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Maximizing reliability of energy constrained parallel applications on heterogeneous distributed systems

Xiongren Xiao [a,b], Guoqi Xie [a,b,*], Cheng Xu [a,b], Chunnian Fan [c], Renfa Li [a,b], Keqin Li [a,d]

[a] College of Computer Science and Electronic Engineering, Hunan University, China
[b] Key Laboratory for Embedded and Network Computing of Hunan Province, China
[c] Nanjing University of Information Science and Technology, China
[d] Department of Computer Science, State University of New York, New Paltz, NY, USA

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ABSTRACT

Energy is one of the primary design constraints in heterogeneous distributed systems ranging from small embedded devices to large-scale data centers, where a parallel application with precedence-constrained tasks is represented by a directed acyclic graph (DAG). Dynamic voltage and frequency scaling (DVFS) has become an important energy control technology by simultaneously scaling down processor's supply voltage and frequency while tasks are running. However, recent studies show that dynamically scaling down the chip's voltage may lead to a sharp rise in transient failures of processors, thereby affecting the reliability of the system. This study solves the problem of maximizing reliability of an energy constrained parallel application on heterogeneous distributed systems based on DVFS. The problem is decomposed into two sub-problems, namely, satisfying energy constraint and maximizing reliability. The first sub-problem is solved by transferring the energy constraint of the application to that of each task, and the second sub-problem is solved by heuristically scheduling each task with maximum reliability value while satisfying its energy constraint. Experiments with real parallel applications show that the proposed MREC algorithm can obtain larger reliability values than the state-of-the-art reliability maximum energy conservation (RMEC) algorithm while satisfying the energy constraints.

1. Introduction

1.1. Background

The trend reflected the ongoing progress in semiconductor technology allows for building fascinating, complex cloud, grid, and cluster computing systems [1–6]. With the continuous improvement in integration and performance of system architecture, power consumption is gradually increasing and has become a major bottleneck in system design. Energy is one of the primary design constraints in heterogeneous distributed systems ranging from small embedded devices to large-scale data centers [7]. Energy has become a major issue affecting the development and use of computing systems, as well as the human environment. Dynamic voltage and frequency scaling (DVFS) has become an important energy control technology by simultaneously scaling down processor's supply voltage and frequency [8,9]. However, recent studies show that dynamically scaling down the chip's voltage may lead to a sharp rise in transient failures of processors, thereby affecting the reliability of the system. A conflicting relationship exists between energy and reliability [1,8,10,11]. Energy and reliability are in conflict lower energy would result in lower reliability, and higher energy would obtain higher reliability.

As heterogeneous multi-processors continue to scale [3,12–16], increasing parallel applications with precedence constrained tasks widely exist in high-performance computing systems. A parallel application with precedence constrained tasks is represented by a directed acyclic graph (DAG) where the nodes represent the tasks and the edges represent the communication messages between tasks [12–16]. The state-of-the-art work investigated the problem of maximizing the reliability of an energy constrained parallel application on heterogeneous distributed systems, where the reliability maximization with energy constraint (RMEC) algorithm is presented [10]. RMEC is implemented by traversing all processor and frequency combinations and selecting the combination based

* Corresponding author at: College of Computer Science and Electronic Engineering, Hunan University, China.

E-mail addresses: xxr@hnu.edu.cn (X. Xiao), xgqman@hnu.edu.cn (G. Xie), chengxu@hnu.edu.cn (C. Xu), fcn@nuist.edu.cn (C. Fan), lirenfa@hnu.edu.cn (R. Li), lik@newpaltz.edu (K. Li).

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on the reliability maximum energy conservative function in each task assignment. However, the RMEC algorithm can be further optimized due to the following reasons:

(1) RMEC does not aim to maximize reliability. Reliability and frequency are monotonically increasing on the same processor according to the relationship function between them (Eq. (7)). As there is monotonic increase between energy-efficient frequency and energy (Eq. (4)), reliability and energy should be monotonically increasing on the same processor. RMEC just implements a tradeoff optimization between enhancing reliability and saving energy and it does not aim to maximize reliability. Moreover, even if it finds an optimal combination, this combination is not necessarily satisfying the total energy constraint of the application. If this optimal combination is skipped, then the process may not be optimal.

(2) Due to the monotonic increase of reliability and frequency, many lower frequencies are not useful in enhancing reliability; hence, these lower frequencies do not need to be verified and can be skipped in traversing.

1.2. Our contributions

Our main work in this study is to maximizing the reliability of an energy constrained parallel application in heterogeneous distributed systems. The problem is divided into two sub-problems: satisfying energy constraint and maximizing reliability. Our contributions, which comparing to the state-of-the-art work [10], are summarized as follows:

(1) Satisfying energy constraint is solved by letting the unassigned tasks be preassigned to the processor with the minimum energy, and the energy constraint of the application is then transferred to that of each task, such that the heuristic algorithm with low time complexity could be used.

(2) Maximizing reliability is solved by considering that the energy of each task can be determined before the task is assigned, we select the processor and frequency combination that has the maximum reliability value while satisfying its energy constraint. Specifically, we verify from the highest to the lowest frequencies. Once we find the frequency that satisfies the energy constraint of the application, then the frequency is optimal in this processor, and the remaining frequencies can be skipped.

(3) The extensive experiments with real parallel applications is done and the results shows that not only do the actual energy values not always exceed and are close to given energy constraints, but also that maximum reliability values are generated compared with the RMEC algorithm.

The rest of this paper is organized as follows. Section 2 reviews related studies. Section 3 builds related models. Section 4 solves the presented problem. Section 5 verifies the performance of the proposed algorithm. Section 6 concludes this study.

2. Related work

This section mostly reviews recent related research on energy, reliability, and their relationship of a DAG-based parallel application.

DVFS-based energy-efficient design techniques have been used for parallel applications with precedence constrained tasks. In [17], the authors presented energy-conscious scheduling to implement joint minimization between schedule length and energy of a parallel application on heterogeneous distributed systems. The problem of minimizing the schedule length of an energy constrained application with precedence constrained sequential tasks [18] and precedence constrained parallel tasks (i.e., a parallel application) [19,20] were solved. These two works were merely interested in homogeneous systems with shared memory. In [7,21], we studied the same problem on heterogeneous distributed systems.

In general, the transient failure-free probability of a processor is subject to the Poisson distribution [2,22–24]. Intuitively, larger reliability could cause longer schedule length of a parallel application and the problem of optimizing schedule length and reliability is considered as a typical Bi-criteria optima or Pareto optima problem [23,25]. In [26], the authors investigated the Bi-criteria optima problem between reliability and scheduled length by merging the Bi-criteria of scheduled length and reliability into a single objective function for joint optimization of them. The method in [26] has better reliability but longer scheduled length than that in [23]. In [25], the authors implemented the bio-objective optimization of maximizing reliability and minimizing scheduled length.

Energy and reliability have a close relationship. In [27], the authors built the relationship model between energy and reliability and solved the problem of maximizing the reliability of a parallel application with deadline and energy constraints on a single-processor. On the basis of [27], the authors further solved the problem of minimizing the energy of a parallel application with deadline constraint and reliability preservation on a single-processor [28]. In [10], the authors studied the problem of maximizing the reliability of a parallel application with energy constraint on heterogeneous distributed systems. The main limitations of [10] are summarized earlier in Section 1.2. In [11], the authors studied the joint optimization between the energy and the reliability of a parallel application with deadline constraint on heterogeneous distributed systems. This study aims to solve the same problem as [10], namely, maximizing the reliability of a parallel application with energy constraint on heterogeneous distributed systems.

3. Models

Table 1 gives the important notations and their definitions used in this study.

Table 1
Important notations in this study.

Notation	Definition
$c_{i,j}$	Communication time between the tasks n_i and n_j
$w_{i,k}$	Execution time of the task n_i running on the processor u_k with the maximum frequency
$f_{k,\mathrm{ee}}$	Minimum energy-efficient frequency of the processor u_k
$E(n_i, u_k, f_{k,h})$	Energy of the task n_i on the processor u_k with the frequency $f_{k,h}$
$R(n_i, u_k)$	Reliability of the task n_i executed on the processor u_k
$R(G)$	Reliability of the parallel application G
$SL(G)$	Schedule length of the parallel application G
$\lambda_{k,h}$	Failure rate per time unit of the processor u_k with the frequency $f_{k,h}$
$R(n_i, u_k, f_{k,h})$	Reliability of the task n_i executed on the processor u_k with the frequency $f_{k,h}$
$u_{pr(i)}$	Assigned processor of the task n_i
$f_{pr(i),hz(i)}$	Assigned frequency of the task n_i on the processor $u_{pr(i)}$
$E_{\min}(n_i)$	Minimum energy of the task n_i
$E_{\max}(n_i)$	Maximum energy of the task n_i
$E_{\min}(G)$	Minimum energy of the parallel G
$E_{\max}(G)$	Maximum energy of the parallel application G
$E_{\mathrm{given}}(G)$	Energy constraint of the parallel application G
$E_{\mathrm{given}}(n_i)$	Energy constraint of the task n_i

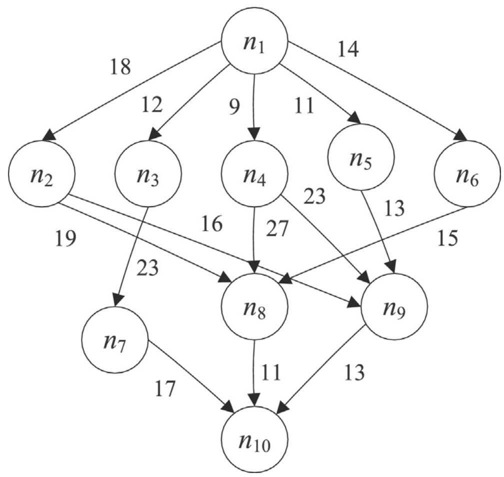

Fig. 1. A motivating example of a DAG-based parallel application with 10 tasks [14,15,7].

3.1. Application model

Let $U=\{u_1, u_2, \ldots, u_{|U|}\}$ represent a set of heterogeneous processors, where $|U|$ represents the size of set U. Note that for any set X, this study uses $|X|$ to denote its size. A parallel application running on processors is represented by a DAG G=(N, W, M, C) [10–16,29,7,21,30]. N represents a set of nodes in G, and each node $n_i \in N$ represents a task. $pred(n_i)$ represents the set of the immediate predecessor tasks of n_i. $succ(n_i)$ represents the set of the immediate successor tasks of n_i. The task which has no predecessor task is denoted as n_{entry}; and the task which has no successor task is denoted as n_{exit}. If an application has multiple n_{entry} or multiple n_{exit} tasks, then a dummy entry or exit task with zero-weight dependencies is added to the graph. W is an $|N| \times |U|$ matrix where $w_{i,k}$ denotes the execution time of n_i and runs on u_k with the maximum frequency [31]. M is a set of communication edges, and each edge $m_{i,j} \in M$ represents the communication message from n_i to n_j. Accordingly, $c_{i,j} \in C$ represents communication time of $m_{i,j}$ if n_i and n_j are not assigned to the same processor.

Fig. 1 shows a motivating example of a DAG-based parallel application. Table 2 is a matrix of execution time with the maximum frequency in Fig. 1. The example shows 10 tasks executed on three processors $\{u_1, u_2, u_3\}$. The weight 14 of n_1 and u_1 in Table 2 represents the execution time denoted by $w_{1,1}$=14. We can see that the same task has different execution time on different processors due to the heterogeneity of the processors [14]. The weight 18 of edge (Fig. 1) between n_1 and n_2 represents the communication time denoted as $c_{1,2}$ if n_1 and n_2 are not assigned to the same processor.

Table 2
Execution time of tasks on different processors with the maximum frequency of the parallel application in Fig. 1 [14,15,7].

Task	u_1	u_2	u_3
n_1	14	16	9
n_2	13	19	18
n_3	11	13	19
n_4	13	8	17
n_5	12	13	10
n_6	13	16	9
n_7	7	15	11
n_8	5	11	14
n_9	18	12	20
n_{10}	21	7	16

3.2. Power and energy model

Considering the almost linear relationship between the voltage and frequency, DVFS scales down the voltage alongside the frequency to save energy. Similar to [32,27,28,10,11,7,21], we use the term frequency change to represent changing the voltage and frequency simultaneously. Considering a DVFS-enable system, we also employ the system-level power model widely accepted in may works [32,27,28,10,11,7,21], where the power consumption at frequency f is calculated by

$$P(f) = P_s + h(P_{\text{ind}} + P_{\text{d}}) = P_s + h(P_{\text{ind}} + C_{\text{ef}} f^m). \quad (1)$$

P_s represents the static power and can be removed only by powering off the whole system. P_{ind} represents frequency-independent dynamic power and can be removed by putting the system into the sleep state. P_{d} represents frequency-dependent dynamic power, and depends on frequencies. h represents system states and indicates whether dynamic powers are currently consumed in the system. When the system is active, h = 1; otherwise, h = 0. C_{ef} represents effective switching capacitance and m represents the dynamic power exponent and is no smaller than 2. Both C_{ef} and m are processor-dependent constants.

Note that there exists an excessive overhead associated with turning on/off a system, P_s is always consumed and is not manageable [32,27,28,10,11,7,21]. Therefore, similar to the aforementioned works, we also concentrate on managing the dynamic power, namely, P_{ind} and P_{d}). Less P_{d} does not result in less dynamic energy due to the P_{ind} according to Eq. (1). Therefore, there is a minimum energy-efficient frequency f_{ee}, [32,27,28,10,11,7,21] and it is denoted by

$$f_{\text{ee}} = \sqrt[m]{\frac{P_{\text{ind}}}{(m-1)C_{\text{ef}}}}. \quad (2)$$

Assuming the frequency of a processor varies from a minimum available frequency $f_{\min}$ to the maximum frequency $f_{\max}$, the lowest energy-efficient frequency to execute a task is

$$f_{\text{low}} = \max(f_{\min}, f_{\text{ee}}). \quad (3)$$

Therefore, any actual effective frequency f_h should belong to the scope of $f_{\text{low}} \leqslant f_{\text{h}} \leqslant f_{\max}$.

Considering that the number of processors is $|U|$ in the system and these processors are completely heterogeneous, each processor should have individual power parameters [7,21], and we define them as follows: The frequency-independent dynamic power set is

$$\{P_{1,\text{ind}}, P_{2,\text{ind}}, \ldots, P_{|U|,\text{ind}}\},$$

The frequency-dependent dynamic power set is

$$\{P_{1,\text{d}}, P_{2,\text{d}}, \ldots, P_{|U|,\text{d}}\},$$

The effective switching capacitance set is

$$\{C_{1,\text{ef}}, C_{2,\text{ef}}, \ldots, C_{|U|,\text{ef}}\},$$

The dynamic power exponent set is

$$\{m_1, m_2, \ldots, m_{|U|}\},$$

The lowest energy-efficient frequency set is

$$\{f_{1,\text{low}}, f_{2,\text{low}}, \ldots, f_{|U|,\text{low}}\},$$

and the actual effective frequency set is

$$\left\{\begin{array}{c}\{f_{1,\text{low}}, f_{1,\alpha}, f_{1,\beta}, \ldots, f_{1,\max}\},\\ \{f_{2,\text{low}}, f_{2,\alpha}, f_{2,\beta}, \ldots, f_{2,\max}\},\\ \ldots,\\ \{f_{|U|,\text{low}}, f_{|U|,\alpha}, f_{|U|,\beta}, \ldots, f_{|U|,\max}\}\end{array}\right\}.$$

Finally, let $E(n_i, u_k, f_{k,h})$ represent the dynamic energy of the task n_i on the processor u_k with frequency $f_{k,h}$ and is calculated as

$$E(n_i, u_k, f_{k,h}) = \left(P_{k,\text{ind}} + C_{k,\text{ef}} \times (f_{k,h})^{m_k}\right) \times w_{i,k} \times \frac{f_{k,\max}}{f_{k,h}}. \tag{4}$$

3.3. Reliability model

For a non-DVFS-enable system, Shatz and Wang first proposed that the reliability probability for a processor is subject to the Poisson distribution [22] and it was widely accepted by numerous works [8,27,28,10,11,22–24]. We use λ_k to represent the failure rate per time unit of the processor u_k, then the reliability of n_i executed on u_k in its execution time is calculated by

$$R(n_i, u_k) = e^{-\lambda_k w_{i,k}}. \tag{5}$$

Similar to most studies [27,28,10,11], the reliability of the parallel application with precedence constrained tasks is denoted by

$$R(G) = \prod_{n_i \in N} R(n_i) = \prod_{n_i \in N} R(n_i, u_{pr(i)}),$$

where $R(n_i)$ represents the actual reliability of n_i and $u_{pr(i)}$ represents the assigned processor of n_i.

In a DVFS-capable system, different frequencies have different failure rates according to relevant research summaries [27,28,10,11]. Hence, we let $\lambda_{k,\max}$ represent the failure rate of the processor u_k with the height frequency, then the failure rate $\lambda_{k,h}$ of the u_k with the frequency $f_{k,h}$ is calculated as

$$\lambda_{k,h} = \lambda_{k,\max} 10^{d(f_{k,\max} - f_{k,h})/(f_{k,\max} - f_{k,\min})}, \tag{6}$$

where d is a constant, which represents the sensitivity of failure rates to voltage scaling.

We then build the relationship between task reliability and the frequency according to Eqs. (5) and (6), namely, the reliability of the task n_i executed on the processor u_k with the frequency $f_{k,h}$ is calculated as

$$\begin{aligned} R(n_i, u_k, f_{k,h}) &= e^{-\lambda_{k,h} \times \frac{w_{i,k} \times f_{k,\max}}{f_{k,h}}} \\ &= e^{-\lambda_{k,\max} 10^{\frac{d(f_{k,\max} - f_{k,h})}{f_{k,\max} - f_{k,\min}}} \times \frac{w_{i,k} \times f_{k,\max}}{f_{k,h}}}. \end{aligned} \tag{7}$$

We can see from Eq. (7) that the relationship between reliability and frequency is monotonically increasing on the same processor. That is, dynamically scaling down the voltage and frequency for reducing energy could result in low reliability. Then the application reliability in a DVFS-capable system is correspondingly adjusted as [27,28,10,11]

$$R(G) = \prod_{n_i \in N} R\left(n_i, u_{pr(i)}, f_{pr(i),hz(i)}\right), \tag{8}$$

where $u_{pr(i)}$ and $f_{pr(i),hz(i)}$ represent the assigned processor and frequency of n_i, respectively,

3.4. Energy constraint

As the execution time of each task on each processor is known, we can get the minimum and maximum energy value denoted by $E_{\min}(n_i)$ and $E_{\max}(n_i)$, respectively, by traversing all the processors [7,21]. $E_{\min}(n_i)$ and $E_{\max}(n_i)$ are obtained by executing the task with the maximum and minimum frequencies, respectively. Both of them are calculated by

$$E_{\min}(n_i) = \min_{u_k \in U} E(n_i, u_k, f_{k,\max}), \tag{9}$$

and

$$E_{\max}(n_i) = \max_{u_k \in U} E(n_i, u_k, f_{k,\text{low}}), \tag{10}$$

respectively.

As the energy of the application G is the sum of that of each task, we can obtain that the minimum and maximum energy value of G are

$$E_{\min}(G) = \sum_{i=1}^{|N|} E_{\min}(n_i), \tag{11}$$

and

$$E_{\max}(G) = \sum_{i=1}^{|N|} E_{\max}(n_i), \tag{12}$$

respectively.

Assume that the given energy constraint of G is $E_{\text{given}}(G)$, then it should be larger than or equal to $E_{\min}(G)$; otherwise, $E_{\text{given}}(G)$ is always satisfied. Meanwhile, $E_{\text{given}}(G)$ should be less than or equal to $E_{\max}(G)$; otherwise, $E_{\text{given}}(G)$ is always not satisfied. Hence, this study assumes that $E_{\text{given}}(G)$ belongs to the scope $E_{\min}(G)$ and $E_{\max}(G)$, namely,

$$E_{\min}(G) \leqslant E_{\text{given}}(G) \leqslant E_{\max}(G).$$

3.5. Problem description

The problem to be addressed in this study is to assign an available processor with a proper frequency for each task, while minimizing the schedule length of the application and ensuring that the consumed energy of the application not exceed the energy constraint. The formal description is finding the processor and frequency assignments of all tasks to minimize the schedule length of the application:

$$R(G) = \prod_{n_i \in N} R\left(n_i, u_{pr(i)}, f_{pr(i),hz(i)}\right),$$

subject to its energy constraint:

$$E_{\text{total}}(G) = \sum_{i=1}^{|N|} E(n_i, u_{pr(i)}, f_{pr(i),hz(i)}) \leqslant E_{\text{given}}(G), \tag{13}$$

and $f_{pr(i),\text{low}} \leqslant f_{pr(i),hz(i)} \leqslant f_{pr(i),\max}$, for $\forall i: 1 \leqslant i \leqslant |N|$, $u_{pr(i)} \in U$.

We know that the problem of mapping tasks to multiple multiprocessors is NP-hard [33]. Therefore, we use heuristic list scheduling to solve the subject problem in this study. List scheduling is the most well-known method for a DAG-based parallel application [12,14,15,17,7,21], and it includes two phases. The first phase orders tasks based on the descending order of priorities (task prioritizing), whereas the second phase allocates each task to the appropriate processor (task allocation). In this study, task allocation is decomposed into two sub-problems: satisfying the energy constraint and maximizing reliability.

Table 3
Upward rank values of the tasks of the motivating parallel application in Fig. 1 [14].

Task	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}
$rank_u(n_i)$	108	77	80	80	69	63.3	42.7	35.7	44.3	14.7

4. Proposed algorithm

4.1. Task prioritizing

We first need to determine the task assignment order before assigning tasks to processors. Similar to [14,17,7,21], we employ the upward rank value ($rank_u$) of a task given by Eq. (14) as the common task priority standard:

$$rank_u(n_i) = \bar{w}_i + \max_{n_j \in succ(n_i)} \{c_{i,j} + rank_u(n_j)\}, \tag{14}$$

where $\bar{w}_i$ represents the average execution time of task n_i and is calculated as

$$\bar{w}_i = \left(\sum_{k=1}^{|U|} w_{i,k}\right) / |U|.$$

All the tasks are ordered according to the decreasing order of $rank_u$. Table 3 shows the upward rank values of all the tasks (Fig. 1). Note that only if all the predecessors of n_i have been assigned to the processors, will n_i prepare to be assigned. Assume that two tasks n_i and n_j satisfy $rank_u(n_i) > rank_u(n_j)$, if no precedence constraint exists between n_i and n_j, n_i does not necessarily take precedence n_j to be assigned. We can draw that the task assignment order in G is $\{n_1, n_3, n_4, n_2, n_5, n_6, n_9, n_7, n_8, n_{10}\}$.

4.2. Satisfying energy constraint

As the task prioritization has been determined, we can then do the following work to implement task's energy constraint. Assume that the task to be assigned is $n_{seq(j)}$, where $seq(j)$ represents the jth assigned task (sequence number), then $\{n_{seq(1)}, n_{seq(2)}, \ldots, n_{seq(j-1)}\}$ represents the task set where the tasks have been assigned, and $\{n_{seq(j+1)}, n_{seq(j+2)}, \ldots, n_{seq(|N|)}\}$ represents the task set where the tasks have not been assigned. To ensure that the energy constraint of the application is satisfied at each task assignment, we let each unassigned task in $\{n_{seq(j+1)}, n_{seq(j+2)}, \ldots, n_{seq(|N|)}\}$ is preassigned to the processor and frequency with the minimum energy value. Hence, when assigning $n_{seq(j)}$, the energy of G is calculated as

$$\begin{aligned} E_{seq(j)}(G) &= \sum_{x=1}^{j-1} E(n_{seq(x)}, u_{pr(seq(x))}, f_{pr(seq(x)),hz(seq(x))}) \\ &\quad + E(n_{seq(j)}, u_k, f_{k,h}) + \sum_{y=j+1}^{|N|} E_{\min}(n_{seq(y)}). \end{aligned}$$

As the unassigned tasks are preassigned to the processor and frequency with the minimum energy value, any task $n_{seq(j)}$, only it satisfies

$$\begin{aligned} E_{seq(j)}(G) &= \sum_{x=1}^{j-1} E(n_{seq(x)}, u_{pr(seq(x))}, f_{pr(seq(x)),hz(seq(x))}) \\ &\quad + E(n_{seq(j)}, u_k, f_{k,h}) + \sum_{y=j+1}^{|N|} E_{\min}(n_{seq(y)}) \\ &\leqslant E_{\text{given}}(G). \end{aligned} \tag{15}$$

then the actual total energy of $E_{\text{total}}(G)$ should be less than or equal to $E_{\text{given}}(G)$.

Then, we can give the energy constraint of each task before we propose the algorithm. According to Eq. (15), we have

$$\begin{aligned} E(n_{seq(j)}, u_k, f_{k,h}) \leqslant E_{\text{given}}(G) \\ - \sum_{x=1}^{j-1} E(n_{seq(x)}, u_{pr(seq(x))}, f_{pr(seq(x)),hz(seq(x))}) \\ - \sum_{y=j+1}^{|N|} E_{\min}(n_{seq(y)}). \end{aligned}$$

Hence, let the energy constraint of the task $n_{seq(y)}$ be

$$\begin{aligned} E_{\text{given}}(n_{seq(j)}) = E_{\text{given}}(G) \\ - \sum_{x=1}^{j-1} E(n_{seq(x)}, u_{pr(seq(x))}, f_{pr(seq(x)),hz(seq(x))}) \\ - \sum_{y=j+1}^{|N|} E_{\min}(n_{seq(y)}), \end{aligned} \tag{16}$$

then, we can transfer the energy constraint of the application to that of each task. That is, we just let $n_{seq(j)}$ satisfy the following constraint:

$$E(n_{seq(j)}, u_k, f_{k,h}) \leqslant E_{\text{given}}(n_{seq(j)}).$$

Hence, when assigning the task $n_{seq(j)}$, we can directly consider the energy constraint $E_{\text{given}}(n_{seq(j)})$ of $n_{seq(j)}$ and do not have to be concerned about the energy constraint of the application G. In this way, a low time complexity heuristic algorithm can be achieved. As the maximum energy constraint of $n_{seq(j)}$ is $E_{\max}(n_{seq(j)})$, $E_{\text{given}}(n_{seq(j)})$ should be required to satisfy the following constraint:

$$E(n_{seq(j)}, u_k, f_{k,h}) \leqslant \min\{E_{\text{given}}(n_{seq(j)}), E_{\max}(n_{seq(j)})\}. \tag{17}$$

4.3. Maximizing reliability with proposed algorithm

Inspired by the above analysis, we propose the algorithm called maximize reliability with energy constraint (MREC). The steps of MREC are described in Algorithm 1.

Algorithm 1. The MREC Algorithm

Input: $U = \{u_1, u_2, \ldots, u_{|U|}\}$, $G = (N, W, M, C)$
Output: $E_{\text{total}}(G)$, $R(G)$

1: Sort the tasks in a list *downward_task_list* by descending order of $rank_u$ values.
2: **while** (there are tasks in *downward_task_list*) **do**
3: n_i = *downward_task_list.out*();
4: Calculate $E_{\min}(n_i)$ and $E_{\max}(n_i)$ using Eqs. (9) and (10), respectively;
5: Calculate $E_{\text{given}}(n_i)$ using Eq. (16); // **1) calculate the energy constraint of n_i before it prepares to be assigned.**
6: var $pr(i) = NULL$, $f_{pr(i),hz(i)} = NULL$, $R(n_i, u_{pr(i)}, f_{pr(i),hz(i)}) = 0$, $E(n_i, u_{pr(i)}, f_{pr(i),hz(i)}) = 0$;
7: **for** (each processor $u_k \in U$) **do**
8: **for** (each frequency $f_{k,h}$ in from $f_{k,\max}$ and $f_{k,\text{low}}$) **do**
9: Calculate $E(n_i, u_k, f_{k,h})$ using Eq. (4);
10: **if** ($E(n_i, u_k, f_{k,h}) > \min\{E_{\text{given}}(n_i), E_{\max}(n_i)\}$) **then**
11: continue; // **2) skip the processor and frequency combinations that do not satisfy the energy constraint of n_i.**
12: **end if**
13: Calculate $R(n_i, u_k, f_{k,h})$ using Eq. (7);
14: **if** ($R(n_i, u_k, f_{k,h}) > R(n_i, u_{pr(i)}, f_{pr(i),hz(i)})$) **then**
15: $pr(i) = k$;
16: $f_{pr(i),hz(i)} = f_{k,h}$;
17: $E(n_i, u_{pr(i)}, f_{pr(i),hz(i)}) = E(n_i, u_k, f_{k,h})$;
18: $R(n_i, u_{pr(i)}, f_{pr(i),hz(i)}) = R(n_i, u_k, f_{k,h})$; // **3) select the processor and frequency combination with the maximum $R(n_i, u_{pr(i)}, f_{pr(i),hz(i)})$.**
19: break; // **4) skip the lower frequencies that generate lower reliability.**
20: **end if**
21: **end for**
22: **end for**
23: **end while**
24: Calculate the actual energy value $E_{\text{total}}(G)$ using Eq. (13);
25: Calculate $R(G)$ using Eq. (8).

The main idea of MREC is that the energy constraint of the application is transferred to that of each task. Each task just selects the processor and frequency with the maximum reliability while satisfying its energy constraint. The main advantages are explained as follows.

(1) MREC has obtained the energy constraint of each task before it prepares to be assigned (Line 5).

(2) MREC skips the processor and frequency combinations that do not satisfy the energy constraint (Lines 10-12). That is, MREC does not need to calculate the total energy value of the application and to determine whether it satisfies the given energy constraint in each task assignment by traversing all the tasks in the parallel application. On the contrary, RMEC (proposed in [10]) must do such operation.

(3) MREC selects the processor and frequency combination with the maximum reliability for each task while satisfying the condition of $E(n_i, u_k, f_{k,h}) \leqslant \min\{E_{\text{given}}(n_i), E_{\max}(n_i)\}$ (Lines 14-20). On the contrary, RMEC just implements a tradeoff optimization between enhancing reliability and saving energy and it does not aim to maximize reliability.

(4) As the monotone increasing relationship between reliability and frequency, once a processor and frequency combination was found, then the remaining lowest frequencies can be skipped (Line 19). On the contrary, RMEC should traverse all the processor and frequency combinations to find an optimal RME.

The time complexity of the MREC algorithm is analyzed as follows. Scheduling all tasks must traverse all tasks, which can be done in O(|N|) time. Calculating the maximum reliability value of each task can be done in O(|U| × |F|) time, where |F| represents the maximum number of discrete frequencies from the lowest to the maximum actual effective frequencies. Hence, the time complexity of the MRCRG algorithm is $O(|N| \times |U| \times |F|)$. Therefore, MREC implements low time complexity scheduling to maximize reliability of an energy constrained parallel application.

Table 4
Power and failure parameters of processors (u_1, u_2, and u_3).

u_k	$P_{k,\text{ind}}$	$C_{k,\text{ef}}$	m_k	$f_{k,\text{low}}$	$f_{k,\max}$	$\lambda_{k,\max}$
u_1	0.03	0.8	2.9	0.26	1.0	0.00015
u_2	0.04	0.7	2.5	0.27	1.0	0.00020
u_3	0.07	1.0	2.5	0.29	1.0	0.00025

4.4. Example of the MREC algorithm

This subsection gives an example to show the results using the MREC algorithm. We assume that the power parameters for all processors are known and shown in Table 4, where the maximum frequency $f_{k,\max}$ for each processor is 1 and the frequency precision is set at 0.01.

We can obtain the lowest energy-efficient frequency $f_{k,\text{low}}$ for each processor according to Eq. (3). We can calculate that the minimum and maximum energy values are $E_{\min}(G) = 19.9463$ and $E_{\max}(G) = 157.74$ according to Eqs. (11) and (12), respectively, for the motivating parallel application. We set the energy constraint of G as $E_{\text{given}}(G) = 3 \times E_{\min}(G) = 59.8390$.

Table 5 shows the task assignment process of the motivating parallel application using MREC, where each row represents a task assignment and all the tasks select individual processor and frequency combinations and satisfy their individual energy constraints. We can see that only partial tasks are assigned to the processors with low frequencies (denoted with bold texts).

Fig. 2 also shows the scheduling of the motivating parallel application G using MREC, where the schedule length is $SL(G) = 147.98$. Note that the arrows in Fig. 2 represent generated communication time between tasks. We can see that n_6, n_9, n_7, n_8, and n_{10} (denoted with bold texts)are assigned to the processors with low frequencies.

Finally, the actual consumed energy of the application is $E_{\text{total}}(G) = 59.8384$, which is less than and close to $E_{\text{given}}(G) = 59.8390$. The final schedule length is $SL(G)$=147.98. This example also verifies that using MREC can ensure that the actual consumed energy does not exceed the given energy constraint, namely, $E_{\text{total}}(G) \leqslant E_{\text{given}}(G)$.

5. Experiments

5.1. Experimental metrics

The performance metrics selected for comparison are the actual energy value $E_{\text{total}}(G)$ (Eq. (13)) and the final reliability $R(G)$ (Eq. (8)) of the application. The compared algorithm with the proposed MREC algorithm is RMEC [10]. Processor and application parameters refer [27,28] and are below: 10 h $\leqslant w_{i,k} \leqslant$ 100 h, 10 h $\leqslant c_{i,j} \leqslant$ 100 h, $0.03 \leqslant P_{k,\text{ind}} \leqslant 0.07$, $0.8 \leqslant C_{k,\text{ef}} \leqslant 1.2$, $2.5 \leqslant m_k \leqslant 3.0$, $f_{k,\max}$ = 1 GHz, and $0.0000001 \leqslant \lambda_k \leqslant 0.0000128$. All frequencies are discrete, and the precision is 0.01 GHz. All parallel applications will be executed in a simulated heterogeneous multi-processor platform with 128 processors by creating 128 process objects. Real parallel applications with precedence constrained tasks are widely used in high-performance computing, such as the GE and the FFT [14], which are two typical parallel applications with high and low parallelism, respectively. To verify effectiveness and reality, we use these two types of real parallel applications to observe the results.

5.2. GE experiments

Experiment 1. This experiment is conducted to compare the actual energy values and final reliability of GE applications for

Table 5
Task assignment process of the motivating parallel application using MREC.

n_i	Task's energy constraint $E_{given}(n_i)$	Assigned processor $u_{pr(i)}$	Assigned frequency $f_{pr(i),hz(i)}$	Actual energy value $E(n_i, u_{pr(i)}, f_{pr(i),hz(i)})$	Final reliability value $R(n_i, u_{pr(i)}, f_{pr(i),hz(i)})$
n_1	11.84	u_1	1.0	11.62	0.9979
n_3	20.33	u_1	1.0	9.13	0.9984
n_4	18.19	u_2	1.0	5.92	0.9984
n_2	19.26	u_1	1.0	10.79	0.9981
n_5	10.7	u_1	1.0	9.96	0.9982
n_6	5.611	u_1	**0.68**	5.5716	0.9799
n_9	2.9958	u_2	**0.3**	2.9803	0.9223
n_7	1.2563	u_1	**0.28**	1.2486	0.9628
n_8	0.8940	u_1	**0.28**	0.8919	0.9733
n_{10}	1.7266	u_2	**0.28**	1.7260	0.9510

$E_{total}(G) = 59.8384 \leqslant E_{given}(G) = 59.8390$, $R(G) = 0.8200$.

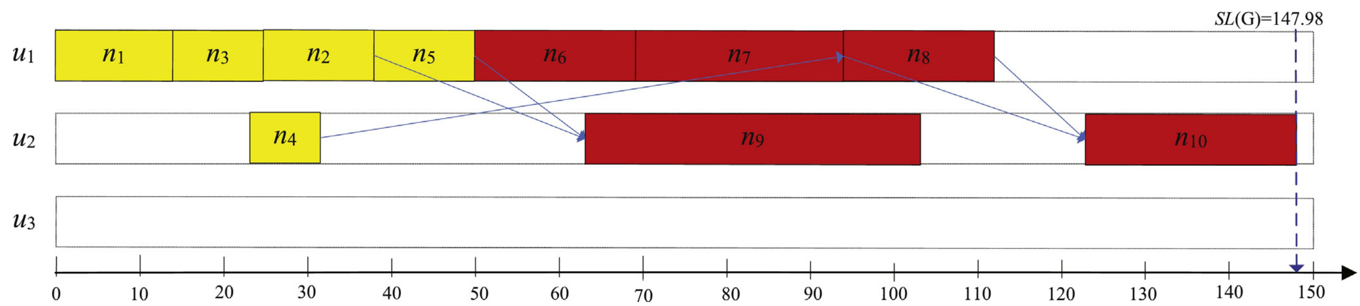

Fig. 2. Scheduling of the motivating parallel application using MREC.

varying energy constraints. A new parameter ρ is used as the matrix size of the GE application, and the total number of tasks is [14]

$$|N| = \frac{\rho^2 + \rho - 2}{2}.$$

Fig. 3 shows an example of the GE parallel application with ρ=5.

We limit the size of the application as ρ = 32 (i.e., $|N|$ = 233). $E_{given}(G)$ is changed from $(E_{min}(G) + E_{max}(G))/10$ to $(E_{min}(G) + E_{max}(G))/6$.

We can see from Table 6 that the actual energy values of the application using both RMEC and MREC can satisfy the energy constraints in all cases; however, RMEC always generates the same energy value 1306.3203, which is close to the minimum energy value $E_{min}(G)$ = 1306.0969 rather than the given energy constraints; such phenomenon reflects the facts that: (1) RMEC is not sensitive to given energy constraints; (2) RMEC just implements a tradeoff between enhancing reliability and saving energy, and it is not to maximize reliability. On the contrary, the generated energy values

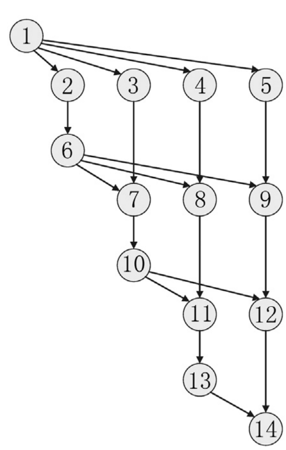

Fig. 3. Example of the GE application with ρ=5.

using MREC are less than and close to given energy constraints in all cases; the results demonstrate that the strategy (i.e., MREC transfers the energy constraint of the application to that of each task) is very effective.

The final reliability values using RMEC are fixed at 0.1898, whereas those using MREC are enhanced gradually from 0.3934 to 0.7113 with the increase of energy constraints, which also verify that energy and reliability are monotonically increasing in energy-efficient frequencies. In a word, MREC can obtain much higher reliability values than RMEC while satisfying the given energy constraints.

5.3. FFT experiments

Experiment 2. To further verify the fact that MREC can obtain much higher reliability values than RMEC while satisfying the given energy constraints, we use another important real parallel application (i.e., the GE application) as experimental object. A new parameter ρ is used as the size of the FFT application, and the total number of tasks is [14]

$$|N| = (2 \times \rho - 1) + \rho \times \log_2^{\rho},$$

where $\rho = 2^y$ for some integer y. Fig. 4 shows an example of the FFT parallel application with ρ=8. Note that ρ exit tasks exist in the FFT application with the size ρ. To adapt the application model of this study, we just add a virtual exit task and the last ρ tasks are set as the immediate predecessor tasks of the virtual task.

This experiment is to compare the actual energy values and the final reliability of the FFT application for varying energy constraints. We limit the size of the application as ρ = 64, i.e., the number of tasks are $|N|$ = 512, which is approximately equal to that of the GE application in **Experiment 1**. $E_{given}(G)$ is also changed from $(E_{min}(G) + E_{max}(G))/10$ to $(E_{min}(G) + E_{max}(G))/6$.

The results of Table 7 in **Experiment 2** illustrate the same patterns as that of Table 6 in **Experiment 1**: (1) RMEC still generates the same energy value 1246.5818, which is close to the minimum energy value $E_{min}(G)$ = 1246.0493 rather than the given energy

Table 6
Actual energy values (GWh) and final reliability values of the GE application with $\rho = 32$ ($|N| = 527$) for varying energy constraints (**Experiment 1**).

$\|N\|$	$E_{\min}(G)$	$E_{\max}(G)$	$E_{\text{given}}(G)$	RMEC [10]		MREC	
				$E_{\text{total}}(G)$	$R(G)$	$E_{\text{total}}(G)$	$R(G)$
527	1306.0969	64,001.7080	6530.7807	1306.3203	0.1898	6530.7808	0.3934
527	1306.0969	64,001.7080	7256.4230	1306.3203	0.1898	7256.4239	0.4394
527	1306.0969	64,001.7080	8163.4759	1306.3203	0.1898	8163.4769	0.4932
527	1306.0969	64,001.7080	9329.6867	1306.3203	0.1898	9329.6876	0.5784
527	1306.0969	64,001.7080	10,884.6345	1306.3203	0.1898	10,884.6354	0.7113

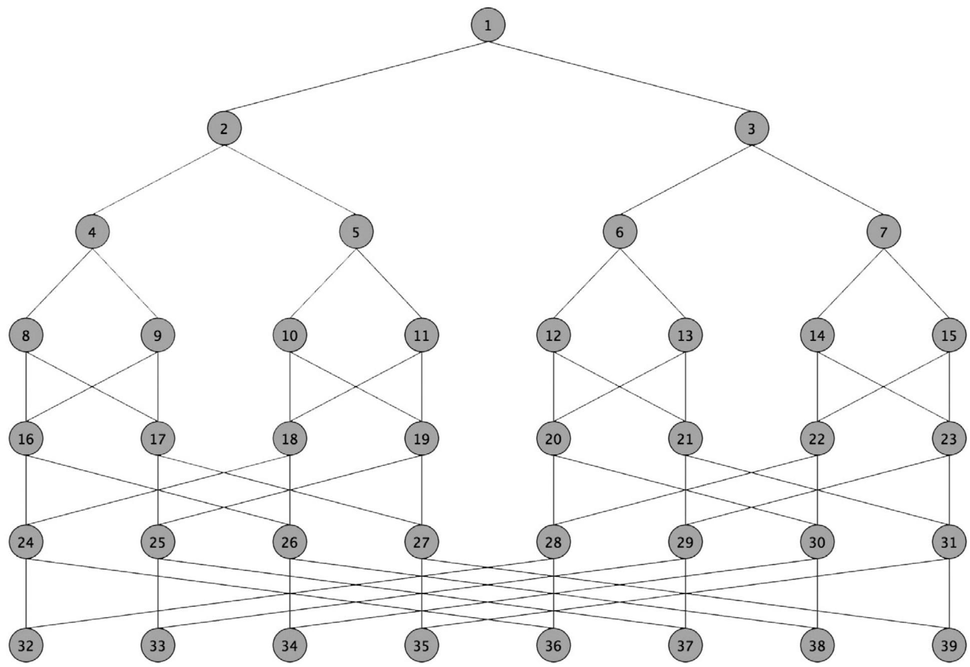

Fig. 4. Example of the FFT application with ρ=8.

constraints. (2) The generated energy values using MREC are still less than and close to the given energy constraints in all cases; (3) the final reliability values using RMEC are fixed at 0.2513, whereas those using MREC are enhanced gradually from 0.4644 to 0.7575 with the increase of energy constraints. Therefore, MREC obtains much higher reliability values than RMEC while satisfying the given energy constraints with different types of parallel applications.

Experiment 3. To observe the performance in different scales of applications, this experiment is conducted to compare the actual energy values and final reliability values of the FFT applications for varying numbers of tasks. We limit $E_{\text{given}}(G)$ as $E_{\text{given}}(G) = (E_{\min}(G) + E_{\max}(G))/6$. ρ is changed from 8 to 128, namely, the number of tasks are changed from 128 (i.e., $|N| = 1152$) to 1024 (i.e., $|N| = 12, 288$).

As can be seen from Table 8, although different scale applications are tested, the energy values generated using RMEC are still close to the minimum energy values, whereas those using MREC are close to the given energy constraints in all cases. The results also show that the reliability values using RMEC and MREC are reduced to unacceptable levels, especially using RMEC. For example, when the task number is 12,288, the reliability value using RMEC is merely 3.6737×10^{-16}, whereas that using MREC is also reduced to 0.0018, but it is much higher than the value using RMEC.

Combined with the results of the FFT and the GE applications, the proposed MREC is very effective in reliability maximization while satisfying given energy constraints. We also find that RMEC is not to maximize reliability but more likely to make a tradeoff between energy and reliability.

Experiment 4. As the reliability values of the FFT application dropped to unacceptable levels in large-scale applications, we should take some measures to enhance the reliability in this situation. A feasible method is to employ the processors with lower failure rates. In this experiment, we compare the obtained reliability values of the FFT application for varying failure rates of processors. We limit $\rho = 1024$ (i.e., $|N| = 12, 288$) and

Table 7
Actual energy values (GWh) and final reliability values of the FFT application with $\rho = 64$ ($|N| = 512$) for varying energy constraints (**Experiment 2**).

$\|N\|$	$E_{\min}(G)$	$E_{\max}(G)$	$E_{\text{given}}(G)$	RMEC [10]		MREC	
				$E_{\text{total}}(G)$	$R(G)$	$E_{\text{total}}(G)$	$R(G)$
512	1246.0493	62,388.5500	6363.4599	1246.5818	0.2513	6530.7808	0.4644
512	1246.0493	62,388.5500	7070.5110	1246.5818	0.2513	7070.5121	0.5052
512	1246.0493	62,388.5500	7954.3249	1246.5818	0.2513	7954.3258	0.5642
512	1246.0493	62,388.5500	9090.6570	1246.5818	0.2513	9090.6582	0.6341
512	1246.0493	62,388.5500	10,605.7665	1246.5818	0.2513	10,605.7676	0.7575

Table 8
Actual energy values (GWh) and final reliability values of FFT applications with $E_{given}(G)=(E_{min}(G)+E_{max}(G))/6$ for varying numbers of tasks (**Experiment 3**).

$\|N\|$	$E_{min}(G)$	$E_{max}(G)$	$E_{given}(G)$	RMEC [10]		MREC	
				$E_{total}(G)$	$R(G)$	$E_{total}(G)$	$R(G)$
1152	2893.3353	138,153.49	23,507.8042	2893.4961	0.0247	23,507.8058	0.2660
2560	5967.0006	311,557.4	52,920.7334	5968.2080	7.3906×10^{-4}	52,920.7348	0.3707
5632	13,037.9147	678,021.5900	115,176.5841	13,042.1533	5.7238×10^{-8}	115,176.5858	0.0066
12,288	28,835.5678	1,469,497.7500	249,722.2196	28,841.1020	3.6737×10^{-16}	249,722.2211	0.0018

Table 9
Actual energy values (GWh) and final reliability values of the FFT application with $\rho=512$ and $E_{given}(G)=(E_{min}(G)+E_{max}(G))/6$ for varying failure rates (**Experiment 4**).

$\|N\|$	$E_{min}(G)$	$E_{max}(G)$	$E_{given}(G)$	RMEC [10]		MREC	
				$E_{total}(G)$	$R(G)$	$E_{total}(G)$	$R(G)$
$[10^{-8}, 128 \times 10^{-8}]$	28,921.0423	1,467,719.61	249,440.1087	28,925.6223	0.03818	249,441.1071	0.2568
$[10^{-9}, 128 \times 10^{-9}]$	28,871.4554	1,480,608.6200	251,580.0126	28,876.5574	0.6808	251,580.0938	0.8835
$[10^{-10}, 128 \times 10^{-10}]$	29,771.3622	1,493,827.09	253,933.0753	29,778.2436	0.9597	253,934.1732	0.9817

set $E_{given}(G)=(E_{min}(G)+E_{max}(G))/6$. The failure rates of processors decrease exponentially.

We can see from Table 9 that reliability values of the FFT application increase with the decrease in the failure rates. When failure rates belong to the scope of $[10^{-10}, 32 \times 10^{-10}]$, the reliability value using MREC reaches 0.9817. We can then draw a conclusion that reducing the failure rates of processors can effectively enhance the reliability of the parallel application. However, lower failure rates of processors would require higher design costs in practice.

6. Conclusions

We have developed a heuristic and low time complexity reliability maximization algorithm MREC for an energy constrained parallel application on heterogeneous distributed systems based on DVFS energy-efficient design technique. First, MREC transfers the energy constraint of the application to that of each task, thereby assigning each task to the processor with the maximum reliability while satisfying its energy constraint. Second, MREC can always generate the energy value that is less than and close to the given energy constraint of the parallel application. MREC overcomes the limitations of RMEC and can obtain larger reliability values than RMEC while satisfying the energy constraints with different types of real parallel applications in different conditions. We believe that the MREC algorithm could effectively improve a part of energy-reliability aware design for parallel applications in heterogeneous distributed environments. In our future work, we will include the timing constraint into the problem and simultaneously satisfy the timing and energy constraint to maximize the reliability for a parallel application on heterogeneous distributed systems.

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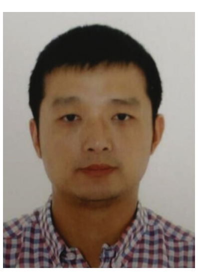
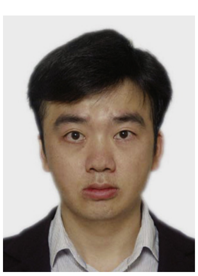
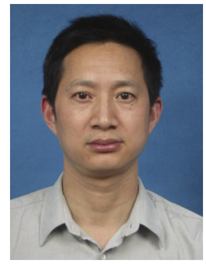


Xiongren Xiao is Ph.D. candidate and assistant professor in College of Computer Science and Electronic Engineering, Hunan University, China. His main research interests include energy-efficient computing, parallel and distributed systems. He is member of ACM and CCF.



Guoqi Xie received his Ph.D. degree in computer science and engineering from Hunan University, China, in 2014. He was a Postdoctoral Researcher at Nagoya University, Japan, from 2014 to 2015. Since 2015 he is working as a Postdoctoral Researcher at Hunan University, China. His major interests include parallel and distributed systems, embedded and real-time systems, software engineering and methodology. He is a member of IEEE and ACM.



Cheng Xu is a professor in College of Computer Science and Electronic Engineering, Hunan University, China. His major research includes embedded systems and cyber-physical systems. He is member of ACM and CCF.

Chunnian Fan received her Ph.D. degree in computer science from Nanjing University in 2011. Her research interests include parallel and distributed system, pattern recognition and image processing.

Renfa Li is a Professor of computer science and electronic engineering, and the Dean of College of Computer Science and Electronic Engineering, Hunan University, China. He is the Director of the Key Laboratory for Embedded and Network Computing of Hunan Province, China. He is also an expert committee member of National Supercomputing Center in Changsha, China. His major interests include computer architectures, embedded computing systems, cyber-physical systems, and Internet of things. He is a member of the council of CCF, a senior member of IEEE, and a senior member of ACM.

Keqin Li is a SUNY Distinguished Professor of computer science. His current research interests include parallel computing and high-performance computing, distributed computing, energy-efficient computing and communication, heterogeneous computing systems, cloud computing, big data computing, CPU-GPU hybrid and cooperative computing, multicore computing, storage and file systems, wireless communication networks, sensor networks, peer-to-peer file sharing systems, mobile computing, service computing, Internet of things and cyber-physical systems. He has published over 460 journal articles, book chapters, and refereed conference papers, and has received several best paper awards. He is currently or has served on the editorial boards of IEEE Transactions on Parallel and Distributed Systems, IEEE Transactions on Computers, IEEE Transactions on Cloud Computing, IEEE Transactions on Services Computing, IEEE Transactions on Sustainable Computing. He is an IEEE Fellow.