Generalized Lagrange based Resource Negotiation Mechanism in MANETs

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Abstract—**With the integration of mobile devices into ubiquitous environments, a wide range of services can be provided by exploiting the resources on heterogeneous devices, especially in MANETs. Because resources on mobile devices are shared out, it is essential to arrange highly-limited resources effectively and reasonably while considering utilities of multi-users and the network. To achieve this goal, abstract Buyer Agent and Seller Agent as well as the concept of resource market are introduced in the Resource Pricing Model. Then a novel Generalized Lagrange based Resource Negotiation Mechanism is proposed including the solution to the problem model using Generalized Lagrange Multiplier technique and the process of multi-round resource negotiation. At last, the experimental results demonstrate that the proposed mechanism is capable of optimizing the response time, maximizing the system utility and balancing the agent utility under the constraints of budget, deadline and energy resource.**

Keywords—Resource Negotiation; MANETs; Generalized Lagrange; agent utility; multi-round iteration

I. INTRODUCTION

Due to the rapid development of pervasive computing, mobile devices have been incorporated into ubiquitous environments to provide more rich resources for complicated ubiquitous services [1][2]. Over the past few years, significant attention has been focused on the integration of mobile devices to explore the broad application prospects in modern healthcare, mobile e-business and other fields [3]. However, such integration is not a simple issue and it could bring a great deal of challenges especially for MANETs (Mobile Ad hoc Networks).

In MANETs, every user request is regarded as a distributed ubiquitous service consisting of many independent, smaller and less-complex atom services which should be carried out via the cooperation of heterogeneous devices [4]. However, mobile devices often have some inherent characteristics: battery life is finite, processing power is low and storage space is constrained [5][6]. These characteristics really pose great difficulty to resource management of MANETs when multiple users request simultaneously. Since network resources can be shared and coordinated by users to content their needs at certain time, it is very important to deal with the issue of resource allocation conflict in multi-user competing environments.

The target of resource allocation in MANETs is to maximize the utility of the system composed by all users and the network according to devices' capabilities and users' requirements. Inspired by the economic strategies in mobile grids [7][8], this paper mainly concentrates on negotiation on the energy resource and attaches a price attribute to it. In RPM (Resource Pricing Model), a buyer agent represents an atom service that intends to purchase energy and a seller agent represents a mobile device that is willing to sell spare energy. The system maximization problem is decomposed into two classes of subproblems. One is for buyer to be subjected to user requirements (e.g. budget, response delay or service distance), and the other is for seller to be subjected to energy capacity. GLRNM (Generalized Lagrange based Resource Negotiation Mechanism) is proposed as an effective resource allocation scheme to solve RPM. Apart from maximizing the system utility, the proposed mechanism can equilibrate every negotiator's utility due to more reasonable market mediation mechanism.

The contributions of this paper are given below:

- Modeling a multi-to-multi problem scene by introducing three economic roles (buyer agent, seller agent and resource market) and associating each agent with a predefined utility function.

- Using the method of GLM (Generalized Lagrange Multiplier) to solve separate optimization subproblems.

- Importing priority and multi-round iteration theory into the proposed negotiation mechanism.

The paper is organized as follows. Section I gives a brief introduction. Section II describes the high-level architecture and defines the problem model. Then GLRNM is proposed in section III comprising the mathematical solution to RPM and the details of the negotiation process. Section IV analyzes the simulation results and verifies the validity of the proposed mechanism. Finally, concluding remarks and future work plans are discussed in the last section.

II. RELATED WORKS

So far, there have been a large number of researchers investigating the resource allocation issue in MANETs and many relative findings have been published.

An ant-based service selection framework was presented in [9] to satisfy different user needs and preferences. In the framework, user satisfaction is the key factor to select devices

based on Ambient User Media Preference and QoS metrics. Thus this approach slips up the network utility and can't work well for system optimization. In literature [10], a novel resource allocation scheme was designed for MANETs aiming to minimize the communication cost for accessing distributed resources. Besides adopting the k-out-of-n system, it employs a widely used technique for reliability control as well to improve the service reliability. However, when it comes to frequently disconnected network, the performance of the scheme goes worse sharply.

Neither related works above look on the resource allocation problem from economic view. Actually there exist some publications aware of the resource pricing concept.

A QoS-aware scheme is proposed in [11] based on virtual price. The virtual price is used to denote the degree of congestion. To guarantee rapid, stable convergence and fairness of the network, feedback flow is combined with the price conception. But the definition of the utility function is somewhat too simple to precisely describe the user profit. Khan [12] studied the power-aware task allocation issue and formulated it as a multi-constrained multi-objective extension of the Generalized Assignment Problem. A solution is also proposed from cooperative game theory based on the concept of Nash Bargaining Solution. What is not quite perfect is that this solution can't ensure the resource allocation is on run-time.Chen came up with a negotiation-based service self-management mechanism based on auction theory to maximize individual negotiator payoff in [13]. The learning mechanism is meanwhile introduced by using genetic algorithm in bidding strategy to be more adaptive to MANETs. But the mechanism is restricted to one-to-many scenario which can't be applied to multi-users environment.

The previous related works show that a good number of resource allocation mechanisms have been put forward from different perspectives. The main differences between ours and the above works are from three aspects. Firstly, the established model is economic and agent based which is abstracted from a multi-to-multi real scenario. Secondly, the proposed mechanism can well handle the issue of utility maximizing and balancing after multi-round bargaining which makes fair negotiation rules. Thirdly, GLM technique is the first time to be deployed in solving this kind of problem.

III. PROBLEM MODEL

In MANETs, an effective resource pricing model should maximize both users and the network utilities simultaneously under the constraints of budget, response time and limited device energy resource. Taken these aspects into consideration, an economic and agent based RPM is formulated in this section.

A. High-level architecture

In the study system (Fig.1), a CS (Central Server) serves as the resource dispatching center where all user requests are registered. Device nodes are organized by cluster-structure, which has a good scalability. Each cluster head will store the information of its cluster members and report it to CS. Thus CS masters the whole system information. Resources can be

centralized mediated by CS. Because a distributed ubiquitous service can be decomposed into several independent atom services, the overall optimization and equilibrium framework which consists of multiple users and the network can be decomposed into separate subproblems for each atom service and mobile device. To formulate RPM, two types of agents are defined: BA (Buyer Agent) and SA (Seller Agent). BA represents an atom service that is willing to purchase energy resource from the underlying network while SA represents a mobile device that offers to sell spare energy resource to earn money. Buyer agents make buying decisions solely on the basis of the most recent price information. Seller agents charge the buyer agents for the portion of energy occupied. All the interactions and transactions among agents are conducted in the resource market. The system in Fig. 1 can be abstracted as shown in Fig. 2.
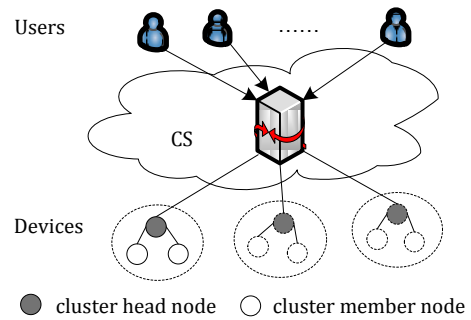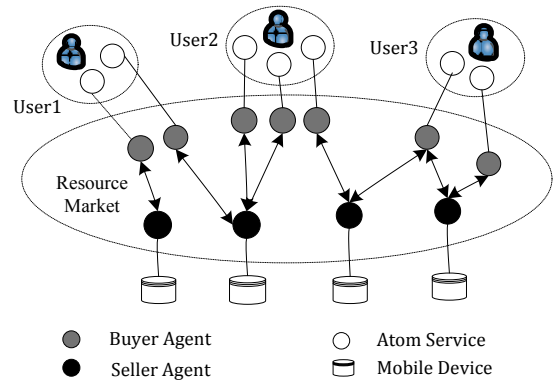

Fig. 1. The system architecture

Fig. 2. Collaboration among agents in MANETs

B. Model formulation

In this section, mathematical models are built in views of BA and SA for resource negotiation issue in MANETs. Each agent is associated with a utility function that indicates its own profit. Firstly some notations and definitions are given below.

- n: Number of users
- l: Number of atom services for each user
- N: Number of BAs, $N=nl$
- M: Number of SAs
- BP_{ij}: Payment for energy resource from BA i to SA j
- SP_j: Unit charge for energy resource from SA j
- C_j: Energy resource capacity of SA j

1) Buyer Agent Model

Each BA is represented by a 6-tuple as < AgentId, Budget, Deadline, ResourceReq, Payment, Utility >.

a) AgentId: An integer to identify the BA, denoted by symbol i ($i=1,\cdots, N$).

b) Budget: The maximum expense for the BA to pay for requested energy resource, denoted by B_i.

c) Deadline: Time limit given by the BA to complete its atom service, denoted by T_i.

d) ResourceReq: The requested amounts of energy resource for the BA to all SAs, defined as a vetor $\boldsymbol{R_i} = \{R_{ij} | j =1,\ldots, M\}$.

e) Payment: The money paid for the requested energy resource from the BA to all SAs, defined as a vetor $\boldsymbol{BP_i} = \{BP_{ij} | j =1,\ldots, M\}$.

f) Utility: Each BA has a utility function U_i that is used as a scoring function to evaluate the benefit this buyer agent will get. BA will decide its payment vector based on the value of utility itself. Many factors have influence on the BA utility function as seen from Formula 1.

$$U_i = (B_i - \sum_{j=1}^{M} BP_{ij}) + K(T_i - \sum_{j=1}^{M} \frac{R_{ij}SP_j}{C_jBP_{ij}}) \qquad (1)$$

Here, the element K, the weight of response delay, indicates the relative importance of response time versus cost in terms of the BA utility.

For a buyer agent, the objective is to maximize its utility function under the constraints of budget and deadline. The BA optimization subproblem can be defined as Formula 2.

$$\begin{aligned} &Max \quad U_i \\ (BA) \quad &s.t. \quad \begin{cases} \sum_{j=1}^{M} BP_{ij} \leq B_i \\ \sum_{j=1}^{M} \frac{R_{ij}SP_j}{C_jBP_{ij}} \leq T_i \end{cases} \end{aligned} \qquad (2)$$

2) Seller Agent Model

Similarly, each SA is represented by a 5-tuple as < AgentId, Capacity, ResourceAlloc, UnitCharge, Utility >.

a) AgentId: An integer to identify the SA, denoted by symbol j ($j=1,\ldots, M$).

b) Capacity: The maximum spare energy resource for the SA to sell, denoted by C_j.

c) ResourceAlloc: Energy resource units allocated to BAs from SA j, defined as a vetor $\boldsymbol{V_j} = \{V_{ij} | i=1,\ldots, N\}$.

d) UnitCharge: Unit price the SA charge for its energy resource, denoted by SP_j.

e) Utility: Each SA has a utility function U_j that is used to calculate the profit this seller agent will get by selling energy resource. SA will decide its resource allocation vector based on its income. The SA utility function is shown in Formula 3.

$$U_j = \sum_{i=1}^{N} BP_{ij} \ln(V_{ij} + 1) \qquad (3)$$

For a seller agent, the objective is to maximize its utility function under the constraint of energy resource capacity. The SA optimization subproblem can be written as Formula 4.

$$\begin{aligned} &Max \quad U_j \\ (SA) \quad &s.t. \quad \sum_{i=1}^{N} V_{ij} \leq C_j \end{aligned} \qquad (4)$$

In general, Subproblem BA and Subproblem SA jointly make up the RPM. The interaction between two sub-problems is controlled through the use of price variable SP_j, which is the energy price charged from buyer agent by seller agent. Based on it, buyers adjust their payments and sellers arrange their energy supplies.

IV. PROPOSED MECHANISM

GLRNM mainly includes two important parts: the mathematical solution to RPM with the method of GLM; a multi-round iteration negotiation under the mediation of resource market. During the negotiation process, multiple BAs and SAs are allowed to interact simultaneously based on the up-to-date energy price in each iteration. The resource market determines the final negotiation results.

A. Mathematical solution

1) Solution for Buyer Agent Model

As can be seen from the BA model formulation, it is a non-linear optimization problem with inequation constraints. Hence, GLM technique is an effective way to solve it.

By introducing relaxation variables y_1 and y_2, Formula 2 is transformed to Formula 5.

$$\begin{aligned} &Min \quad f(\boldsymbol{BP_i}) = -U_i \\ &s.t. \quad \begin{cases} g_1(\boldsymbol{BP_i}) - y_1^2 = B_i - \sum_{j=1}^{M} BP_{ij} - y_1^2 = 0 \\ g_2(\boldsymbol{BP_i}) - y_2^2 = T - \sum_{j=1}^{M} \frac{R_{ij}SP_j}{C_jBP_{ij}} - y_2^2 = 0 \end{cases} \end{aligned} \qquad (5)$$

Using GLM technique, the Lagrange for Formula 5 is given in Formula 6 where γ and λ_m ($m=1, 2$) are generalized Lagrange multipliers.

$$L(\boldsymbol{BP_i}) = f + \frac{\gamma}{2}\sum_{m=1}^{2}(g_m - y_m^2)^2 - \sum_{m=1}^{2}\lambda_m(g_m - y_m^2) \qquad (6)$$

With the method of completing the square, Formula 6 is equivalent to the form in Formula 7.

$$L(\boldsymbol{BP_i}) = f + \sum_{m=1}^{2}\{\frac{\gamma}{2}[y_m^2 - \frac{1}{\gamma_m}(\gamma_m g_m - \lambda_m)]^2 - \frac{(\lambda_m)^2}{2\gamma_m}\} \qquad (7)$$

To achieve minimum value of $L(\boldsymbol{BP_i})$ with respect to y_m, we get $y_m^2 = \max\{0, \gamma g_m(x) - \lambda_m\}/\gamma$, $m=1, 2$.

Therefore, $L(\boldsymbol{BP_i})$ is redefined without the variable y_m. The optimization subproblem in Formula 2 is transformed to

unconstrained problem in Formula 8 which is quite easy to be solved by the method referred in [14].

$$MinL(\boldsymbol{BP_i}) = f + \frac{1}{2\gamma}\sum_{m=1}^{2}\{[\max(0,\lambda_m - \gamma g_m)]^2 - (\lambda_m)^2\} \quad (8)$$

To obtain the optimal solution of the original problem, Algorithm 1 is deployed on the basis of iteration. Finally, mark the optimal payment from BA i to SA j as BP_{ij}^*.

2) Solution for Seller Agent Model

Considering the SA model in Formula 4, it is also a non-linear optimization problem with inequation constraints, so the solution for BA model is applicable to it as well.

By using mathematic theories referred to in the previous section, it is obvious that the optimal solution of Formula 4 is the same as that of Formula 9.

$$MinL(SP_j) = f + \frac{1}{2\gamma}\{[\max(0,\lambda - \gamma g_3)]^2 - \lambda^2\} \quad (9)$$

Here, $f = -U_j$, $g_3 = C_j - \sum_{i=1}^{N}V_{ij}$. Then let $X_0 = V_j$ and run Algorithm 1 to get final result. Mark the best allocation amount of energy resource from SA j to BA i with V_{ij}^*.

Algorithm 1
1: Initialize iteration counter $k=1$, initial point $X_0 = \boldsymbol{BP_i}$, multipliers $\lambda_m^{(0)}$, factor γ_0, amplification factor $\alpha > 1$, tolerance error $\varepsilon > 0$, parameter $\omega \in (0,1)$
2:   **while** true **do**
3:          Make X_{k-1} the starting point
4:          Solve problem $MinL(\boldsymbol{BP})$
5:          Mark the optimal solution with X_k
6:          **if** $\|g_m(X_k)\| < \varepsilon$
7:              **then return** X_k
8:          **end if**
9:          **if** $\|g_m(X_k)\|/\|g_m(X_{k-1})\| \geq \omega$
10:            **then** $\gamma_{k+1} = \alpha\gamma_k$
11:         **else** $\gamma_{k+1} = \gamma_k$
12:         **end if**
13:         $\lambda_m^{(k+1)} = \lambda_m^{(k)} + \gamma_k g_m(X_k), m=1,2$
14:         $k = k+1$
15: **end while**

B. Mechanism description

The overall flowchart of the proposed mechanism is illustrated in Fig. 2. It mainly includes three procedures and the details are described below.

StepA: Users register their requested ubiquitous services. Sort all ubiquitous services into different batches according to the priority based on SLA (Service Layer Agreement).

StepB: Ubiquitous services in the highest priority batch request for access into the resource market. If the request fails,

back to StepA, otherwise the resource market and the network begin the resource negotiation. If it comes to a successful agreement, go to StepC, or else back to StepA. The process of resource negotiation is described in detail as Algorithm 2 shows. The interaction between BAs and SAs is similar to a multi-round game on resource payments and charging prices. Resource market, acting as a third party, is responsible to determine whether the negotiation completes.

StepC: Set up the ubiquitous services which have been successfully allocated energy resource in ready. Check whether there exist other batches, if so, back to StepB, and otherwise perform the ubiquitous services in ready.
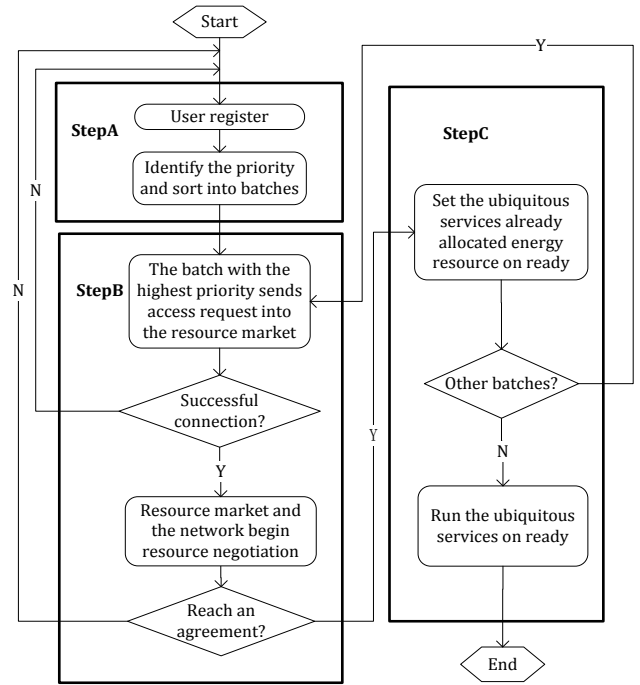

Fig. 3. The flowchart of GLRNM

Algorithm 2. Process of resource negotiation
/ * n is negotiation round * η is small step iteration factor * a is the lower bound of unit charge */
Buyer Agent
Input: unit resource price $SP_j^{(n)}$ from various SA j
Output: optimal payment $BP_{ij}^{(n+1)}$ from BA i to SA j
1: Calculate optimal payment BP_{ij}^* using GLM technique based on $SP_j^{(n)}$, $BP_{ij}^* = Max\{U_i(SP_j^{(n)})\}, \forall i$
2: **if** $\sum_j BP_{ij}^* \leq B_i$
3:      **then** $BP_{ij}^{(n+1)} = BP_{ij}^*$
4:          **return** $BP_{ij}^{(n+1)}$ to SA j
5: **else return** null
6: **end if**

Input: payment $BP_{ij}^{(n)}$ from various BA i

Output: new unit price $SP_j^{(n+1)}$ from SA j to all BAs

1: Calculate optimal unit resource price using GLM
technique based on $BP_{ij}^{(n)}$, $v_{ij}^* = Max\{U_j(BP_{ij}^{(n)})\}, \forall j$

2: **if** $\sum_i v_{ij}^* \leq C_j$

3:     **then** Compute a new unit resource price $SP_j^{(n+1)}$

$$SP_j^{(n+1)} = \max\{a, SP_j^{(n)} + \eta(SP_j^{(n)} \sum_i V_{ij} - C_j)\}$$

4:     **return** $SP_j^{(n+1)}$ to all BAs

5: **else return** null
6: **end if**

V. SIMULATION AND RESULT ANALYSIS

A. Simulation environment

To make effective evaluation, we mimic the actual scenario by C++ and Matlab programming. The simulation environment is a MANET with an area of $150m \times 150m$. Initially, 8 users and 15 mobile devices are randomly scattered and move following a random-walking mobility model with the average speed $3m/s$. Assume all ubiquitous services share the same priority. The total numbers of BAs and SAs are 20 and 10 according to the topologies of services and the network, respectively. Other parameters are listed in Table I. Acctually, larger scenarios are also simulated and can give similar results. Hence the small senario is chosen to make clear analysis in the next subsection.

In simulation RPS (a resource pricing strategy using non-cooperative bargaining game) from literature [15] is cited as the contrast algorithm. The reason is that two algorithms are both economic-based and need to make transactions via multi-round iterations. They also consider deadline and energy capacity as constraints. Thus, the results are comparatively significant.

TABLE I.   SIMULATION PARAMETERS

Parameter	Value
BA Budget	[100, 800]
BA Deadline (*ms*)	[50, 100]
Initial BA ResourceReq	[30, 100]
SA Capacity	[100, 300]
Initial SA UnitCharge	[10, 20]

B. Result Analysis

In order to make evaluation of the proposed mechanism, convergence, equilibrium and response time(*ms*) are elected as three evaluation indexes.

1) Convergence

We study the convergence performance of GLRNM in terms of the system utility which is the sum of all agents'

utilities. Fig. 4 gives data about the variation tendency of the system utility over multi-round iteration. It is visible that the system utility almost continuously goes up with the increase of iteration round and converges to a maximal value nearly at round 13. Since the negotiation mechanism is distributed, every agent solves its optimal subproblem separately to obtain the most profit. If one trade tends to decrease its utility, the agent wouldn't like to reach an agreement. So in every round, each BA and each SA adjust its offer price to maximize its own utility function. As a whole, the overall utility is pushed higher gradually and approximates to a peak due to budget, deadline and energy constrains.
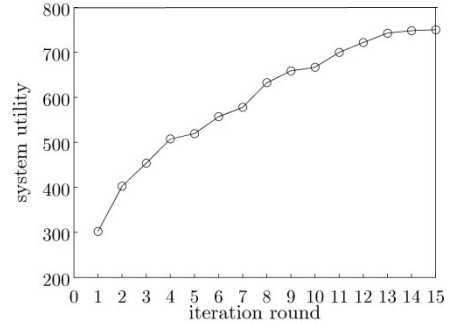

Fig. 4.   System utility over iteration

2) Equilibirum

Fig. 5 and Fig. 6 show the comparison results of RPS and GLRNM with regard to the BA or SA utility.
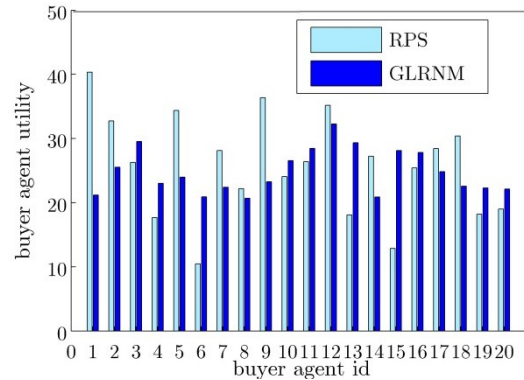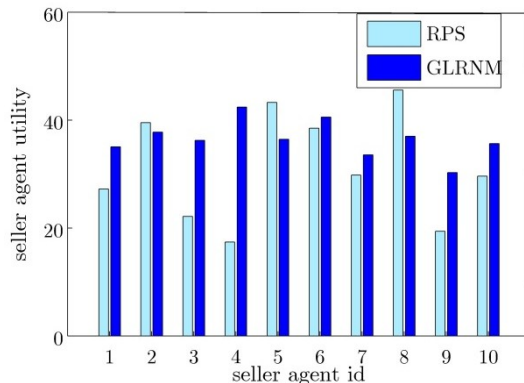

Fig. 5.   Buyer agent utility

Fig. 6.   Seller agent utility

As seen from Fig. 5, one main advantage of GLRNM over RPS is that it has better equilibrium effect, meaning there is no great difference in utility between any two BAs. The bar height of GLRNM also fluctuates more smoothly indicating more balanced resource allocation to atom services. That's because the resource market mechanism is useful in mediating BAs' payment actions according to their current situations. Similar phenomenon is apparent to be discovered in Fig. 6. The utility values change sharply among different SAs as for RPS while GLRNM is otherwise. Although each SA has no information about other selling competitors, the resource market as a mediator, is responsible for the equilibrium issue by price policy. Thus the seller agent utilities are more balanced under GLRNM.

3) Response time

The total response time, viewed as a performance index, is examined here. It is defined as the sum of time to complete resource negotiation and get all users' requested ubiquitous services done. Fig. 7 illustrates the impact of different budget constraint on the total response time. It can be observed that as the budget increases GLRNM outperforms RPS because it would cost less time. The key reason is that response time is considered as an influence factor in the BA utility function. Maximizing the BA utility will meanwhile shorten the cost time.
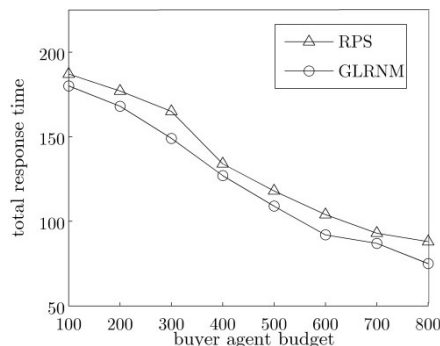

Fig. 7. Total response time under various budget

VI. CONCLUSION AND FUTURE WORK

This paper proposes a multi-to-multi, economic and agent based model named RPM. Distinct utility functions are defined as the standards to quantify different agents' benefits. Then GLRNM is put forward aiming at maximizing system utility and equilibrating the utilities of internal agents. Simulation results show the proposed mechanism indeed has better performance in MANETs, which has tremendous meanings to future studies about service automation, resource management and task scheduling in ubiquitous environments.

As this paper just attaches the price property to energy resource, the future work is to account for more resources (e.g. CPU or memory) to extend the system model to a multi-attribute pricing problem. What's more, the proposed mechanism stipulates that each seller agent offers uniform charging price to buyers, so more flexible price strategies can be investigated in the following research.

REFERENCES

[1] Luttenberger, Norbert, Hagen P, et al. A resilient and energy-saving incentive system for resource sharing in MANETs. 17th GI/ITG Conference on Communication in Distributed Systems, Dagstuhl, Germany, 2011, pp: 109-120.

[2] Jaramillo, José J, and Srikant R. Optimal scheduling for fair resource allocation in ad hoc networks with elastic and inelastic traffic. INFOCOM, San Diego, CA, USA, 2010, pp: 1-9.

[3] Furthmuller J, Waldhorst O P. Evaluating the energy consumption of an incentive system for resource sharing in MANETs. Communications (ICC) 2012 International Conference, Ottawa, ON, Canada, 2012, pp: 6293-6297.

[4] Guo Shaoyong, Rui Lanlan, Qiu Xuesong, et al. An Effective Cooperation Mechanism among Multi-devices in Ubiquitous Network. In: Network and Service Management (CNSM) 2012 8th International Conference, Las Vegas, NV, USA, 2012, pp. 199- 203.

[5] Urgaonkar, Rahul, Kozat, et al. Dynamic resource allocation and power management in virtualized data centers. In Network Operations and Management Symposium (NOMS), Osaka, Japan, 2010, pp: 479-486.

[6] Furthmüller, Jochen, Oliver P Waldhorst. Energy-aware resource sharing with mobile devices. Computer Networks, 2012, 56(7): 1920-1934.

[7] Haryanti S C, Sari R F. Task execution reliability of resource allocation with tasks replication in mobile ad hoc grid. QiR (Quality in Research) 2013 International Conference, Yogyakarta, Indonesia, 2013, pp: 86-89.

[8] Shah S C, Park M S. Energy efficient resource allocation in mobile ad hoc computational grids. Communication Systems and Networks (COMSNETS) 2011 3rd International Conference, Bangalore, India, 2011, pp: 1-10.

[9] Hossain M S, Hossain S K A, Alamri A, et al. Ant-based service selection framework for a smart home monitoring environment. Multimedia tools and applications, 2013, 67(2): 433-453.

[10] Chen C A, Won M, Stoleru R, et al. Resource allocation for energy efficient k-out-of-n system in Mobile Ad Hoc Networks. Computer Communications and Networks (ICCCN) 2013 22nd International Conference, Nassau, Bahamas, 2013, pp: 1-9.

[11] Han B Q, Feng G F. A novel QoS-aware resource allocation scheme for wireless ad hoc networks. Intelligent Computing and Intelligent Systems (ICIS) 2009 International Conference, Shanghai, China, 2009, pp: 358-362.

[12] Khan S U, Ardil C. Energy efficient resource allocation in distributed computing systems. World Academy of Science, Engineering and Technology, 2009, 8(56): 667-673.

[13] Chen Kan, Qiu Xuesong, Yang Yang, et al. Negotiation-based service self-management mechanism in the MANETs. Asia-Pacific Network Operations and Management Symposium (APNOMS) 2011 13th IEEE Conference, Taipei, Taiwan, 2011, pp: 1-7.

[14] Karthikeyan K., V. M. Chandrasekaran. Few numerical algorithms for minimization unconstrained non-linear functions. Int. J. Pure Appl. Sci. Technol, 2012, 8(1): 38-46.

[15] Birje M N, Manvi S S, Das S K. Resource pricing strategy in wireless grid using non-cooperative bargaining game. In: Parallel Distributed and Grid Computing (PDGC) 2012 2nd International Conference, Solan, India, 2012, pp. 61-66.