j_{\tau_i^d}$) is the time increase of task τ_i in configuration j, compared to the current selected configuration SC_i. The final selected configuration NC_i is the one with the minimum energy consumption (Line 6). After selecting a new task configuration, all task mappings are updated accordingly (Line 7). The new application mapping AM_i (Line 8) and its schedule length SL_{AM_i} (Line 9) are obtained. The difference of SL_{AM_i} with the schedule length of the current mapping SL provides the Schedule Length Increase (SLI_i), when task τ_i changes its current configuration SC_i to NC_i (Line 10). With this in-

formation, the overall gain ($Gain_i$), considering both energy and time, that this configuration modification will bring to the overall mapping, is computed (Line 11). After the local search finishes, the global decision takes place (Lines 13-22). The time slack of each task in the current mapping ($slack_{AM_i}$) based on task mobility through Eqs. 7, 9, 10 (Lines 13-15):

$$slack_{AM_i} = LFT_i - EST_i - et_i. \tag{9}$$

The Latest Finish Time (LFT) of τ_i is:

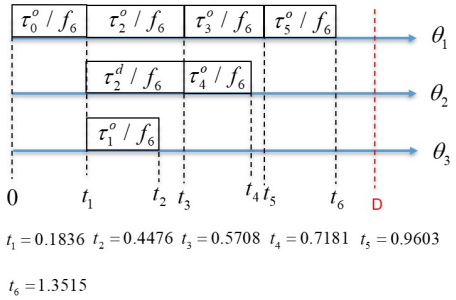
$$LFT_i = \begin{cases} D, if\ \tau_i = \tau_{exit} \\ \min \left\{ \begin{array}{l} \min\limits_{\tau_p \in Proc\{\tau_i\}} \{LST_{\tau_p}\}, \\ \min\limits_{\tau_j \in Succ\{\tau_i\}} \{LST_{\tau_j}\}, \end{array} \right\}, else \end{cases} \tag{10}$$

where $LST_i = LFT_i - et_i$ is the Latest Start Time (LST) of task τ_i. $Proc\{\tau_i\}$ is the processor that the task is allocated, and τ_p are the tasks, scheduled after task τ_i, on the same processor. The task (and its corresponding configuration) to be relaxed (τ_{rel}) is the task with highest overall gain, whose time increase in this new configuration is not larger than its available slack in the current mapping (Line 16). Last, the selected configuration (SC) for the relaxed task, the application mapping and its schedule length are updated (Lines 17-18) and all configurations that have a higher energy consumption than the selected one are removed from $rPC_{\tau_{rel}}$ (Lines 19-21).

Fig. 2, Fig. 3 and Fig. 4 illustrate the application mapping process for the DAG in Fig 1, when $M = 3$ processors and $D = 1.4$. Fig 2 shows on the left the initial application mapping AM_0 (**step 1** and **step 2**) and on the right the initial schedule configuration for each task. The total energy consumption of AM_0 is $E_{AM_0} = 48.12$ mJ and schedule length is $SL_{AM_0} = 1.3515$ sec. Since the schedule length is lower than the deadline, there exists some time slack. During relaxation (**step 3**), the task τ_1 is selected, along with the configuration where both original and duplication copies are executed with frequency f_2, since this task and configuration provide the highest gain, since the energy consumption is reduced without increasing the schedule length (Inf means positive infinity in Fig. 3 and the one with most energy saving is selected if there are multiple Inf cases). The updated application mapping is depicted in Fig. 3. The algorithm continues to apply relaxation, as long as time slack is still available, by selecting the next task and configuration with the highest gain. The final application mapping is depicted in Fig 4, with an energy consumption equal to $E = 41.67$ mJ and a schedule length of $SL = 1.3971$ sec.

3.3 Time complexity

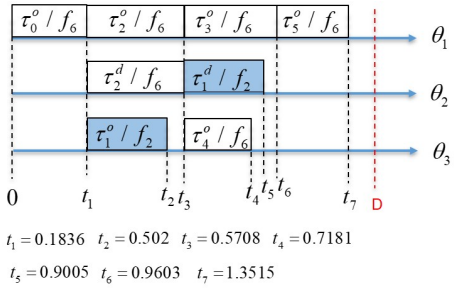
In the proposed heuristic approach, the maximum number of possible configurations for each task is $L + \binom{2}{L}$ (denoted as K). Phase A takes $O(NK)$ time to obtain the possible configuration space for all tasks. Phase B firstly



*Scheduled configuration

C_i^j	f_i^o (GHz)	f_i^d (GHz)	SLI_i (sec)	$Gain_i$
C_0^0	1.0	-	-	-
C_1^0	1.0	-	-	-
C_2^0	1.0	1.0	-	-
C_3^0	1.0	-	-	-
C_4^0	1.0	-	-	-
C_5^0	1.0	-	-	-

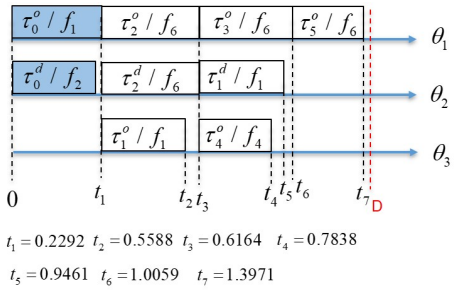
Fig. 2: Illustration example (Fig. 1): Initial application mapping AM_0.



*Scheduled configuration

C_i^j	f_i^o (GHz)	f_i^d (GHz)	SLI_i (sec)	$Gain_i$
C_0^0	1.0	-	0.031	2,246.9
C_1^0	0.8291	0.8291	0	Inf
C_2^0	1.0	1.0	0.066	2,309.2
C_3^0	1.0	-	0.08	858.9
C_4^0	1.0	-	0	Inf
C_5^0	1.0	-	0.07	1,054.3

Fig. 3: Illustration example (Fig. 1): AM_1 with task τ_1 relaxed.



*Scheduled configuration

C_i^j	f_i^o (GHz)	f_i^d (GHz)	SLI_i (sec)	$Gain_i$
C_0^0	0.801	0.8291	0.008	13013.0
C_1^0	0.801	0.801	-	-
C_2^0	1.0	1.0	0.066	2309.2
C_3^0	1.0	-	0.41	168.2
C_4^0	0.8797	-	0.12	472.7
C_5^0	1.0	-	0.066	1054.3

Fig. 4: Illustration example (Fig. 1): Final application mapping.

requires $O(NlogN)$ time to create the priority list (PL). When task mapping is computed based on Eq. 7, for each single task mapping, the complexity is $O(2logN)$ considering the worst case that both original and duplication copies are executed. For each single application mapping, it traverses N tasks, so the time complexity is $O(2NlogN)$. For each experiment, considering the worst case when deadline is very relaxed so that all configurations for all tasks have to be explored in the relaxation algorithm, the total complexity of the whole application mapping under this very relaxed deadline is $O(2N^2KlogN)$.

Table 3: Processor characteristics

v_l (V)	0.85	0.90	0.95	1.00	1.05	1.1
f_l (GHz)	0.801	0.8291	0.8553	0.8797	0.9027	1.0
C_{eff}	7.3249	8.6126	10.238	12.315	14.998	18.497

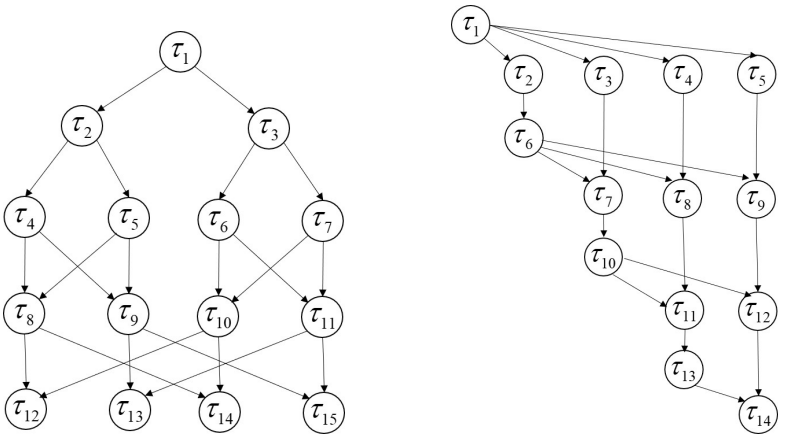
4 Experimental Results

This section evaluates the proposed heuristic (H_RAFTM) with i) the optimal solver using Gurobi 9.0.2 (O_RAFTM) as in [14], and ii) two SoA heuristics a) the Reliability-Aware Mapping (H_RAM), that meets the reliability constraint without task duplication, similar to [5] and ESRG algorithm in [4], and b) the Task Duplication Mapping (H_TDM), applying task duplication for all tasks, similar to [1,4], when the number of replicas is two, or to [17], with 100% task duplication. To evaluate the approaches, the following metrics are used:

1. Feasibility, i.e., the number of experiments where a solution is found out of the total number of experiments (NE).
2. Energy Consumption (EC) of proposed heuristic approach, compared to the energy consumption of the optimal approach O_RAFTM and two SoA heuristic approaches H_RAM and H_TDM.
3. Reliability Improvement (RI) ($RI = R_i - R_i^{th}$), i.e., the task reliability *above* the task reliability threshold.
4. Computation time (CT), i.e., the time required for each approach to find a solution.

Note that, an approach may fail to find a solution, especially in strict deadlines. In order to fairly compare the energy consumption, reliability improvement and the computation time, we present the average values of the experiments where both compared approaches (i.e., O_RAFTM vs H_RAFTM, H_RAFTM vs H_RAM, or H_RAFTM vs H_TDM) were able to find a solution.

The model of the processor is based on a 32-bit RISC-V Instruction Set Architecture (ISA) with 5-stage pipeline [18]. Regarding DVFS, $L = 6$ voltage/frequency levels are used [19] (Table 3), considering 64 nm technology. The number of processors in the experiments is $M = 2, 4, 6$. The task graphs are obtained both from real-world applications and randomly generated tasks. Regarding real-word applications, two commonly used parallel applications with different shapes of parallelism have been considered, i.e., Fast Fourier Transformation (FFT) ($N = 15$) and Gaussian Elimination (GE) ($N = 14$) [4,5]. Fig 5 depicts the shape of parallelism obtained by FFT and GE DAGs. Random generation is used for comparison with optimal approach ($N = 10$) and for evaluation of the scalability of the heuristics (100). To obtain realistic values for the W_i of a task, common benchmarks from MiBench suite were executed on the processor. The execution cycles and memory accesses are counted and WCEC is computed, assuming that all cores may conflict during a memory access. The obtained range is $[1 \times 10^8, 4 \times 10^8]$, and it is used to randomly select the W_i of a task. The reliability threshold R_i^{th} of a task is selected within



(a) Fast Fourier Transform (FFT) (b) Gaussian Elimination (GE)

Fig. 5: Real-world application DAG.

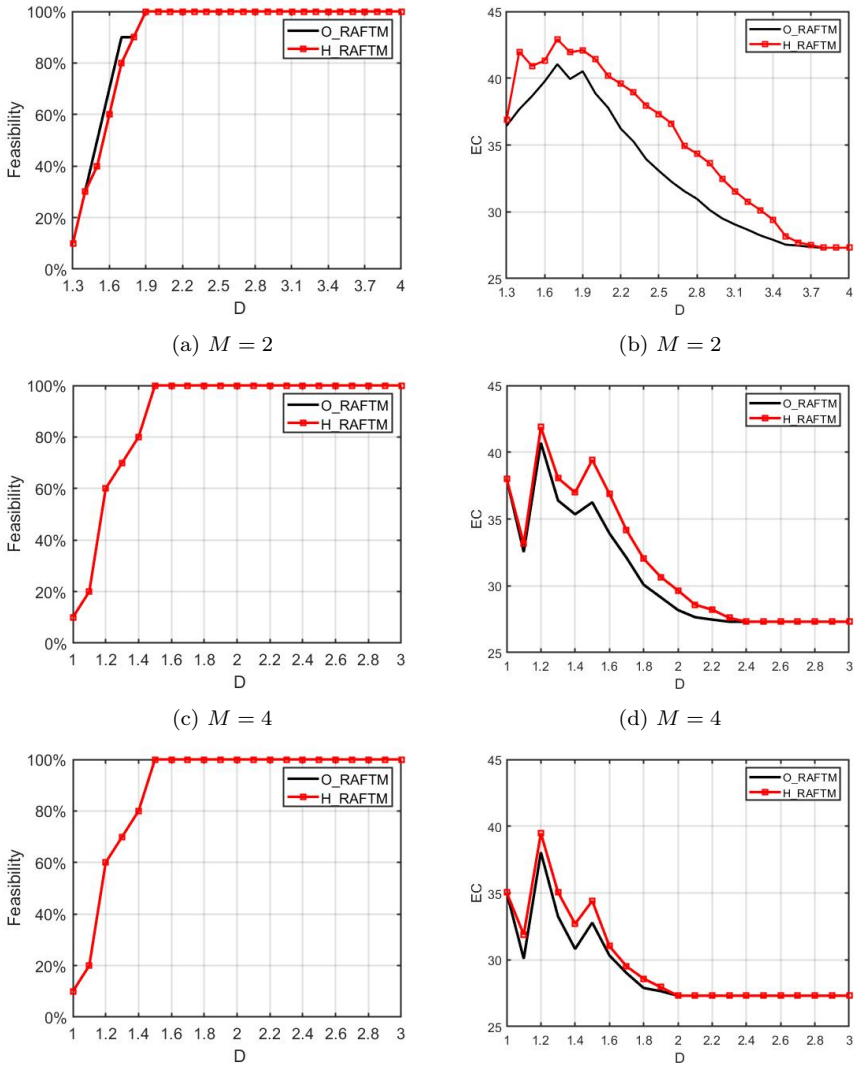
the range $[0.9990, 0.9995]$, considering a typical magnitude 10^{-3} for reliability target [1]. For each application task graph, a number of experiments (denoted as NE) is performed, each time with different task characteristics (W_i and R_i^{th}). For each experiment, D is tuned from strict to relaxed deadlines, starting from SL_{AM_0} of the initial application mapping and increased with a step of 0.1 seconds for small randomly generated DAGs and real-world DAGs and 0.5 seconds for large randomly generated DAG.

4.1 Comparison with optimal approach

Fig. 6 and 7 compare the quality of solutions obtained by O_RAFTM and H_RAFTM approaches. We present the results of $NE = 10$ considering random graphs with $N = 10$ tasks, $M = 2$, $M = 4$ and $M = 6$ processors.

Regarding feasibility, when $M = 2$, the H_RAFTM feasibility is very close to the optimal feasibility, as shown in Fig. 6a, except for a few cases when the deadline is strict. The average difference before achieving 100% feasibility is 3.3%. With the number of processors increasing to $M = 4$ (Fig. 6c) and $M = 6$ (Fig. 6e), H_RAFTM and O_RAFTM achieve the same feasibility, since more resources are available to execute the original and potentially duplicated tasks.

Regarding energy consumption in Fig. 6b, Fig 6d, and Fig 6f, H_RAFTM generally consumes slightly more energy than O_RAFTM. When deadline is relaxed, H_RAFTM and O_RAFTM obtain solutions with the same energy consumption. H_RAFTM consumes on average 7.3% ($M = 2$), 4.4% ($M = 4$) and 3.38% ($M = 6$) more energy than the optimal solutions. With the processor number increasing, the energy consumption of both proposed heuristic and optimal solution flattens at earlier deadlines, since there are more processors



(a) $M = 2$ (b) $M = 2$

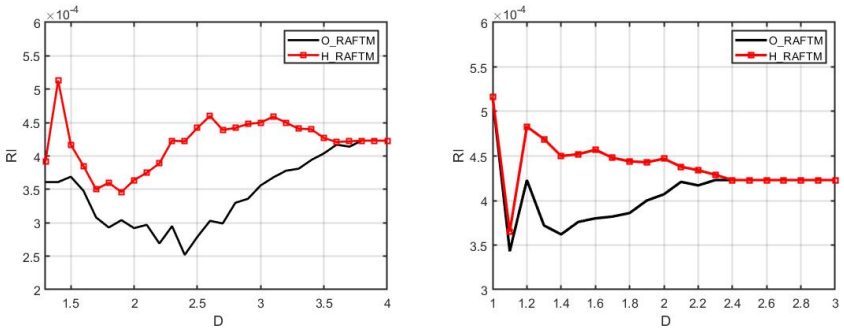
(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

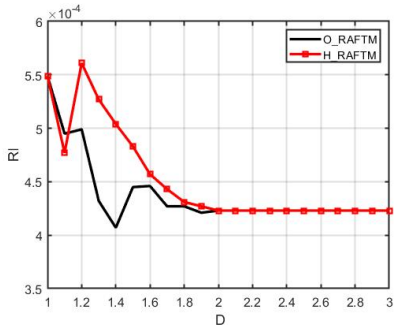
Fig. 6: Feasibility and Energy Consumption (EC in mJ) of optimal and heuristic approached for $M = 2$, $M = 4$ and $M = 6$ ($N = 10$)

resource available to perform the task mapping, and thus, more options to start the tasks earlier.

Regarding reliability improvement, H_RAFTM provides more reliability improvement than optimal solutions at the price of consuming slightly more energy under the same deadlines, as depicted in Fig. 7a, Fig 7b, and Fig 7c.



(a) $M = 2$ (b) $M = 4$



(c) $M = 6$

Fig. 7: Reliability Improvement (RI) of optimal and heuristic approached for $M = 2$, $M = 4$ and $M = 6$ ($N = 10$)

The average computation time of O_RAFTM and H_RAFTM is computed over the number of experiments than found a feasible solution. Table 4, Table 5 and Table 6 show the results in seconds per deadline D. It can be observed that although few tasks and processors are used, the time to obtain the optimal solution is very long, on average 10^4 more than the proposed H_RAFTM.

Table 4: Computation time (seconds) for $N = 10$, $M = 2$

D	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**	**1.8**	**1.9**	**2.0**	**2.1**
O_RAFTM	424.8	523.4	537.1	275.5	432.2	739.7	832.7	1,645.6	2,349.0
H_RAFTM	0.15	0.13	0.14	0.17	0.17	0.20	0.22	0.23	0.29
D	**2.2**	**2.3**	**2.4**	**2.5**	**2.6**	**2.7**	**2.8**	**2.9**	**3.0**
O_RAFTM	3,358.1	5,368.3	4,543.9	9,335.6	11,974.2	13,038.4	19,364.5	27,312.9	19,378.6
H_RAFTM	0.32	0.31	0.36	0.33	0.36	0.35	0.41	0.42	0.42
D	**3.1**	**3.2**	**3.3**	**3.4**	**3.5**	**3.6**	**3.7**	**3.8-4**	
O_RAFTM	13,155.9	21,493.1	24,228.4	77,477.5	5,472.0	4,868.6	4,096.3	2.5	
H_RAFTM	0.49	0.52	0.47	0.52	0.56	0.58	0.59	0.63	

Table 5: Computation time (seconds) for $N = 10$, $M = 4$

D	**1.0**	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**	**1.8**	**1.9**	**2.0**
O_RAFTM	14.9	61.0	74.9	138.2	202.1	256.9	327.3	219.0	1039.3	1054.7	126.8
H_RAFTM	0.19	0.26	0.27	0.30	0.35	0.27	0.33	0.43	0.47	0.50	0.57
D	**2.1**	**2.2**	**2.3**	**2.4**	**2.5**	**2.6**	**2.7**	**2.8**	**2.9**	**3.0**	-
O_RAFTM	58.7	123.1	4.9	1.9	1.4	0.6	1.8	1.0	1.8	2.3	-
H_RAFTM	0.59	0.66	0.64	0.70	0.68	0.67	0.68	0.69	0.66	0.78	-

Table 6: Computation time (seconds) for $N = 10$, $M = 6$

D	**1.0**	**1.1**	**1.2**	**1.3**	**1.4**	**1.5**	**1.6**	**1.7**	**1.8**	**1.9**	**2.0**
O_RAFTM	0.83	58.10	26.95	89.89	81.87	109.82	58.60	62.77	59.77	14.69	2.49
H_RAFTM	0.32	0.27	0.33	0.48	0.54	0.50	0.58	0.68	0.69	0.70	0.67
D	**2.1**	**2.2**	**2.3**	**2.4**	**2.5**	**2.6**	**2.7**	**2.8**	**2.9**	**3.0**	-
O_RAFTM	0.74	0.65	0.63	0.66	0.66	0.64	0.64	0.63	0.60	0.60	-
H_RAFTM	0.76	0.74	0.76	0.80	0.84	0.77	0.76	0.76	0.71	0.72	-

Overall, the obtained results show that i) H_RAFTM provides near-optimal solutions, and the solutions tend to converge to the optimal ones with the number of processors increasing, ii) as expected, H_RAFTM takes significantly less time to obtain the results compared to the optimal approaches.

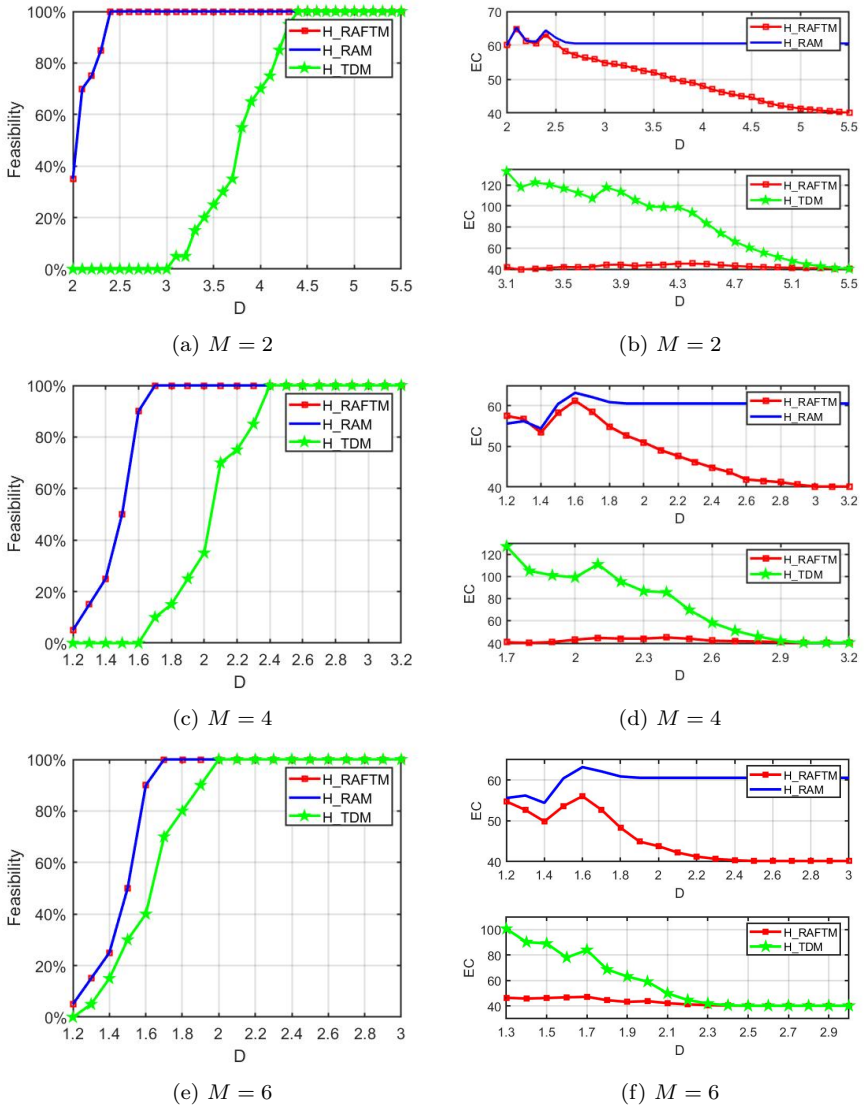
4.2 Comparison with other heuristics

This section evaluates the behavior of the proposed H_RAFTM heuristic to H_RAM and H_TDM heuristics, considering real-world application DAGs and large random generated DAGs.

4.2.1 Real-word DAG

The quality of solutions obtained by H_RAFTM, H_RAM and H_TDM heuristics for the FFT ($N = 15$) are compared in Fig. 8 and Fig. 10, and for the GE ($N = 14$) in Fig. 9 and Fig. 11, considering $M = 2$, $M = 4$ and $M = 6$ processors, and $NE = 20$ experiments.

The feasibility of the three heuristics for FFT and GE benchmarks is depicted in the left column of Fig. 8 and Fig. 9. Comparing to H_TDM, the proposed H_RAFTM can find solutions in significantly more experiments than H_TDM, especially when the deadline is not fully relaxed or number of cores is reduced. When tasks meet their reliability constraint, H_RAFTM does not need to duplicate these tasks. However, H_TDM duplicates all tasks, and thus, it is able to find solutions only when the deadline is relatively relaxed or several processors exist to run the tasks in parallel. Before obtaining 100% feasibility for both approaches, on average, H_RAFTM finds a solution in more experiments than H_TDM, i.e., 70.2% for FFT and 59.4% for GE ($M = 2$), 47.5%



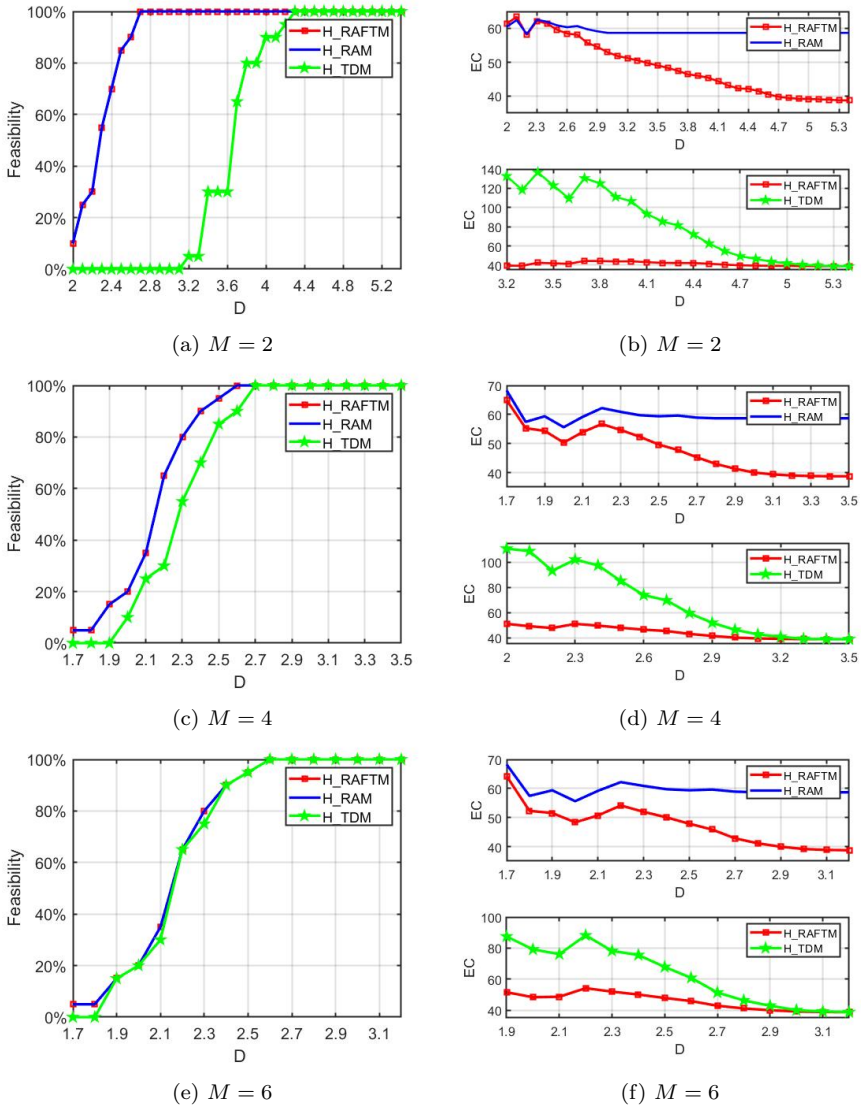
(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 8: Feasibility and energy consumption (EC in mJ) of FFT ($N = 15$) for $M = 2$, $M = 4$ and $M = 6$.

for FFT and 14.5% for GE ($M = 4$) and 47.5% for FFT and 2.2% for GE ($M = 6$). Note that, H_RAFTM and H_RAM have the same feasibility. This behavior is explained as follows: when H_RAM finds a solution, it means the reliability constraint of all tasks can be met by executing only the original task with a high frequency. In this case, H_RAFTM is also able to find this solution.



(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 9: Feasibility and Energy Consumption (EC in mJ) of GE ($N = 14$) for $M = 2$, $M = 4$ and $M = 6$.

The energy consumption obtained by the solutions of the three heuristics for FFT and GE is depicted in the right column of Fig. 8 and Fig. 9. Comparing H_RAFTM and H_RAM, we observe that they consume similar energy at very strict deadlines, when the number of processors is small. In this case, H_RAFTM behaves similarly to H_RAM, i.e., mainly executing the original tasks with the frequency required to achieve the reliability constraint. With

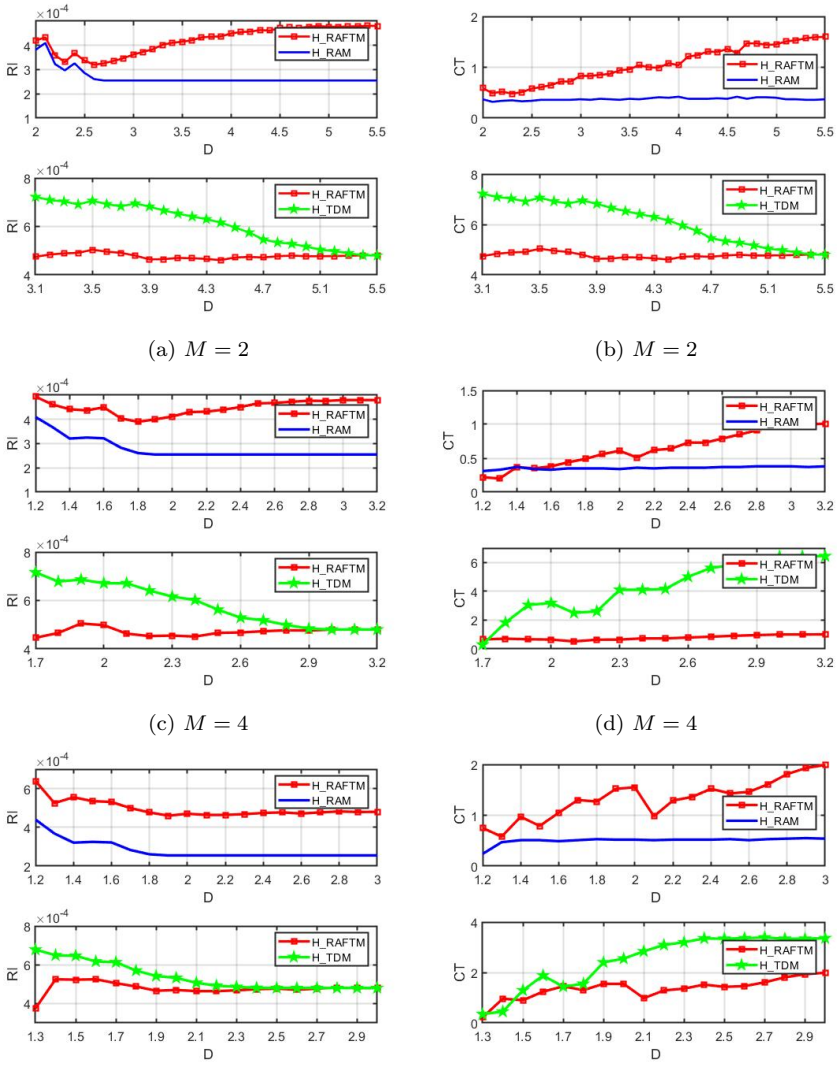
deadline relaxing, H_RAFTM starts to consume less energy than H_RAM. H_RAFTM achieves this gain by exploring the available time slack to duplicate tasks in order to save energy, e.g., up to ∼50.9% for FFT at relaxed deadlines. Similarly, when more processors are available, H_RAFTM can take advantage of these resources and execute duplicated task in parallel. Comparing H_RAFTM and H_TDM, as H_TDM applies task duplication for every task, it cannot find solutions in very strict deadlines. H_RAFTM consumes significantly less energy than H_TDM. H_RAFTM selects the task configuration, if exists, with only the original task, meeting the reliability constraint and consuming less energy than configurations with duplicated tasks. Since H_TDM duplicates all tasks, its energy consumption can be significant, when it finds a solution. In relaxed deadlines, H_RAFTM behaves similar to H_TDM, i.e. duplicates the tasks when less energy is consumed.

The average reliability improvement obtained by the solutions of the three heuristics is depicted in the left column of Fig. 10 and Fig. 11. H_RAFTM achieves higher reliability than RAM, except in very strict deadlines. As explained above, when there is not available time slack to perform duplication, H_RAFTM behaves similarly to H_RAM as most of the tasks are executed with only their original copy. Compared to H_TDM, H_RAFTM provides lower reliability for tight deadlines, as it duplicates only a part of the task-set. The same reliability improvement can be achieved in relaxed deadlines, since both H_RAFTM and H_TDM duplicate tasks similarly.

The computation time of H_RAFTM, H_RAM and H_TDM heuristics is depicted in the right column of Fig. 10 and Fig. 11. Overall, when the deadline increases, the trend of computation time for H_RAM is to remain stable, for H_RAFTM to slightly increase and for H_TDM to increase with a higher factor. The computation time to obtain a feasible solution increases with deadline relaxing, due to the fact that the proposed heuristic explores the PC space for each task, based on the deadline constraints. Therefore, the more relaxed the deadline is, the larger is the PC space to be explored per task, and thus, more time is needed. Note that, H_TDM is the most expensive approach in terms of computation time. This behavior is due to the fact that all tasks are duplicated, which increases the total number of tasks to be scheduled and the number of PCs in each task PC space, and thus, the time to find a solution. For H_RAM, it only executes original tasks, thus it has a reduced number of PCs in the PC space, taking the least time to obtain a solution. However, it provides less energy savings as explained above, especially at relaxed deadlines.

4.2.2 Large random generated DAGs

Fig. 12 and Fig. 13 compare the quality of solutions obtained by H_RAFTM, H_RAM and H_TDM heuristics for a large randomly generated task graph with $N = 100$, $M = 2$, $M = 4$ and $M = 6$ processors, and $NE = 10$ experiments. Previous observations regarding feasibility, energy consumption, reliability improvement and computation time for the three heuristics are also verified by the experiments with the large randomly generated DAG. For instance, as



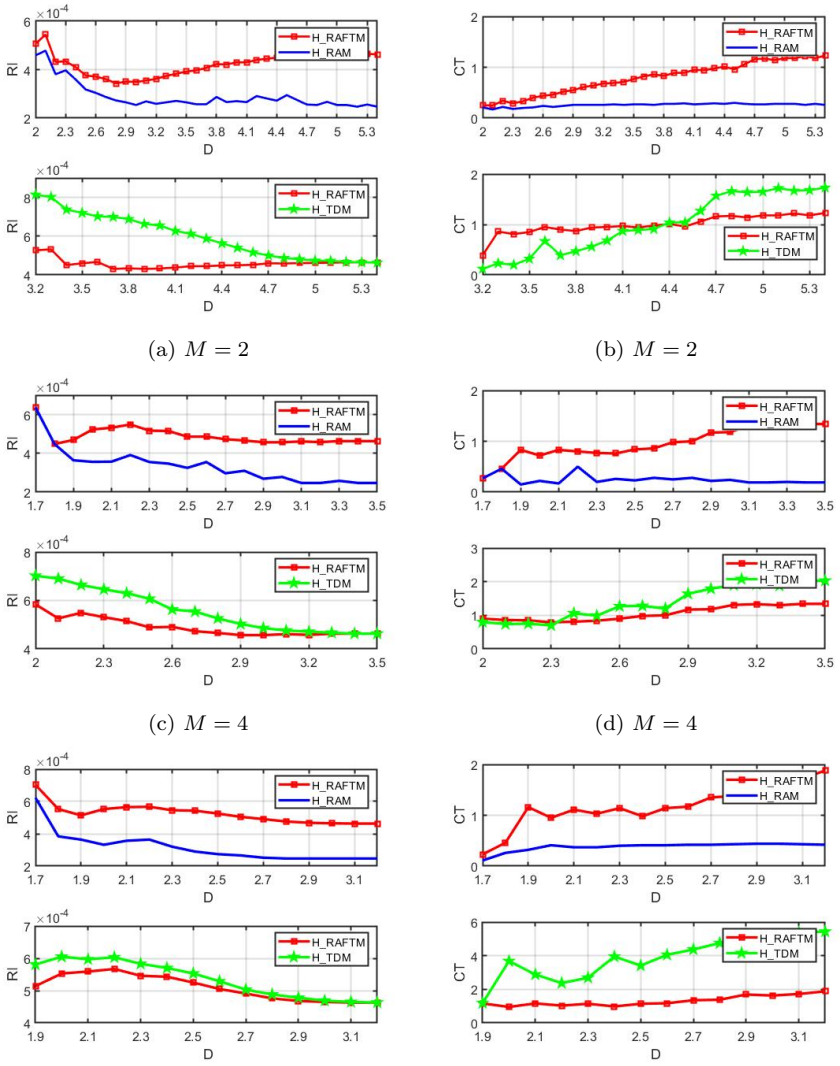
(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 10: Reliability improvement (RI) and Computation Time (CT in seconds) of FFT ($N = 15$) for $M = 2$, $M = 4$ and $M = 6$.

the deadline is not fully relaxed or number of cores is reduced H_RAFTM has increased feasibility compared to H_TDM, i.e., 84.8% for $M = 2$, 85.7% for $M = 4$ and 83.8% for $M = 6$. Moreover, as the number of processors is increased the energy consumption is reduced as lower frequencies can be selected and partial task duplication can be applied by H_RAFTM, as long as the reliability constraint is met.



(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 11: Reliability improvement (RI) and Computation Time (CT in seconds) of GE ($N = 14$) for $M = 2$, $M = 4$ and $M = 6$.

Regarding computation time, it is increased when the number of tasks increases as expected, but still remains low compared to the prohibited computation time required for the optimal approach. For a small randomly generated task with $N = 10$ (Table 5 when $M = 4$ and Table 6 when $M = 6$), the proposed heuristic takes less than 1 sec to find a solution for all experiments whereas for a large randomly generated task with $N = 100$, the average com-

putation time (considering all experiments and deadlines) is 144 sec ($M = 2$), 159 sec ($M = 4$) and 212 sec ($M = 6$). Comparing the computation time of the three heuristics for large DAGs $N = 100$, the average computation time for H_RAM is 52 sec ($M = 2$), 66 sec ($M = 4$) and 75 sec ($M = 6$). For H_TDM, the average computation time is 488 ($M = 2$), 501 sec ($M = 4$) and 718 sec ($M = 6$). Overall, we observe that the H_TDM is the more time consuming approach, and H_RAM the least time consuming approach. However, H_TDM is not able to always find solutions, whereas H_RAFTM finds solutions with always same or less energy consumption compared to H_RAM and H_TDM.

5 Conclusion

A heuristic algorithm is proposed to obtain the task mapping of parallel applications, under real-time, reliability and task dependency constraints. The goal is to minimize total energy consumption by deciding frequency assignment, task allocation, task scheduling and task duplication. Based on the experimental results from real-world applications and randomly generated task graphs, the proposed heuristic achieves near-optimal results, with low computation time. Compared to similar heuristics, it achieves better energy consumption and is able to find solutions even when the other approaches fail. As future work, we will propose similar heuristics for other DVFS schemes provided by platforms, such as assigning a common frequency at cluster, processor and platform level.

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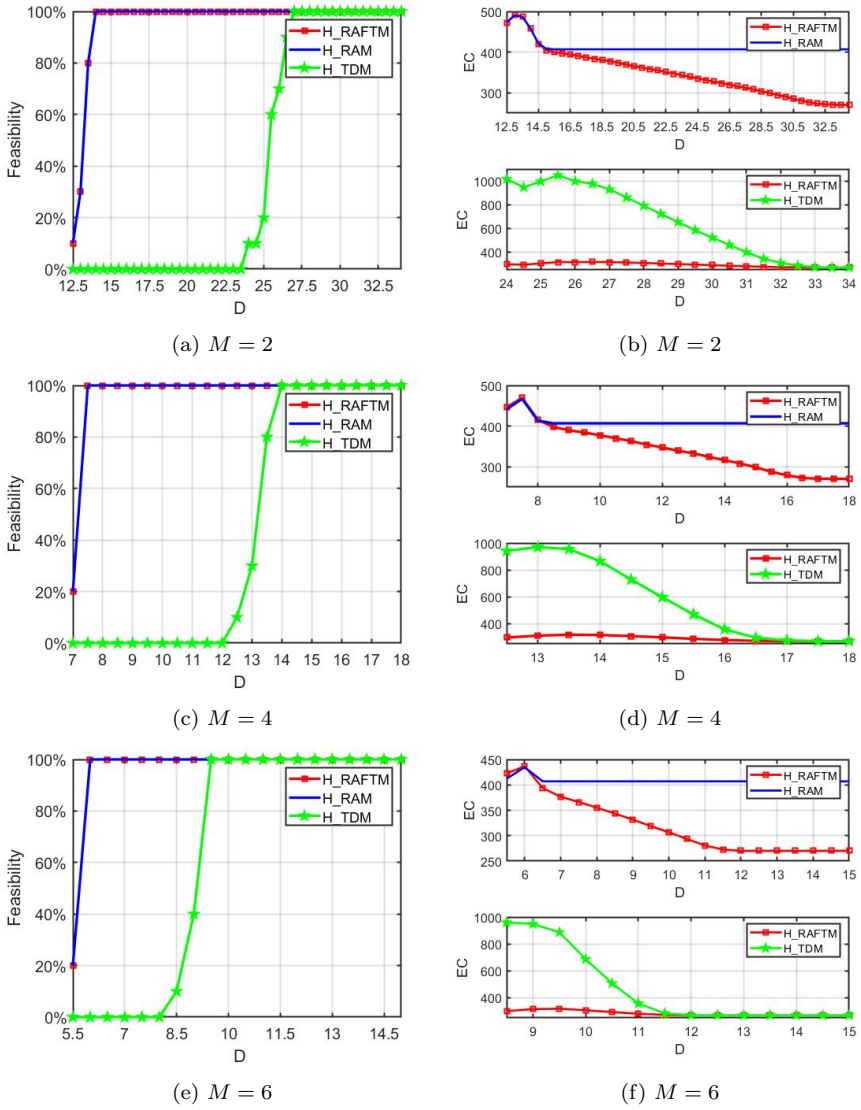

(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 12: Feasibility and Energy Consumption (EC in mJ) of large randomly generated DAG ($N = 100$) for $M = 2$, $M = 4$ and $M = 6$.

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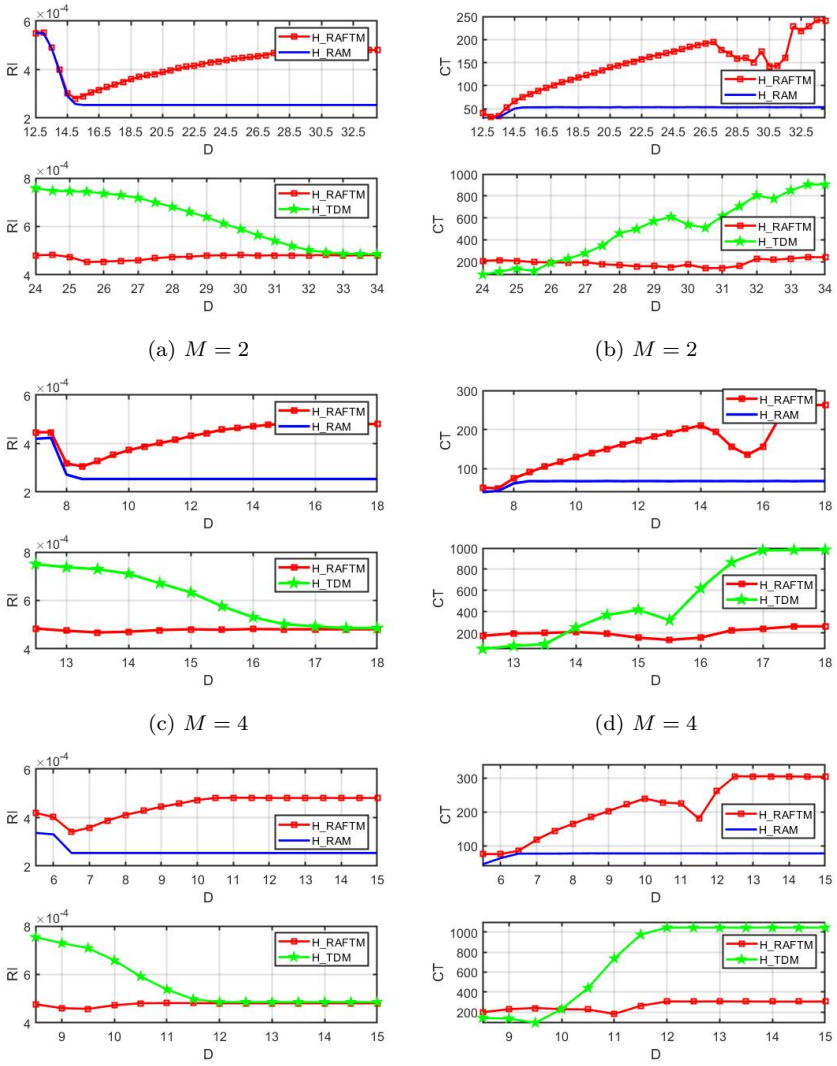

(a) $M = 2$ (b) $M = 2$

(c) $M = 4$ (d) $M = 4$

(e) $M = 6$ (f) $M = 6$

Fig. 13: Reliability Improvement (RI) and Computation Time (CT in seconds) of large randomly generated DAG ($N = 100$) for $M = 2$, $M = 4$ and $M = 6$.

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