

Energy efficient resource management in mobile grid

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Abstract. Energy efficient computing has recently become hot research area. Many works have been carried out on conserving energy, but considering energy efficiency in grid computing is few. This paper proposes energy efficient resource management in mobile grid. The objective of energy efficient resource management in mobile grid is to maximize the utility of the mobile grid which is denoted as the sum of grid application utility. The utility function models benefits of application and system. By using nonlinear optimization theory, energy efficient resource management in mobile grid can be formulated as multi objective optimization problem. In order to derive a distributed algorithm to solve global optimization problem in mobile grid, we decompose the problem into the sub problems. The proposed energy efficient resource management algorithm decomposes the optimization problem via iterative method. To test the performance of the proposed algorithm, the simulations are conducted to compare proposed energy efficient resource management algorithm with other energy aware scheduling algorithm.

Keywords: Mobile grid, resource management, energy efficient

1. Introduction

Mobile grid means that movable wireless devices are integrated into traditional wired grid through wireless channel to share grid resources (CPU power, storage capacity, instrument, devices, data, software, etc.), meanwhile, mobile devices can provide service or resource to grid users, such as PDAs, cellular phones, handsets or wearable computers, laptops with GPS service, mobile service, etc. [1]. Mobile grid can provide end users with grid services such as music, medical, accounting, message alert service, function estimation, data mining, assurance, and so on. Mobile grid may be constructed on current network infrastructure, integrate continually developing wireless network technologies, enrich network contents and software platform function. Mobile grid includes various kinds of mobile devices, and then leads to the grid system more complicated than wired grid system due to the mobile grid node dynamically behavior in the grid system. Mobile grid requires dynamic management of distributed resources, and such management needs to meet application quality requirements and prolong application lifetimes. Mobile grid application' lifetime is determined by available energy on the mobile devices. Mobile devices are battery-driven, and hence operate on an extremely frugal energy budget. Considering energy efficiency in mobile grid is an important challenge.

This paper proposes energy efficient resource management in mobile grid. The objective of energy efficient resource management in mobile grid is to maximize the utility of the mobile grid which is denoted as the sum of grid application utility. The utility function models benefits of application and

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system. By using nonlinear optimization theory, energy efficient resource management in mobile grid can be formulated as multi objective optimization problem. In order to derive a distributed algorithm to solve global optimization problem in mobile grid, we decompose the problem into the sub problems. The proposed energy efficient resource management algorithm decomposes the optimization problem via iterative method. To test the performance of the proposed algorithm, the simulations are conducted to compare proposed energy efficient resource management algorithm with other energy aware algorithm.

The rest of the paper is structured as followings. Section 2 discusses the related works. Section 3 presents energy efficient resource management in mobile grid. Section 4 presents energy efficient resource management algorithm in mobile grid. In Section 5 the simulations are conducted. Section 6 gives the conclusions to the paper.

2. Related work

Energy efficient computing has recently become hot research area. Many works have been carried out on conserving energy, but considering energy in grid computing is few. Tao Xie et al. [2] address the issue of allocating tasks of parallel applications in heterogeneous embedded systems with an objective of energy-saving and latency-reducing. They proposed BEATA (Balanced Energy-Aware Task Allocation), a task allocation scheme considering both energy consumption and schedule length, is developed to solve the energy-latency dilemma. Y. Huang et al. [3] present techniques for exploiting intermittently available resources in grid infrastructures to support QoS-based multimedia applications on mobile devices. They integrate power aware admission control, grid resource discovery, dynamic load-balancing and energy adaptation techniques to enable power deficient devices to run distributed multimedia applications. Ziliang Zong et al. [4] design energy efficient scheduling algorithms for parallel applications running on clusters, they propose a scheduling strategy called energy efficient task duplication schedule, which can significantly conserve power by judiciously shrinking communication energy cost when allocating parallel tasks to heterogeneous computing nodes. Tarek A. AlEnawy et al. [5] propose to minimize the number of dynamic failures while remaining within the energy budget. They propose techniques to statically compute the speed of the CPU in order to meet the (m,k)-firm deadline constraints. Kyong Hoon Kim et al. [6] provide power-aware scheduling algorithms for bag of tasks applications with deadline constraints on DVS enabled cluster systems in order to minimize power consumption as well as to meet the deadlines specified by application users. Eunjeong Park et al. [8] designed an entire process of multimedia service composition for mobile computing. Their approach adapts the composition graph and the use of service routing for the context of mobile devices with the support of monitoring components. The works [9–13] mainly deal with resource allocation, QoS optimization in the computational grid and don't consider energy consumption for mobile grid. Narottam Chand et al. [17] propose a utility based cache replacement policy, least utility value (LUV), to improve the data availability and reduce the local cache miss ratio. Markus Aleksy et al. [18] present a generic architecture, which can be used for the development of context-sensitive mobile applications. Vincent Reinhard et al. [19] propose a mechanism for the introduction of application data in the network with respect to CARRIOCAS architecture. P. Hellinckx et al. [18] introduced a new multipurpose Lightweight Grid (LWG) system under the acronym Computational Basic Reprogrammable Adaptive (CoBRA) grid. The methods and contributions of this paper are different from above works. This paper is targeted to manage energy consumption without compromising system's performance in mobile grid.

3. Energy efficient resource management in mobile grid

3.1. Energy efficient resource management mathematic model

In mobile grid, energy resources distribution and computation workloads are not balanced within mobile devices. It is important for the mobile grid system to design energy efficient resource management. Firstly, let consider the notations used in the following sections. e_i^l is the energy obtained by grid application i from energy resource l . Ce_l is the capacity of energy resource l . Cn_k is the capacity of network resource k . Cc_j is the capacity of computing power j . t_i^n is the time taken by the grid application i to complete n th job. Pc_i^j is the payments of the grid application i to the computing power j . Pn_i^k is the payments of the grid application i to the network resource k . Pe_i^l is the payments of the grid application i to energy resource l . B_i is the expense budget of grid application i . er_l is the energy consumption rate of energy resource l . e_i^n is energy dissipation caused by grid application i 's n th job. cq_i^n is the computation task of i th grid application's n th job. bq_i^n is the transmission task of i th grid application's n th job. eq_i^n is the energy storage task of i th grid application's n th job. np_k the price of network resource k . cp_j is the price of computing resource j . ep_l is the price of energy resource l . T_i is the deadline given by the grid application i to complete its all jobs. y_i^k is the network allocation obtained by grid application i from the network resource k . x_i^j is the computing power obtained by grid application i from computing power j .

We assume that the mobile grid has heterogeneous nodes with different system performance rates and network conditions. This means that the energy consumption of the mobile device can vary with the response time of the application and the network bandwidth. We denote e_i^l is the consumed energy fraction of the energy l (e.g. a battery) by grid application i . Total consumed energy of all grid applications $\sum_{i=1}^I e_i^l$ does not exceed the total capacity Ce_l of energy l . Energy consumption rate of each node in the system is measured by Joule per unit time. Let e_i^n be an energy dissipation caused by grid application i 's n th job, t_i^n is the execution time of job n of grid application i on the grid node. er is the energy consumption rate of energy resource l . If the energy consumption is proportional to execution time of job n , as is the case with battery energy. We define the energy consumption of each application A_i as the sum of the energy consumed by N grid jobs $\sum_{n=1}^N e_i^n$. The energy consumption of all grid jobs of each application A_i should be less than the available resources of e_i^l which is limited energy budget of grid user application i .

Now, we formulate the problem of energy efficient resource management in mobile grid as constraint optimization problem, the utility of the mobile grid $U_{\text{mobilegrid}}$ is defined as the sum of grid application utilities $\sum_{i=1}^I U_i$. The objective of energy efficient resource management in mobile grid is to maximize the utility of the mobile grid $U_{\text{mobilegrid}}$. By using nonlinear optimization theory, energy efficient resource management in mobile grid can be formulated as follows.

$$\text{Max} U_{\text{mobilegrid}}$$

$$\text{s.t. } T_i \geq \sum_{n=1}^N t_i^n, Cn_k \geq \sum_{i=1}^I y_i^k, \sum_{n=1}^N e_i^n \leq e_i^l, Cc_j \geq \sum_{i=1}^I x_i^j, \sum_{i=1}^I e_i^l \leq Ce_l \quad (1)$$

$$B_i \geq \sum_{l=1}^L Pe_i^l + \sum_{j=1}^J Pc_i^j + \sum_{k=1}^K Pn_i^k$$

Where e_i^l is the energy obtained by grid application i from the energy l . x_i^j is CPU allocation obtained by grid application i from the computing resource provider j . y_i^k is bandwidth allocation obtained by grid application i from the network resource provider k . The utility function for application A_i depends on allocated resources x_i^j, y_i^k and consumed energy e_i^l . In the problem Eq. (1), the first type of constraints is related with different resource capacity. The QoS constraint implies that the aggregate network resource units $\sum_{i=1}^I y_i^k$ do not exceed the total capacity Cn_k of network resource provider k , aggregate consumed energy of all grid application $\sum_{i=1}^I e_i^l$ does not exceed the total Ce_l of energy l , aggregate computing power $\sum_{i=1}^I x_i^j$ does not exceed the total resource Cc_j of the computing resource provider j . The second type of constraints is related with grid application expense budget. Grid application needs to complete a sequence of jobs in a specified amount of time, T_i , while the payment overhead accrued cannot exceed B_i , which is the expense budget of grid application i . Pe_i^l, Pc_i^j, Pn_i^k are the payments of the grid application i to the energy storage provider l , computing resource provider j and network resource provider k . The total payments of the grid application

$$i \sum_{l=1}^L Pe_i^l + \sum_{j=1}^J Pc_i^j + \sum_{k=1}^K Pn_i^k$$

do not exceed B_i . The total energy consumed by all jobs of grid application i $\sum_{n=1}^N e_i^n$ cannot exceed the energy budget e_i^l which is the available energy obtained by grid application i from the energy storage l .

3.2. Solutions to mathematic model

We apply the Lagrangian method to solve such a problem Eq. (1). The Lagrangian approach can be used to solve constrained optimization problems. Let us consider the Lagrangian form of energy efficient resource management in mobile grid:

$$L = \sum_{i=1}^I U_i - \lambda_i \left(\sum_{i=1}^I e_i^l - Ce_l \right) - \beta_i \left(\sum_{i=1}^I x_i^j - Cc_j \right) - \varphi_i \left(\sum_{i=1}^I y_i^k - Cn_k \right) \\ - \gamma_i \left(\sum_{l=1}^L Pe_i^l + \sum_{j=1}^J Pc_i^j + \sum_{k=1}^K Pn_i^k - B_i \right) - \mu_i \left(\sum_{n=1}^N e_i^n - e_i^l \right) - \alpha_i \left(\sum_{n=1}^N t_i^n - T_i \right)$$

where λ_i, β_i and φ_i are the Lagrange multipliers of grid application with their interpretation of energy price, computing resource capacity price, and network resource capacity price, respectively. Since the Lagrangian is separable, this maximization of Lagrangian over (x_i^j, y_i^k, e_i^l) can be conducted in parallel at each application A_i . In problem Eq. (1), though the allocated resources x_i^j, y_i^k and consumed energy e_i^l are coupled in their constraints, respectively, but they are separable. Given that the grid knows the utility functions U of all the grid applications, this optimization problem can be mathematically tractable. However, in practice, it is not likely to know each application's utility, and it is also infeasible for mobile grid environment to compute and allocate resources in a centralized fashion. In order to derive a distributed algorithm to solve problem Eq. (1), we decompose the problem into the sub problems.

The mobile grid utility denoted as the sum of grid application utility can be defined as follows Eq. (2):

$$U_{\text{mobilegrid}} = \left(B_i - \sum_{l=1}^L P e_i^l - \sum_{j=1}^J P c_i^j - \sum_{k=1}^K P n_i^k \right) + \left(T_i - \sum_{n=1}^N t_i^n \right) + \sum_{i=1}^I (P e_i^l \log e_i^l + P c_i^j \log x_i^j + P n_i^k \log y_i^k) + \left(e_i^l - \sum_{n=1}^N e_i^n \right) \quad (2)$$

Mobile grid utility function is maximally optimized with specific constraints. In Eq. (2), $P e_i^l \log e_i^l + P c_i^j \log x_i^j + P n_i^k \log y_i^k$ present the revenue of energy storage resource, computing power and network resource provider. We could have chosen any other form for the utility that increases with x_i^j, y_i^k, e_i^l . But we chose the \log function because the benefit increases quickly from zero as the total allocated resource increases from zero and then increases slowly. Moreover, \log function is analytically convenient, increasing, strictly concave and continuously differentiable. The benefits of grid resource provider are affected by payments of grid applications and allocated resources. It means that the revenue increases with increasing allocated resources and increasing payment.

The Lagrangian form of the problem Eq. (1) can be reformulated as follows Eq. (3):

$$L = \left(B_i - \sum_{l=1}^L P e_i^l - \sum_{j=1}^J P c_i^j - \sum_{k=1}^K P n_i^k \right) + \sum_{i=1}^I (P e_i^l \log e_i^l + P c_i^j \log x_i^j + P n_i^k \log y_i^k) + \left(T_i - \sum_{n=1}^N t_i^n \right) + \left(e_i^l - \sum_{n=1}^N e_i^n \right) - \lambda_i \left(\sum_{i=1}^I e_i^l - C e_l \right) - \beta_i \left(\sum_{i=1}^I x_i^j - C c_j \right) - \varphi_i \left(\sum_{i=1}^I y_i^k - C n_k \right) - \gamma_i \left(\sum_{l=1}^L P e_i^l + \sum_{j=1}^J P c_i^j + \sum_{k=1}^K P n_i^k - B_i \right) - \mu_i \left(\sum_{n=1}^N e_i^n - e_i^l \right) - \alpha_i \left(\sum_{n=1}^N t_i^n - T_i \right) \quad (3)$$

The system model presented by Eq. (1) is a nonlinear optimization problem with N decision variables. Since the Lagrangian is separable, the maximization of the Lagrangian can be processed in parallel for grid user applications and grid resource providers respectively. From Eq. (3), the resource allocation $\{e_i^l, x_i^j, y_i^k\}$ solves problem Eq. (1) if and only if there exist a set of nonnegative shadow costs $\{\lambda_i, \beta_i, \varphi_i\}$. Generally solving such a problem by typical algorithms such as steepest decent method and gradient projection method is of high computational complexity, which is very time costing and impractical for implementation. In order to reduce the computational complexity, we decompose the utility optimization problem Eq. (1) into two subproblems for grid user applications and grid resource providers so that the computational complexity is reduced. The shadow costs suggest a mechanism to distribute the resource optimization between the grid applications and the grid system. The problem Eq. (1) maximizes the utility of grid applications on the energy price, computing power capacity price, and network resource capacity price, $\sum_{i=1}^I U_i(e_i^l, x_i^j, y_i^k)$ is the total utility of mobile grid system, $\beta_i \sum_{i=1}^I x_i^j$ is the computing power cost, $\lambda_i \sum_{i=1}^I e_i^l$ is the energy cost, $\varphi_i \sum_{i=1}^I y_i^k$ is the network resource cost. By decomposing

the Kuhn-Tucker conditions into separate roles of consumer and supplier at grid market, the centralized problem Eq. (1) can be transformed into a distributed problem. Grid application's payment is collected by the resource providers. The payments of grid applications paid to resource providers are the payments to resolve the optimality of resource allocation in the grid market. We decompose the problem into the following two subproblems Eq. (4) which is grid users optimization problem and Eq. (5) which is grid resource providers optimization problem, seek a distributed solution where the grid resource provider does not need to know the utility functions of individual grid user application. Equations (4), (5) derived from the distributed approach are identical to the optimal conditions given by centralized energy efficient resource management problem Eq. (1). This means if two subproblems converge to its optimal points, then a globally optimal point is achieved. Total user application benefit of the mobile grid is maximized when the equilibrium prices, obtained through the two subproblems Eqs (4) and (5), equal the Lagrangian multipliers λ_i , β_i and φ_i , where λ_i , β_i and φ_i are the optimal prices charged by resource providers including energy, computing power and network resource to grid applications. Two maximization subproblems correspond to grid application optimization problem as denoted by Eqs (4) and (5).

$$\begin{aligned}
 MaxU_{GA} &= \left(T_i - \sum_{n=1}^N t_i^n \right) + \left(e_i^l - \sum_{n=1}^N e_i^n \right) + \left(B_i - \sum_{l=1}^L P e_i^l - \sum_{j=1}^J P c_i^j - \sum_{k=1}^K P n_i^k \right) \\
 B_i &\geq \sum_{l=1}^L P e_i^l + \sum_{j=1}^J P c_i^j + \sum_{k=1}^K P n_i^k \\
 \sum_{n=1}^N e_i^n &\leq e_i^l, T_i \geq \sum_{n=1}^N t_i^n,
 \end{aligned} \tag{4}$$

$$\begin{aligned}
 MaxU_{GR} &= \sum_{i=1}^I (P e_i^l \log e_i^l + P c_i^j \log x_i^j + P n_i^k \log y_i^k) \\
 C c_j &\geq \sum_{i=1}^I x_i^j, \quad C n_k \geq \sum_{i=1}^I y_i^k, \quad \sum_{i=1}^I e_i^l \leq C e_l
 \end{aligned} \tag{5}$$

In Eq. (4), the grid application gives the unique optimal payment to resource provider under the energy budget, expense budget and the deadline constraint to maximize the user's satisfaction.

$$\left(B_i - \sum_{l=1}^L P e_i^l - \sum_{j=1}^J P c_i^j - \sum_{k=1}^K P n_i^k \right)$$

represents the money surplus of grid application i , which is obtained by expense budgets subtracting the payments to various resource providers. $(T_i - \sum_{n=1}^N t_i^n)$ represents the saving times for grid application i , which is gotten by time limit subtracting actual spending time. $(e_i^l - \sum_n e_i^n)$ represents the energy surplus of grid application i which is obtained by the energy budgets subtracting actual energy dissipation. So, the objective of Eq. (4) is to get more surpluses of money and more energy savings, at the same time, complete task for grid user application as soon as possible. In Eq. (5), different resource providers

compute optimal resource allocation for maximizing the revenue of their own. Grid application i submits the payment Pe_i^l to the energy resource provider l , Pn_i^k to network resource provider k and Pc_i^j to computing power provider j . $Pe_i^l \log e_i^l$ presents the revenue obtained by energy resource l from grid application i . $Pc_i^j \log x_i^j$ presents the revenue obtained by computing power j from grid application i . $Pn_i^k \log y_i^k$ presents the revenue obtained by network resource k from grid application i . The objective of resource providers is to maximize

$$Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k$$

under the constraints of their provided resource amounts. Grid resource providers can't sell the resources to grid applications more than total capacity. In Eq. (4), the grid application adaptively adjusts its payments to computing power, network resource and energy based on the current resource conditions, while in Eq. (5), the grid resource provider adaptively allocates energy, CPU and bandwidth required by the grid application in the Eq. (4). The interaction between two sub-problems is controlled through the use of the price variable λ_i , β_i and φ_i , which is the energy price, computing power price, and network resource price charged from grid applications by grid energy resource, computing power and network resource. The interaction between two sub-problems also coordinates the grid application's payment and the supply of grid resource providers.

Lagrange relaxation and gradient optimization can be applied to decompose such an overall optimization problem into a sequence of two sub-problems, each only involving variables from the grid application and resource providers respectively. In Eq. (4), grid application maximizes its satisfaction and gives the unique optimal payment to resource provider under the energy budget, expense budget and the deadline constraint. We assume that grid application i submits Pe_i^l to energy resource l , Pc_i^j to computing power j and Pn_i^k to network resource k . Then, $Pe_i = [Pe_i^1, \dots, Pe_i^l]$ represents all payments of grid applications for energy resource l , $Pc_i = [Pc_i^1, \dots, Pc_i^j]$ represents all payments of grid applications for computing power j , $Pn_i = [Pn_i^1, \dots, Pn_i^k]$ represents all payments of grid applications for the network resource k . Let

$$m_i = \sum_l Pe_i^l + \sum_j Pc_i^j + \sum_k Pn_i^k,$$

m_i is the total payment of the i th grid application. N grid applications compete for grid resources with finite capacity. The resource is allocated using a market mechanism, where the partitions depend on the relative payments sent by the grid applications. Let ep_l , cp_j , np_k denote the price of the resource unit of energy resource l , the price of the resource unit of computing power j and network resource k respectively. Let the pricing policy, $ep = (ep_1, ep_2, \dots, ep_l)$, denote the set of resource unit prices of all the energy resources in the grid, $cp = (cp_1, cp_2, \dots, cp_j)$, denote the set of resource unit prices of all the computing powers, $np = (np_1, np_2, \dots, np_k)$ is set of network resource unit prices. The i th grid application receives the resources proportional to its payment relative to the sum of the resource provider's revenue. Let e_i^l , x_i^j , y_i^k be the fraction of resource units allocated to grid application i by energy l , computing power j and network resource k .

The time taken by the i th grid application to complete n th job is:

$$t_i^n = \frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n ep_l}{Ce_l Pe_i^l}$$

The energy dissipation used by the i th grid user to complete n th job is:

$$e_i^n = er.t_i^n = er \cdot \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right)$$

Grid user optimization can be reformulated as

$$\begin{aligned} MaxU_{GA} = & \left(B_i - \sum_{l=1}^L Pe_i^l - \sum_{j=1}^J Pc_i^j - \sum_{k=1}^K Pn_i^k \right) + \left(T_i - \sum_{n=1}^N \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \\ & + \left(e_i^l - \sum_{n=1}^N er \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \end{aligned}$$

The Lagrangian for the grid application' s utility is $L_1(Pe_i^l, Pc_i^j, Pn_i^k)$.

$$\begin{aligned} L_1(Pe_i^l, Pc_i^j, Pn_i^k) = & \left(B_i - \sum_{l=1}^L Pe_i^l - \sum_{j=1}^J Pc_i^j - \sum_{k=1}^K Pn_i^k \right) \\ & + \left(T_i - \sum_{n=1}^N \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \\ & + \left(e_i^l - \sum_{n=1}^N er \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \\ & + \nu_i \left(B_i - \sum_{l=1}^L Pe_i^l - \sum_{j=1}^J Pc_i^j - \sum_{k=1}^K Pn_i^k \right) \\ & + \sigma_i \left(T_i - \sum_{n=1}^N \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \\ & + \varepsilon_i \left(e_i^l - \sum_{n=1}^N er \left(\frac{cq_i^n cp_j}{Cc_j Pc_i^j} + \frac{bq_i^n np_k}{Cn_k Pn_i^k} + \frac{eq_i^n epl}{Ce_l Pe_i^l} \right) \right) \end{aligned}$$

Where $\varepsilon_i, \sigma_i, \nu_i$ is the Lagrangian constant. From Karush-Kuhn-Tucker Theorem we know that the optimal solution is given $\partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pe_i^l = 0$ for $\varepsilon_i, \sigma_i, \nu_i > 0$.

$$\begin{aligned} \partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pe_i^l = & -1 - \nu_i + \frac{eq_i^n epl}{Ce_l (Pe_i^l)^2} + er \frac{eq_i^n epl}{Ce_l (Pe_i^l)^2} \\ & + \sigma_i \frac{eq_i^n epl}{Ce_l (Pe_i^l)^2} + \varepsilon_i \cdot er \frac{eq_i^n epl}{Ce_l (Pe_i^l)^2} \end{aligned}$$

Let $\partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pe_i^l = 0$ to obtain

$$Pe_i^l = \left(\frac{(1 + er + \sigma_i + \varepsilon_i \cdot er) eq_i^n ep_l}{(1 + \nu_i) C_{el}} \right)^{1/2}$$

Using this result in the constraint equation, we can determine $\theta = (1 + er + \sigma_i + \varepsilon_i \cdot er) / (1 + \nu_i)$ as

$$(\theta)^{-1/2} = \frac{T_i}{\sum_{m=1}^N \left(\frac{ep_m eq_i^n}{C_{em}} \right)^{1/2}}$$

We obtain Pe_i^{l*}

$$Pe_i^{l*} = \left(\frac{eq_i^n ep_l}{C_{el}} \right)^{1/2} \frac{\sum_{m=1}^N \left(\frac{eq_i^n ep_m}{C_{em}} \right)^{1/2}}{T_i}$$

It means that grid application wants to pay Pe_i^{l*} to energy resource l for needed energy consumed to execute grid jobs under completion time constraint.

$$\begin{aligned} \partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pc_i^j = & -1 + \frac{cq_i^n cp_j}{Cc_j (Pc_i^j)^2} + er_i^n \frac{cq_i^n cp_j}{Cc_j (Pc_i^j)^2} - \nu_i \\ & + \sigma_i \frac{cq_i^n cp_j}{Cc_j (Pc_i^j)^2} + \varepsilon_i \cdot er \frac{cq_i^n cp_j}{Cc_j (Pc_i^j)^2} \end{aligned}$$

Let $\partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pc_i^j = 0$ to obtain

$$Pc_i^j = \left(\frac{(1 + er + \sigma_i + \varepsilon_i \cdot er) cq_i^n cp_j}{(1 + \nu_i) Cc_j} \right)^{1/2}$$

Using this result in the constraint equation, we can determine $\xi = (1 + er + \sigma_i + \varepsilon_i \cdot er) / (1 + \nu_i)$ as

$$(\xi)^{-1/2} = \frac{T_i}{\sum_{m=1}^N \left(\frac{cp_m cq_i^n}{C_{cm}} \right)^{1/2}}$$

We obtain Pc_i^{j*}

$$Pc_i^{j*} = \left(\frac{cq_i^n cp_j}{Cc_j} \right)^{1/2} \frac{\sum_{m=1}^N \left(\frac{cq_i^n cp_m}{C_{cm}} \right)^{1/2}}{T_i}$$

It means that grid application wants to pay Pc_i^{j*} to computing power j for needed resource to execute grid jobs under completion time constraint.

$$\partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pn_i^k = -1 + \frac{bq_i^n np_k}{Cn_k (Pn_i^k)^2} + er_i^n \frac{bq_i^n np_k}{Cn_k (Pn_i^k)^2} - \nu_i$$

$$+\sigma_i \frac{bq_i^n np_k}{Cn_k(Pn_i^k)^2} + \varepsilon_i \frac{bq_i^n np_k}{Cn_k(Pn_i^k)^2}$$

Let $\partial L_1(Pe_i^l, Pc_i^j, Pn_i^k) / \partial Pn_i^k = 0$ to obtain

$$Pn_i^k = \left(\frac{(1 + er + \sigma_i + er \cdot \varepsilon_i) bq_i^n np_k}{(1 + \nu_i) Cn_k} \right)^{1/2}$$

Using this result in the constraint equation, we can determine $\tau = (1 + er + \sigma_i + er \cdot \varepsilon_i) / (1 + \nu_i)$ as

$$(\tau)^{-1/2} = \frac{T_i}{\sum_{m=1}^N \left(\frac{np_m bq_i^n}{Cn_m} \right)^{1/2}}$$

We obtain Pn_i^{k*}

$$Pn_i^{k*} = \left(\frac{bq_i^n np_k}{Cn_k} \right)^{1/2} \frac{\sum_{m=1}^N \left(\frac{bq_i^n np_m}{Cn_m} \right)^{1/2}}{T_i}$$

It means that grid application wants to pay Pn_i^{k*} to network resource k for needed resource to execute grid jobs under completion time constraint.

In Eq. (5), different resource providers compute optimal resource allocation for maximizing the revenue of their own under constrains of resource capacity Ce_l, Cc_j, Cn_k , the objective of resource providers is to maximize

$$Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k$$

under the constraints of their resource capacity.

We take first derivative and second derivative with respect to x_i :

$$U'_{GR}(e_i^l) = Pe_i^l / e_i^j \quad U''_{GR}(e_i^l) = -Pe_i^l / e_i^{l2}$$

$U''_{GR}(e_i^l) < 0$ is negative due to $0 < e_i^l$. The extreme point is the unique value maximizing the revenue of energy provider. The Lagrangian for (3.8) is $L_2(e_i^l, x_i^j, y_i^k)$.

$$\begin{aligned} L_2(e_i^l, x_i^j, y_i^k) &= \sum (Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k) \\ &+ \lambda_i \left(Ce_l - \sum_i e_i^l \right) + \beta_i \left(Cc_j - \sum_i x_i^j \right) + \varphi_i \left(Cn_k - \sum_i y_i^k \right) \\ &= \sum (Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k - \lambda_i e_i^l - \beta_i x_i^j - \varphi_i y_i^k) \\ &+ \lambda_i Ce_l + \beta_i Cc_j + \varphi_i Cn_k \end{aligned}$$

Where λ_i , β_i and φ_i , is the Lagrangian constant. From Karush-Kuhn-Tucker Theorem we know that the optimal solution is given $\partial L_2(e_i^l, x_i^j, y_i^k) / \partial e_i^l = 0$ for $\lambda_i, \beta_i, \varphi_i > 0$.

Let $\partial L_2(e_i^l, x_i^j, y_i^k) / \partial e_i^l = 0$ to obtain $e_i^l = P e_i^l / \lambda_i$

Using this result in the constraint equation $C e_l \geq \sum e_i^l$, we can determine λ_i as

$$\lambda_i = \frac{\sum_{d=1}^n P e_i^d}{C e_l}$$

We substitute λ into e_i^l to obtain

$$e_i^{l*} = \frac{P e_i^l C e_l}{\sum_{d=1}^n P e_i^d}$$

e_i^{l*} is the unique energy allocation for maximizing the revenue of energy provider l .

Using the similar method, we can solve computing power allocation optimization problem.

Let $\partial L_2(e_i^l, x_i^j, y_i^k) / \partial x_i^j = 0$ to obtain $x_i^j = P c_i^j / \beta_i$

Using this result in the constraint equation $C c_j \geq \sum x_i^j$, we can determine β_i as

$$\beta_i = \frac{\sum_{d=1}^n P c_i^d}{C c_j}$$

We substitute β into x_i^j to obtain

$$x_i^{j*} = \frac{P c_i^j C c_j}{\sum_{d=1}^n P c_i^d}$$

x_i^{j*} is the unique optimal computing power allocation for maximizing the revenue of computing power provider j .

Using the similar method, we can solve network resource allocation optimization problem.

Let $\partial L_2(e_i^l, x_i^j, y_i^k) / \partial y_i^k = 0$ to obtain $y_i^k = P n_i^k / \varphi_i$

Using this result in the constraint equation $C n_k \geq \sum y_i^k$, we can determine φ_i as

$$\varphi_i = \frac{\sum_{d=1}^n P n_i^d}{C n_k}$$

We substitute φ into y_i^k to obtain

$$y_i^{k*} = \frac{P n_i^k C n_k}{\sum_{d=1}^n P n_i^d}$$

y_i^{k*} is the unique optimal network resource allocation for maximizing the revenue of network resource provider k .

4. Energy efficient resource management algorithm in mobile grid

Energy efficient resource management algorithm decomposes energy consumption optimization problem into a sequence of sub-problems via an iterative algorithm. In each iteration, in the routine of grid user optimization, the grid application computes the unique optimal payment to resource provider under the energy budget, expense budget and the deadline constraint to maximize the grid application's satisfaction. The grid application individually solves its fees to pay for energy resources, computing power and network resource to complete its all jobs, adjusts its grid resource demand and notifies the grid resource provider about this change. In the routine of grid resource provider optimization, different resource providers compute optimal resource allocation for maximizing the revenue of their own. Grid resource provider updates its price according to optimal payments from grid application, and then sends the new prices to the grid applications and allocates the resource for grid application, and the cycle repeats. The algorithm that achieves energy efficient resource management in mobile grid is described as follows.

Algorithm 1 Energy Efficient Resource Management Algorithm (EERM)

Sub-algorithm 1

- Step 1: Receives the new price ep_l from the energy provider l ;
- Step 2: $Pe_i^{l*} = \text{Max}\{U_{app}(Pe_i^l, Pc_i^j, Pn_i^k)\}$;
- Step 3: If $B_i \geq \sum_j Pc_i^j + \sum_k Pn_i^k + \sum_l Pe_i^l$
Then Return Pe_i^{l*} to energy resource l ;
- Step 4: Else Return Null;
- Step 5: Receives the new price cp_j from the computing power j ;
- Step 6: $Pc_i^{j*} = \text{Max}\{U_{app}(Pe_i^l, Pc_i^j, Pn_i^k)\}$;
- Step 7: If $B_i \geq \sum_j Pc_i^j + \sum_k Pn_i^k + \sum_l Pe_i^l$
Then Return Pc_i^{j*} to computing power j ;
- Step 8: Else Return Null;
- Step 9: Receives the new price np_k from the network resource provider k ;
- Step 10: $Pn_i^{k*} = \text{Max}\{U_{app}(Pe_i^l, Pc_i^j, Pn_i^k)\}$;
- Step 11: If $B_i \geq \sum_j Pc_i^j + \sum_k Pn_i^k + \sum_l Pe_i^l$
Then Return Pn_i^{k*} to network resource k ;
- Step 12: Else Return Null;

Sub-algorithm 2

- Step 1: Receives optimal payments $Pe_i^{l*}, Pc_i^{j*}, Pn_i^{k*}$ from grid application i ;

Step 2: If $Ce_l \geq \sum_{i=1}^I e_i^l$

Then

$$e_i^{l(n+1)*} = \text{Max}\{U_{resource}(e_i^l, x_i^j, y_i^k) = \sum_{i=1}^I (Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k)\};$$

$$ep_l^{(n+1)} = \max\{\varepsilon, ep_l^{(n)} + \eta(e^l ep_l^{(n)} - Ce_l)\};$$

Return energy resource price $ep_l^{(n+1)}$ to all grid applications;

Step 3: Else Return Null;

Step 4: If $Cc_j \geq \sum_{i=1}^I x_i^j$

Then

$$x_i^{j(n+1)*} = \text{Max}\{U_{resource}(e_i^l, x_i^j, y_i^k) = \sum_{i=1}^I (Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k)\};$$

// Calculates its optimal computing power $x_i^{j(n+1)*}$

$$cp_j^{(n+1)} = \max\{\varepsilon, cp_j^{(n)} + \eta(x^j cp_j^{(n)} - Cc_j)\}; \quad // \text{ Computes a new price}$$

// $x^j = \sum_i x_i^j, \eta > 0$ is a small step size parameter, n is iteration number

Return computing power price $cp_j^{(n+1)}$ to all grid applications;

Step 5: Else Return Null;

Step 6: If $Cn_k \geq \sum_{i=1}^I y_i^k$

Then

$$y_i^{k(n+1)*} = \text{Max}\{U_{resource}(e_i^l, x_i^j, y_i^k) = \sum_{i=1}^I (Pe_i^l \log e_i^l + Pc_i^j \log x_i^j + Pn_i^k \log y_i^k)\};$$

// Calculates its optimal network resource demand $y_i^{k(n+1)*}$

$$np_k^{(n+1)} = \max\{\varepsilon, np_k^{(n)} + \eta(y^k np_k^{(n)} - Cn_k)\}; \quad // \text{ Computes a new price}$$

// $y^k = \sum_i y_i^k, \eta > 0$ is a small step size parameter, n is iteration number

Return network resource price $np_k^{(n+1)}$ to all grid applications;

Step 7: Else Return Null;

5. Simulations

In this section, we present the performance evaluation of energy efficient resource management algorithm using the JAVASIM [15] simulator. Network generator BRITE [16] generates the computer network topology. We simulate a mobile grid environment with a 2 dimension area of 500m*500m to study mobile device's behavior. Each mobile device in the simulated environment has a maximal radio range of 100m, and moves following a random-walking mobility model. The average speed of

each mobile device is 5 meters per second. The average distance between neighboring devices is 25 meters. Mobile devices dynamically enter and leave the mobile grid. There are a number of parameters associated with each device such as energy budget, expense budget, and a two-dimension position value. Each mobile device's battery capacity is initialized with a random value in the range of [700, 800], and reduced automatically by a random value in the range of [0, 5] in each iteration. There are a total of 150 resources and 600 applications are taken for experimental evaluation of the system. A LAN consists of 90 nodes all of which contribute resources to the grid. The LAN acts as the main Grid infrastructure into which we want to integrate mobile devices. Device schedulers residing in WLANs, acting as the interface point between the mobile devices. All Wi-Fi interfaces operate at a rate of 11Mb/s. All Ethernet interfaces operate at a rate of 10Gb/s. The selective grid applications for simulation are computation-intensive applications such as image processing applications and mpeg players. We assume that each grid application can use any of grid resources including computation, communication and energy resources. Processor capacity varies from 220 to 580 MIPS. The wireless network bandwidth is from 10Kbps to 1Mbps. The main memory is set by 128M, 256M, 512M, and 2G. The disk capacity is set by 80G, 30G, 20G. Energy consumption is represented as a percentage of the total energy required to meet all job deadlines. Assume that the maximum power, P_{\max} , corresponds to running all jobs with the maximum processing frequency. The maximum frequency is assumed to be $f_{\max} = 1$ and the maximum frequency-dependent power is $P_{\max} = 1$. When the energy budget for each interval is limited, we can only consume a fraction of P_{\max} when processing requests during a given interval. Jobs arrive at each site $s_i, i = 1, 2, \dots, n$ according to a Poisson process with rate α . The capacities of the energy resources were chosen uniformly in the interval [50,500]. The energy cost can be expressed in grid dollar that can be defined as unit energy processing cost. The initial price of energy is set from 10 to 500 grid dollars. Users submit their jobs with varying deadlines. The deadlines of grid application are chosen from 100ms to 400 ms. The budgets of grid applications are set from 100 to 1500 grid dollars. Each experiment is repeated 6 times and 95% confidence intervals are obtained. The simulation results shown in the figures represent mean values.

The experiments are conducted to compare energy efficient resource management algorithm (EERM) with low-energy earliest deadline-first (LEDF) scheduling algorithm proposed by V. Swaminathan and K. Chakrabarty [7] studied scheduling workloads containing periodic tasks in real-time systems. The proposed approach minimizes the total energy consumed by the task set and guarantees that the deadline for every periodic task is met. They present a mixed-integer linear programming model for the NP-complete scheduling problem. They proposed a low-energy earliest deadline-first (LEDF) scheduling algorithm. The operation of the low-energy earliest deadline first (LEDF) is as follows: LEDF maintains a list of all released tasks, called the *ready list*. When tasks are released, the task with the nearest deadline is chosen to be executed. A check is performed to see if the task deadline can be met by executing it at the lower voltage (speed). If the deadline can be met, LEDF assigns the lower voltage to the task and the task begins execution. During the task's execution, other tasks may enter the system. These tasks are placed automatically on the *ready list*. LEDF again selects the task with the nearest deadline to be executed. As long as there are tasks waiting to be executed, LEDF does not keep the processor idle. This process is repeated until all the tasks have been scheduled. In the simulation, we compare EERM with LEDF by varying energy budget and price to study how they affect the performance of two algorithms. To investigate mobile grid settings and proposed energy efficient resource management algorithm, we evaluate them with respect to two criteria: application efficiency and resource efficiency which includes execution success ratio, energy consumption ratio, allocation efficiency and resource utilization. Energy consumption ratio is defined as the percentage of consumed energy among total

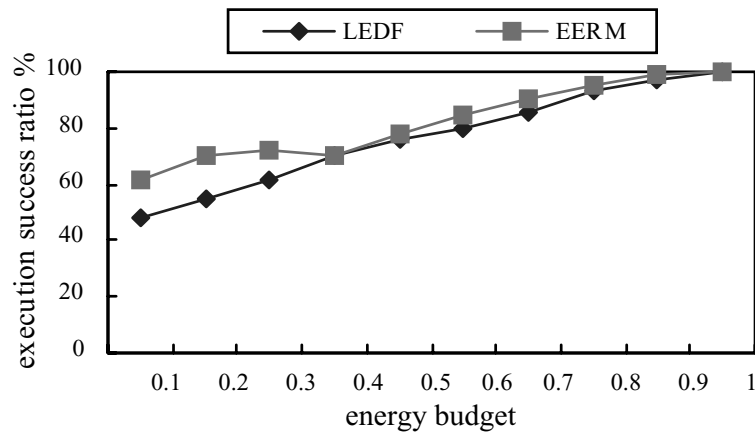


Fig. 1. Execution success ratio under various energy budget.

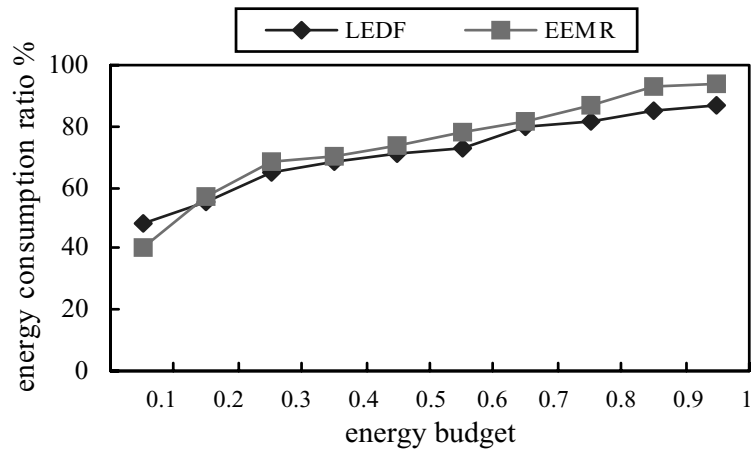


Fig. 2. Energy consumption ratio under various energy budget.

available energy resources. Execution success ratio is the percentage of tasks executed successfully before their deadline. Resource utilization is the ratio of the consumed resources to the total resources available as a percentage, commonly refers to the percent of time a resource is busy. Allocation efficiency is a measure of the efficiency of the allocation process, which is computed using the number of all requests and number of accepted requests.

The effects of energy budget on execution success ratio, energy consumption ratio, allocation efficiency and resource utilization were illustrated in Figs 1–4 respectively. Figure 1 is to show the effect of energy budget on execution success ratio. When increasing energy budget values, the execution success ratio becomes higher. A larger energy budget enables grid user to have enough energy to meet the deadlines and complete the task before its deadline. When energy budget increases ($E = 0.8$), execution success ratio is as much as 30% more than that with $E = 0.3$. Figure 2 shows the energy consumption ratio under different energy budgets. When the energy budget is high, the impact of different energy budget constraint on the energy consumption ratio is obvious; the energy consumption ratio is also high, because grid user tends to choose more energy-consuming resource to complete tasks within deadline. When $E = 0.8$, the energy consumption ratio of EERM is 35% less than $E = 0.3$. Under same energy budget ($E =$

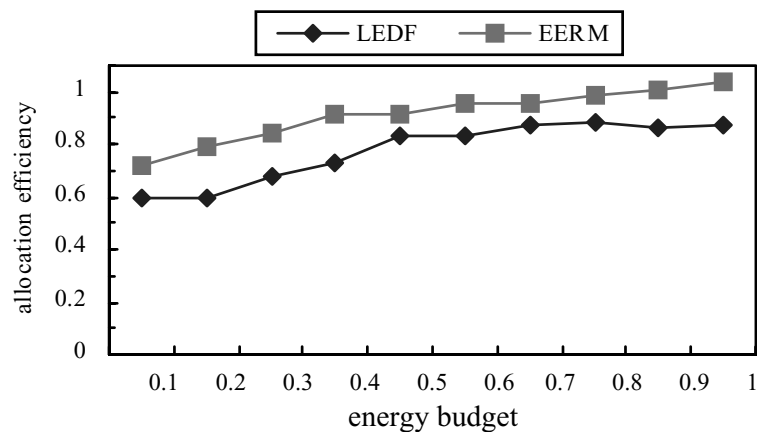


Fig. 3. Allocation efficiency under various energy budget.

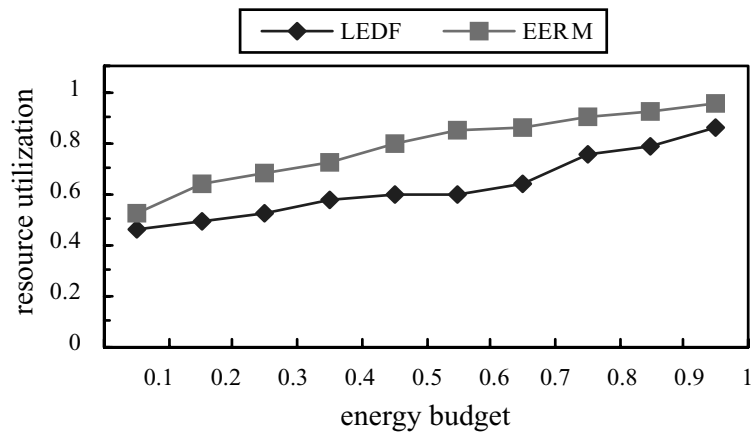


Fig. 4. Resource utilization under various energy budget.

0.3), the energy consumption ratio of LEDF is 6% less than EERM. Figure 3 shows the improvement of allocation efficiency as energy budget E increases. When the energy budget E is low, the system is very energy-constrained and it is crucial to utilize any excess energy due to achieve the performance objective on time. As energy budget E increases, the system becomes less energy-constrained; more jobs can be executed, the allocation efficiency is increased. When energy budget reaches maximum ($E = 100\%$), because the system has enough energy to meet all the deadlines and the allocation efficiency reaches its maximum value. Figure 4 shows the resource utilization under different energy budgets. As the energy budget is higher, the resource utilization becomes higher. When $E = 0.9$, the resource utilization is as much as 39% more than utilization by $E = 0.2$. Because when the energy budget decreases quickly, the users will be prevented from obtaining energy consuming resources. So, some energy consuming resources will be underutilized.

The impacts of the price on resource utilization, energy consumption ratio, execution success ratio, allocation efficiency were illustrated in Figs 5–8 respectively. The resource price (p) is set from 10 to 500 grid dollars. From the results in Fig. 5, as price is higher, the resource utilization becomes lower. When $p = 500$, the resource utilization of EERM is as much as 28% less than utilization by $p = 100$. Because

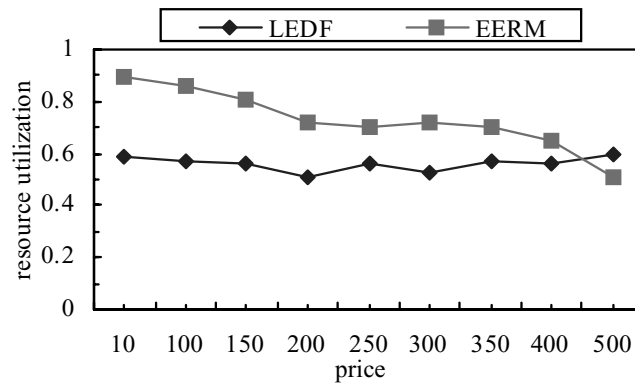


Fig. 5. Resource utilization vs. price.

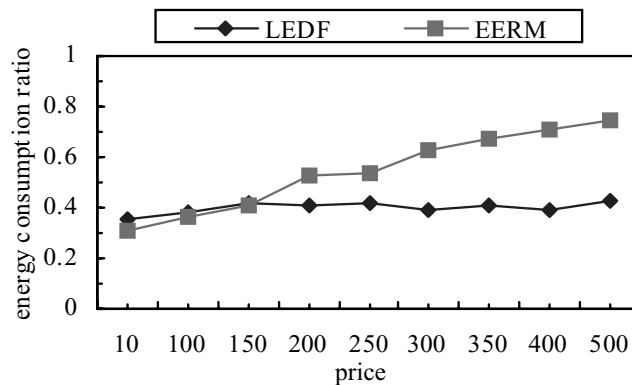


Fig. 6. Energy consumption ratio vs. price.

when the price increases quickly, the users with low expense budget will be prevented from obtaining resources. The smaller is p , the lower is the energy consumption ratio as shown in Fig. 6. Because when price becomes high, users will afford more payment to obtain energy-consuming resource, some tasks can't be completed before their deadlines. Price increasing quickly leads to some users with low budget can't be satisfied to fulfill their achievements. When $p = 500$, energy consumption ratio of EERM is as much as 34% more than that by $p = 100$. Considering the execution success ratio, the results of Fig. 7 show that when increasing price values, the execution success ratio become lower. Because when price becomes high, grid users will afford more payment to obtain the grid resource, some users with low budget will not complete tasks before their deadlines. When price increases ($p = 500$), execution success ratio of EERM is as much as 39% less than that with $p = 10$. Considering the allocation efficiency, the results of Fig. 8 show that when increasing p , the allocation efficiency become lower. Increasing prices of resource provider will prevent users from being admitted by the system, fewer users will exploit the resources. When $p = 500$, the allocation efficiency reduce to nearly 42% compared with $p = 10$.

6. Conclusions

This paper considers energy efficient resource management in mobile grid. The objective of energy efficient resource management in mobile grid is to maximize the utility of the mobile grid which is

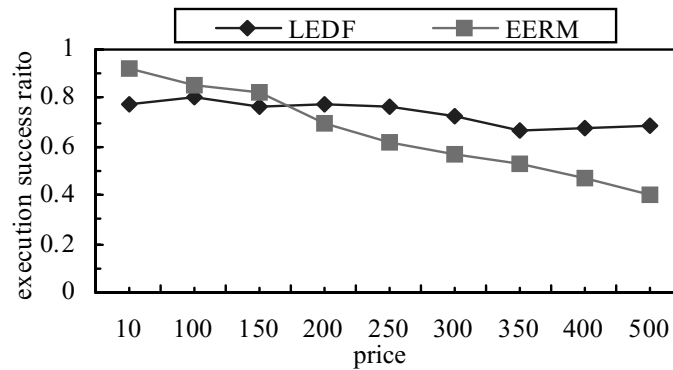


Fig. 7. Execution success ratio vs. price.

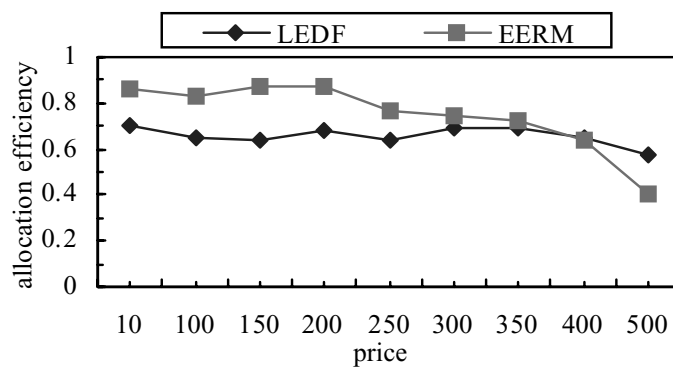


Fig. 8. Allocation efficiency vs. price.

denoted as the sum of grid application utility. The utility function models benefits of application and system. By using nonlinear optimization theory, energy efficient resource management in mobile grid can be formulated as multi objective optimization problem. In order to derive a distributed algorithm to solve global optimization problem in mobile grid, we decompose the problem into the sub problems. The proposed energy efficient resource management algorithm decomposes the optimization problem via iterative method. To test the performance of the proposed algorithm, the simulations are conducted to compare energy efficient resource management algorithm with other energy aware scheduling algorithm.

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