DESP: A Distributed Economics-Based Subcontracting Protocol for Computation Distribution in Power-Aware Mobile Ad Hoc Networks

Li Shang, *Student Member*, *IEEE*, Robert P. Dick, *Member*, *IEEE*, and Niraj K. Jha, *Fellow*, *IEEE*

Abstract—In this paper, we present a new economics-based power-aware protocol, called the *distributed economic subcontracting protocol* (DESP), that dynamically distributes task computation among mobile devices in an ad hoc wireless network. Mobile computation devices may be energy buyers, contractors, or subcontractors. Tasks are transferred between devices via distributed bargaining and transactions. When additional energy is required, buyers and contractors negotiate energy prices within their local markets. Contractors and subcontractors spend communication and computation energy to relay or execute buyers' tasks. Buyers pay the negotiated price for this energy. Decision-making algorithms are proposed for buyers, contractors, and subcontractors, each of which has a different optimization goal. We have built a wireless network simulator, called ESIM, to assist in the design and analysis of these algorithms. When the average communication energy required to transfer a task is less than the average energy required to execute a task, our experimental results indicate that markets based on our protocol and decision-making algorithms fairly and effectively allocate energy resources among different tasks in both cooperative and competitive scenario

Index Terms—Ad hoc network, economics-based protocol, distributed computing, power-aware computing, resource management.

1 Introduction

In ad hoc wireless networks [1], mobile computation devices are usually battery-powered. A limited energy budget constrains the computation and communication capacity of each device. Energy resources and computation workloads have different distributions within the network. Some mobile devices have spare energy. Devices that expend all their energy can only be recharged when they leave the network. Therefore, it is beneficial to redistribute spare energy resources to satisfy unevenly distributed workloads. In this paper, we propose a protocol for computation distribution that solves this dynamic energy resource allocation problem.

This work is motivated by dynamic workload balancing techniques used in parallel and distributed computing, e.g., task migration and process migration. In wireless networks, the ratio of computation energy consumption to communication energy consumption varies in a wide range, depending on the application type. In some application domains, e.g., microsensor networks, communication accounts for the majority of energy consumption [2], [3]. In other application domains, e.g., many military applications, voice, face, and handwriting recognition, map searching, image processing, simulation, classification, artificial intelligence, target detection, pattern matching, decision making, etc., computation energy consumption generally dominates communication energy consumption. Previous work [4], [5], [6], [7], [8], [9] has demonstrated that the energy efficiency of the mobile devices can be improved using remote computation for those computation extensive applications. Therefore, within the mobile ad hoc network, if devices with excess computation-intensive tasks can, for a fee, transfer these tasks to devices with spare energy and time, both buyer and seller devices benefit; sellers may use their earnings to buy energy in the future.

Mobile ad hoc networks have no centralized infrastructure to control devices and communication among them. In some scenarios, e.g., large-scale military or commercial operations, mobile devices collaborate. In others, they compete. Competitive and cooperative scenarios must both be considered.

In distributed computing systems, economics-based techniques have been used to balance resource utilization. Market-based infrastructures were proposed for computational resource allocation and balancing in computer networks [10], [11], [12], [13]. Kurose and Simha proposed an economic model for file resource allocation in distributed systems [14]. An auction-based approach was proposed for energy management in hosting centers [15]. Game-theoretic approaches were used to do power control in code division multiple access (CDMA) wireless networks [16], [17]. Stonebraker et al. used a distributed microeconomic approach to optimize query and storage management in

- *L. Shang and N.K. Jha are with the Department of Electrical Engineering, Princeton University, Princeton, NJ 08544. E-mail: {lshang, jha}@ee.princeton.edu.*
- *R.P. Dick is with the Computer Engineering Group, Department of Electrical and Computer Engineering, Technology Institute, L477, Northwestern University, Evenston IL 60208. E-mail: dickrp@ece.northwestern.edu.*

Manuscript received 13 Sept. 2002; revised 31 Mar. 2003; accepted 14 Aug. 2003.
For information on obtaining reprints of this article, please send e-mail to: tmc@computer.org, and reference IEEECS Log Number 12-092002.

wide-area database systems [18]. A market-based approach was used to allocate bandwidth to control quality of service [19]. An economics-based approach was also used for packet forwarding in mobile ad hoc networks [20]. Distributed utility-based decision-making mechanisms were proposed to maximize a global objective in wireless sensor networks [21]. Energy consumption is a significant issue in mobile ad hoc networks [22], [23]. Some wireless works reduce mobile device power consumption by migrating tasks from mobile clients to fixed-position servers, i.e., computers with line power [4], [5], [6], [7], [8], [9].

We propose a *distributed economic subcontracting protocol* (DESP) to dynamically distribute task computation among mobile or fixed-position devices in an ad hoc network. Online bargaining is used to control the distribution of tasks for which the energy to transfer the task to another device is less than its local computation energy. Energy sellers may be contractors or subcontractors. They automatically adjust their energy prices based upon market conditions. Local market sizes are dynamically adjusted in order to balance communication energy and the lowest prices available to buyers. DESP supports a new class of economic agents, called subcontractors. Subcontracting allows transitive transfers of task execution among devices; subcontractors tie local markets together into a global market. Subcontracting can be seen as a computational version of multihop communication. We propose policies to handle both competitive scenarios, where mobile devices try to maximize their own profit, and cooperative scenarios, where the only goal of mobile devices is to provide their spare energy to others. In our current work, we assume the mobile devices are well-behaved, which means each mobile device obeys the transaction protocol and agreement, i.e., the contractors and subcontractors spend spare energy to execute the communication and computation workload, and the buyers make payments based on the agreement. We will discuss related security issues in a later section. We believe that this first study demonstrates the effectiveness of an economics-based approach as a power-aware computation distribution mechanism for mobile ad hoc networks.

The rest of this paper is organized as follows: In Section 2, we present related concepts and a brief overview of our work. In Section 3, we introduce the economics-based protocol in detail. We present the network simulator in Section 4. We experimentally demonstrate the feasibility of our approach in Section 5. Finally, we conclude in Section 6.

2 Preliminaries and Modeling

In this section, we introduce related economic and wireless communication models. We then define our subcontracting protocol, DESP.

2.1 Basic Economic Concepts

In this section, we present basic economic definitions.

Rational decision. Agents are modeled as rational decision makers [24]. Each rational decision maker makes decisions based on preferences, $\succ$, over a set of options, and chooses the option that is expected to yield the best consequence. The preferences of the rational decision makers are numerically represented by utility functions, which are defined below.

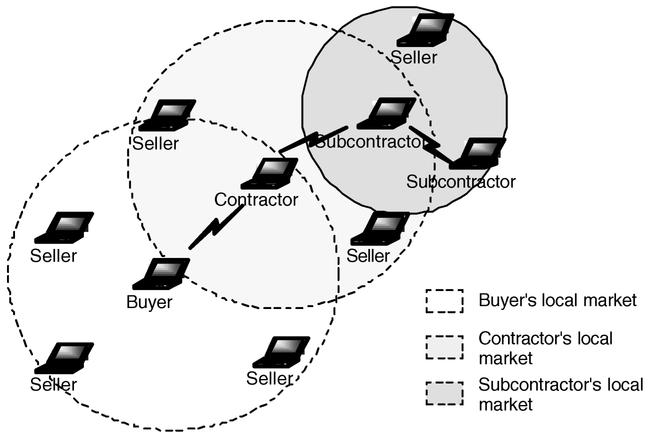


Fig. 1. DESP example.

Utility: Given preferences, $\succ$, over a set of options, X, a numerical representation for the preferences is a utility function U with a domain of X and a range of the real numbers such that

$$x \succ y \textit{ iff } U(x) > U(y), \quad (1)$$

where $x, y \in X$ [24].

There is not necessarily a utility function for a given preference relationship. Utility theory investigates the possibility of using a numerical function to represent a preference relation [23].

2.2 Wireless Communication Energy Model

We use the wireless communication path loss model to calculate transmission energy consumption [25], [26]. In this model, the received signal power is dependent on the distance between devices. The received signal power is proportional to $1/d^n$, where d is the transmission distance and n is an environmentally dependent path loss exponent [25].

2.3 Distributed Economic Subcontracting Protocol

DESP performs dynamic allocation of energy resources in ad hoc wireless mobile networks through online transactions within markets. Mobile computation devices are modeled as rational decision makers. This model is valid for devices that use optimization algorithms to maximize predefined utility functions during their transactions.

As illustrated in Fig. 1, DESP consists of the following elements:

- **Buyers**. A device that intends to purchase energy from other devices is a buyer. A buyer uses an advertising broadcast to construct a local market in which it may purchase energy.
- **Sellers**. A device that is willing to sell spare energy to other devices joins one or more local markets as a seller.
- **Contractors**. In a local market, sellers compete with each other. The winner signs a contract with the

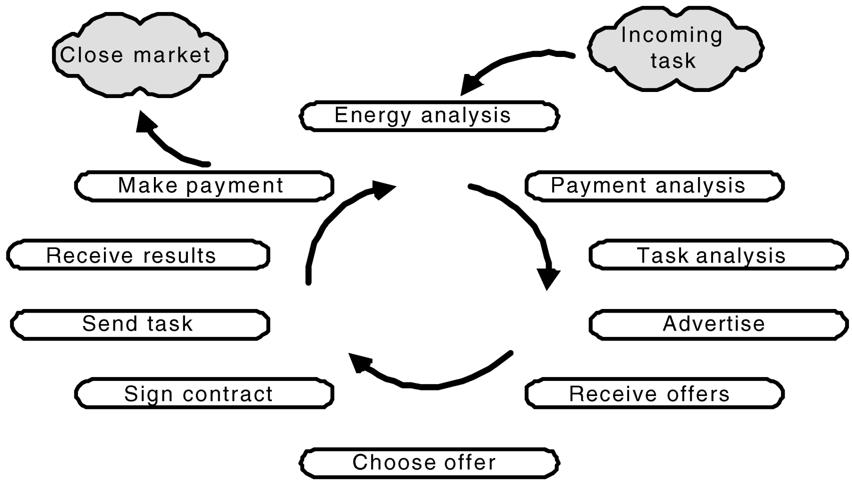


Fig. 2. Transaction protocol for buyers.

buyer: It is a contractor. A contractor may decide to execute a buyer's task. However, it may, alternatively, decide to create another local market to find subcontractors. A contractor is a seller. However, if it uses a subcontractor, it is also a buyer.

- **Subcontractors**. A subcontractor is a contractor that sells to another contractor or subcontractor, instead of selling directly to a buyer.
- **Local market**. Every energy transaction occurs within a local market. Each local market is dynamically constructed by a market owner that may be a buyer, contractor, or subcontractor. The market owner's advertising broadcast energy controls the market's area. Multiple sellers within the local market send out their, potentially encrypted, offers to the market owner, which chooses the winner and signs a contract.

3 The Subcontractor Market

In this section, we explain the transaction protocols and corresponding optimization algorithms for the economic agents in our protocol.

3.1 Transaction Protocols

In DESP, there are energy transactions between buyers and sellers. Each device bases its judgment about market conditions on a history of its recent transactions. Note that contractors and subcontractors can be both buyers and sellers. Next, we present the transaction protocols used by each agent.

3.1.1 Transaction Protocol for the Buyer Market

Fig. 2 shows the buyer transaction protocol. First, the buyer analyzes its pending tasks, remaining energy, remaining money, and transaction history. Based on this information, it decides whether to execute a pending task or become a buyer and pay other devices to execute the task for it. A buyer makes an advertising broadcast to construct a local market. The advertising broadcast energy controls the advertising range and, thereby, market area. Among other things, the buyer's advertisement includes its original signal strength, task type, and task communication data quantity, as well as bid and decision deadlines. The original signal strength may be used by a seller to estimate the internode distance based on the received signal strength [27], [28]. Alternatively, if mobile devices are equipped with low-power global positioning system (GPS) receivers, they can be used to determine interdevice distances. Task type and communication data quantity information allow a seller to estimate a task's execution time and energy. Bid and decision deadlines allow a seller to determine when to send its bids and expect the buyer's decision. The sellers within the buyer's local market may make bids. The buyer accepts offers until its bid deadline. After the bid deadline, and before the decision deadline, the buyer may choose one of the bids it has received and send out an acceptance message. It then signs a contract with the corresponding seller, thereby changing the seller to a contractor. Finally, the buyer sends its tasks to the contractor, receives the computation results, and pays the contractor. At the end of the transaction, the local market automatically closes.

Fig. 3 shows the seller transaction protocol. First, a device that is willing to sell energy becomes a seller and begins to monitor the advertising channel. If a seller receives an advertisement, it analyzes the incoming task, its energy budget, and its transaction history. Based on this information, the seller returns its bid, including price and position information. It then waits for the buyer's decision until the buyer's decision deadline. If the seller's offer is not accepted by this time, it assumes the offer is rejected, and the transaction is closed. If, instead, its offer is accepted, the seller signs a contract and receives the task from the buyer, thereby becoming a contractor. This contractor may decide to construct another, overlapping, local market to find a subcontractor. After the resulting data have been computed, either by the contractor or by a subcontractor, the contractor sends them to the buyer. Finally, the seller receives its payment and pays a subcontractor, if necessary.

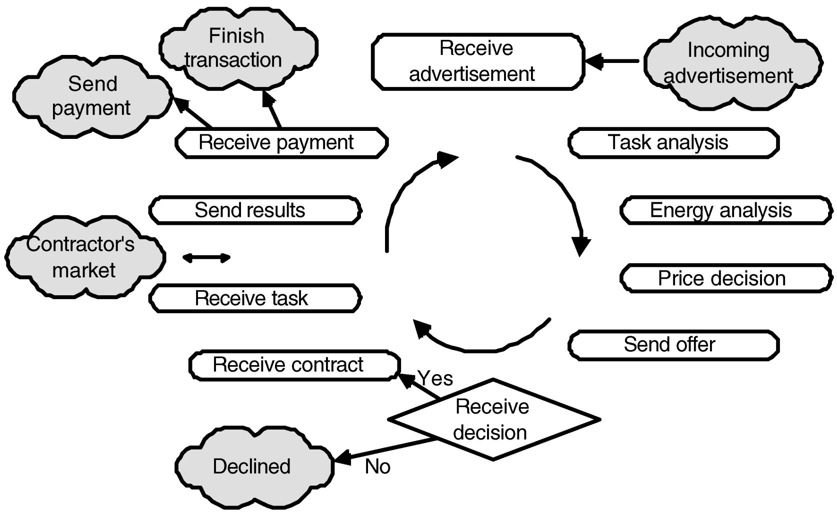


Fig. 3. Transaction protocol for sellers.

3.1.2 *Transaction Protocol for the Contractor and Subcontractor Markets*

When a seller becomes a contractor, it may construct its own local market to find subcontractors. The transaction protocol for contractors is shown in Fig. 4. The contractor transaction protocol is similar to the buyer protocol. In essence, the contractor becomes a relay node between the buyer and the subcontractor, transferring tasks from the buyer to the subcontractor and returning the results. For this work, the contractor earns the difference between the buyer's payment and the subcontractor's bid. This protocol allows contractors and subcontractors to cooperate in providing resources to a buyer and share the buyer's payment.

3.2 Transaction Policies for Buyers

In the absence of a central controller, mobile devices must make their own energy purchasing decisions. In DESP, buyers do local advertising broadcasts. A buyer may only carry out direct transactions with sellers in its advertising area. It is desirable to reduce communication energy and price. However, these costs conflict with each other, i.e., it is often possible to decrease one only by increasing the other. Communication energy is the energy expended by a buyer during the advertising broadcast and task transmission for remote computation. It is correlated with the advertising broadcast area. Price is correlated with the energy scarcity of the available seller devices. In other words, increasing the number of sellers in a market will, on average, reduce the minimum price available. It is necessary to decide upon a broadcast range that results in a good trade off between price and communication energy.

Buyers face a similar decision when choosing between a nearby seller and a more distant one that has a lower price. In order to reduce communication energy, buyers prefer sellers that are close; buyers will tolerate higher prices from such sellers. Nearby sellers can take advantage of this and bid at higher prices than other, more distant, sellers. Each

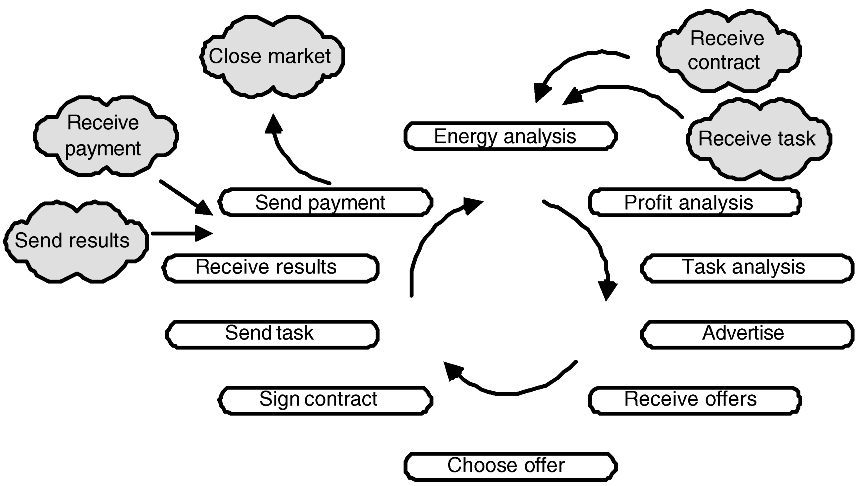


Fig. 4. Transaction protocol for contractors.

bid has two costs, price and communication energy, i.e., the energy used by the buyer to send the task to the seller and receive the resulting data from it. It may not be possible to find a bid with a lower price and communication energy than all other bids. Therefore, buyers need to choose a bidder that offers the best trade off between price and communication energy.

In our protocols, buyers dynamically adjust their advertising distance in the following way:

1. For task k, the buyer calculates an upper bound on communication distance D_k, subject to the constraint that communication energy is lower than computation energy. The buyer also predicts the communication distance lower bound d_h, based on previous successful transactions. If $D_k < d_h$, then the buyer executes the task locally. Otherwise, it proceeds to Step 2.
2. If the last transaction succeeded, the buyer multiplies the advertising range by a user-defined constant, e.g., 0.9. Otherwise, the advertising range is similarly increased, under the constraint that advertising range is less than D_k.
3. Periodically, the buyer doubles its broadcast distance to probe for superior offers available only beyond its current advertising range, under the constraint that this range is less than D_k.

In order to evaluate a seller's price, buyers use a unit energy price upper bound P_{u_i}, defined as

$$P_{u\_i} = \frac{M_{rem\_j}}{E_{pending\_i} \times Ratio_{hist}}, \tag{2}$$

where M_{rem_i} is buyer i's remaining money and $E_{pending\_i}$ is the estimated energy consumption for local computation of buyer i's remaining tasks. $Ratio_{hist}$ is an energy purchase ratio obtained via analysis of the transaction history: the total purchased energy during the buyer's transaction history divided by the total energy consumed for its finished tasks, including purchased energy and its own energy consumption due to local computation. $E_{pending\_i}$ times $Ratio_{hist}$ is used to predict the amount of energy that can be purchased from other sellers. Considering the remaining money budget M_{rem_i}, P_{u_i} is the expected value of the unit energy price the buyer can afford.

From all the received offers, buyers use the following algorithm to choose, at most, one offer.

1. For each offer j, calculate the equivalent unit energy price $p_{ij} = P_j/E_{ik}$, where P_j is the price of offer j for task k, and E_{ik} is the energy required by device i to execute task k locally. If $p_{ij} > P_{u\_i}$, reject offer j.
2. Calculate the average unit energy price, p_e, in the transaction history. For each offer, calculate the equivalent total price P_j^* based on the following equation:

$$P_j^* = p_e \times E_{comm\_j} + P_j, \tag{3}$$

   where E_{comm_j} is the communication energy for offer j and P_j is offer j's price.
3. Choose the offer with the lowest equivalent price.

During any transaction, if the buyer declines all bids, the transaction fails; otherwise, it succeeds.

3.3 Transaction Policies for Sellers

Multiple sellers may exist within a local market, each competing to maximize its own optimization criterion. In this subsection, two optimization criteria are proposed: one for competitive scenarios and one for cooperative scenarios.

In local markets, we assume that energy demand is a nonincreasing function of price, i.e., we assume that, as energy price increases, demand remains constant or decreases. Each device, i, has a monetary budget M_i, an energy budget E_i, and a lifetime T_i, the duration the device remains in the network.

3.3.1 Competitive Sellers

In competitive ad hoc mobile networks, sellers have the goal of maximizing their total profits subject to their energy budgets and lifetime constraints, i.e., they attempt to maximize

$$profit = \max\left\{\sum_{t=1}^{T_i}(x_i(t) - cost_i) \times e_i(x_i(t), t)\right\} \tag{4}$$

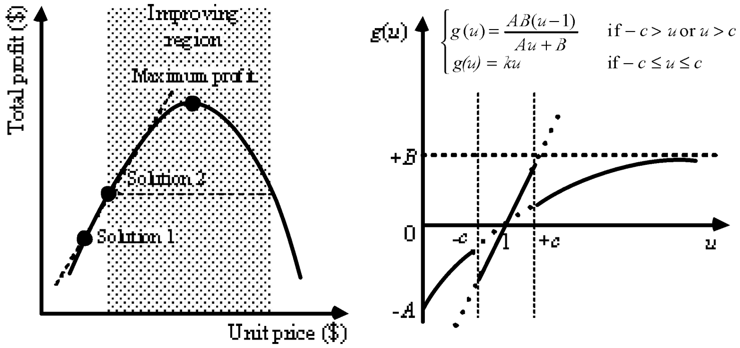
subject to the following constraint:

$$\sum_{t=1}^{T_i} e_i(x_i(t), t) \le E_i, \tag{5}$$

where $x_i(t)$ is seller i's unit energy price for the transaction at time t, $e_i(x_i(t), t)$ is the total amount of energy that seller i sells at time t, $cost_i$ is the unit cost of seller i's energy, T_i is seller i's lifetime, and E_i is seller i's spare energy.

In order to guarantee optimal profit, it would be necessary to perfectly predict the market conditions during the device's entire lifetime. The mobile network is a dynamic system; guaranteeing optimal profit would require global information and perfect prediction of future market conditions. In reality, each device has only imperfect information and must base its predictions on its recent transaction history, thus guaranteeing an optimal profit is not possible. Furthermore, energy efficiency requires a simple implementation. Therefore, in this work, we use an incremental greedy derivative-following strategy to maximize profit.

We assume that the utility function is always concave, as shown in Fig. 5a. Intuitively, initial increases in price do not substantially reduce sales, allowing an increase in total profit. Eventually, price increases result in a significant reduction in sales, reducing total profit. The point between these regions is the unit price resulting in maximal profit. Marginal utility is equivalent to the profit gradient, which is positive at the beginning and nonincreasing. Maximum profit is achieved when the profit gradient is zero, i.e., given that $E_i(t)$ is the remaining energy at time t, $f_i(x_i(t), t)$ is the energy consumption rate at time t and $T_i(t)$ is device i's remaining time in this network:



(a) (b)

Fig. 5. (a) Competitive optimization curve and (b) adaptive step-size transformation function.

$$profit_{\max} = \max_{x_i(t)} \left\{ (x_i(t) - cost_i) \times f_i(x_i(t), t) \times \min \left\{ \frac{E_i(t)}{f_i(x_i(t), t)}, T_i(t) \right\} \right\}. \tag{6}$$

We define the equivalent lifetime $T_i(t)^*$ of device i as follows:

$$T_i(t)^* = \min\left\{ \frac{E_i(t)}{f_i(x_i(t), t)}, T_i(t) \right\}. \tag{7}$$

If $T_i(t)^* < T_i(t)$, it implies that, given the current energy consumption rate, device i will use all its spare energy before it leaves the network.

The incremental greedy derivative-following algorithm has the following properties:

1. It avoids bids with negative profit and does boundary checks to guarantee that the bid price is higher than the energy cost.
2. It increases its unit energy price if, based on its transaction history, this is expected to increase profit.
3. It decreases its unit energy price if this is expected to increase profit.
4. After arriving at a stable unit energy price, it dynamically probes and adapts to changing market conditions.

We use an adaptive step-size strategy to change the seller's unit energy price:

$$price_{j+1} = price_j + price_j \times sign\big(price_j - price_{j-1}\big) \times g\left(\frac{profit_j}{profit_{j-1}}\right), \tag{8}$$

where $price_{j+1}$ is the predicted unit energy price to be used in the next transaction $j+1$, $price_j$, and $price_{j-1}$ are unit energy price estimates, $profit_j$ and $profit_{j-1}$ are profit estimates. These estimates are based on the transaction history. Basically, parameters j and $j-1$ are based on different previous transactions. In the simplest case, j can be the most recent transaction and $j-1$ the transaction before j. However, mobile networks are dynamic and noisy. We use an exponential weighted average to filter out network noise and smooth estimates. Function $sign(x) = -1$ if x is negative, otherwise $sign(x) = +1$.

We use a transformation function, $g(u)$, as shown in Fig. 5b, to dynamically adapt the step-size. Two problems must be considered. First, during fast changes in profit, we want to ensure that the price adaptation policy is stable. In such a scenario,

$$g(u) = \frac{AB(u-1)}{Au+B}.$$

When the profit ratio u is very high, $g(u) \rightarrow B$. When the profit ratio is very low (close to 0), $g(u) \rightarrow -A$. A and B are predefined values used to constrain the maximum changes to the price adaptation step size. Second, under slow changes in profit, i.e., when u is close to 1, we want the price adaptation policy to be sensitive enough to probe the network and adapt to a higher profit. In this scenario, if we use the previously stated function, the incremental price will tend to zero. Instead, we use $g(u) = ku$. Parameter k is made large enough to ensure that each seller periodically probes the network.

In summary, our strategy ensures that, when the change in profit is small, the change in unit energy price is also small. To ensure stability, we bound changes to unit energy price during rapid profit change.

Filter and stability. The mobile network experiences two types of dynamic changes: short-term fluctuations, i.e., noise, and long-term changes. A price adaptation strategy should filter out short-term fluctuations and adapt to long-term changes.

Our price adaptation strategy is based on two techniques. The first of these analyzes a window of recent transactions to predict future market changes. The window size is predefined and can be dynamically adjusted according to the network's detected long-term rate of change.

The second strategy is based on exponential weighted average (EWA) filtering to smoothen price estimation. The EWA filter assigns a different weight to each transaction in its history, giving the highest weights to recent transactions and lower weights to earlier transactions:

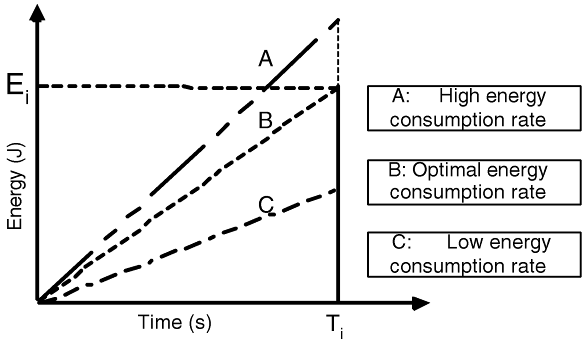


Fig. 6. Energy consumption rate.

$$E_i = w \times S_i + (1 - w) \times E_{i-1}, \tag{9}$$

where the price estimation, E_i, of the current market is based on S_i, the transaction price in the most recent transaction i, and E_{i-1}, the estimated price of the transaction history before transaction i. The weights for each transaction decrease exponentially depending on value w.

3.3.2 Cooperative Sellers

In a *fair* market, a rational decision maker receives a quantity of service proportional to the amount of money it spends. DESP can be tailored to optimize fairness. Within a wireless market, energy price is determined by energy supply and demand. An increase in demand, relative to supply, increases price. Therefore, market price can be used to regulate buyer policy. A low price indicates that more energy is available; buyers react by migrating more tasks to sellers. A high price indicates that less energy is available. In this situation, buyers can only afford to buy energy for their most important tasks; they must locally compute, delay, or drop others.

In the cooperative market scenario, a seller adjusts its price to finish expending its energy at the moment it exits the network, instead of attempting to maximize its total profit. The seller dynamically adjusts its price to maintain an energy consumption rate E_r, defined as E_i/T_i, where E_i is its remaining energy and T_i is its lifetime, as shown in Fig. 6. A cooperative seller attempts to provide energy to buyers at a constant rate. This stability promotes market fairness. In addition to changing its bid price, a seller reacts to a change in its energy consumption rate by appropriately adjusting the bid price it will tolerate from subcontractors.

We use an incremental greedy goal-directed strategy for energy resource allocation. Each seller decides its pricing policy based on the following algorithm.

1. Respond to a negative transaction profit by increasing the unit energy price. During each transaction, this algorithm performs a boundary check to guarantee that the offer price is higher than the monetary cost of carrying out the necessary transactions.
2. Compute the recent energy consumption rate based on the transaction history. Use this rate as a predictor for future market conditions. If this energy consumption rate is higher than E_r, increase the unit energy price.
3. If the energy consumption rate is lower than E_r, decrease the unit energy price.

We use an adaptive step-size strategy to change the seller's unit energy price. Given that $price_{j+1}$ is the predicted unit energy price to be used in the next transaction $j+1$, $price_j$ is a unit energy price estimate based on the transaction history, E_{rate_j} is the energy consumption rate from the transaction history, E_{rem_j} is the remaining energy, and T_{rem_j} is the remaining lifetime:

$$price_{j+1} = price_j + price_j \times g\left(\frac{E_{rate\_j} \times T_{rem\_j}}{E_{rem\_j}}\right). \tag{10}$$

We dynamically adjust the step size with the same transformation function, $g(u)$, described in Section 3.3.1. We use the previously described transaction history window and EWA filter to stabilize the price computation.

3.4 Transaction Policies for Contractors

In this section, we explain the transaction policies for contractors. We first describe the policies used by competitive contractors, i.e., contractors that optimize their own profit. We then describe cooperative contractors, i.e., contractors that attempt to maintain steady energy usage.

3.4.1 Competitive Contractors

In the competitive scenario, the contractor tries to maximize its total profit subject to its lifetime and energy budget constraints. It may be in the contractor's economic interest to collaborate with a subcontractor. If a contractor has little remaining energy, its equivalent lifetime, $T_i(t)^*$, is less than $T_i(t)$. This implies that it will expend all its spare energy before it leaves the network. Although collaboration requires the contractor to share the buyer's payment with a subcontractor, subcontracting may allow it to reach a higher equivalent unit price, $x_i(t)$, than possible by locally executing every task. The contractor's only cost is the communication energy required to relay the task and computation results. As a result, collaborating with a subcontractor can increase a contractor's equivalent lifetime, $T_i(t)^*$, allowing a higher profit. If, based on its buyer and subcontractor transaction histories, a contractor predicts that collaborating with a subcontractor will be more profitable than executing a task locally, the contractor forms a local market to find a subcontractor.

3.4.2 Cooperative Contractors

In the cooperative scenario, the contractor's decision is based on the following criteria.

1. If the contractor's current energy consumption rate is higher than E_r, finding a subcontractor may extend its equivalent lifetime. Collaborating with subcontractors provides the additional advantage of making prices in the network more homogeneous; local regions, in which the price decided by the balance between supply and demand is extreme, are dispersed.
2. Although profit is not directly considered in a collaborative contractor's pricing policy, it is considered when deciding whether to collaborate

with a subcontractor. Collaboration only occurs if it results in a profit. If a subcontractor has a higher price than a contractor, this implies that the subcontractor has a higher workload than the contractor, relative to its spare energy. In this situation, task execution by contractors balances the network's workload distribution and prevents high communication energy consumption from causing inefficient energy resource allocation.

3.5 Energy Overhead Analysis

Our power-aware computation distribution protocol introduces some energy overhead. We first analyze the energy overhead of the buyer protocol. Both computation and communication consume energy. Computation energy is consumed when buyers determine the scope of local markets and choose from among multiple received bids. This energy consumption is linearly proportional to the number of received bids. Let us estimate the computation energy, assuming the use of a StrongArm SA-1100 microprocessor running at 1.5V and 206MHz. We set the average number of received bids to a conservative value of 50; based on our simulations, most auctions have fewer than 50 bidders. Based on these assumptions, 53 uJ of energy is required to decide which bid to accept, if any. For comparison purposes, we also estimated the energy consumption of a simple 64-pixel discrete cosine transform computation as 15,816 uJ. These results demonstrate that the computation energy overhead of the buyer protocol is negligible.

The communication energy of the buyer protocol has three components. First, buyers broadcast messages to create local markets. Second, buyers receive bid messages from sellers. Third, if a buyer accepts an offer, it sends out acceptance and payment messages. Each of these messages only requires a few bits of data. The communication energy overhead is related to the communication distance. In DESP, due to the help from contractors and subcontractors, buyers only contact local sellers within each local market. Each buyer dynamically adjusts the size of its local market. In general, when there are more sellers in the local market, the buyers decrease market size. Therefore, the number and size of messages and communication distance are all quite constrained.

The energy overhead is not highly sensitive to seller decisions because a device can become a seller only if it has spare energy. However, energy-efficient seller protocols are still beneficial; they leave more spare energy for sellers to provide to buyers. Before seller devices become contractors, its energy overhead is composed of the energy required to determine and send out its bids. Due to the efficiency of the proposed policies, this energy overhead is even lower than that of the buyer protocol. If a seller becomes a contractor, it may create another local market and find subcontractors. However, this is analogous to the buyer protocol and the energy overhead is, similarly, negligible.

3.6 Security

Security is an important metric in the design of wireless networks. Various techniques have been proposed for secure mobile ad hoc network design. The Terminodes project [20] is based on a public-key infrastructure. Each mobile device is assumed to contain trusted hardware that prevents illegitimate access in addition to controlling the packet forwarding and synchronization protocols. Researchers have considered both security and energy consumption issues, leading them to propose energy-efficient public-key encryption algorithms targeting mobile wireless networks [29], [30]. In our current work, we assume the mobile devices are well-behaved in that they obey the transaction protocols and agreements. To extend DESP to the application scenario with misbehaved devices, where both buyer and seller devices can misbehave—buyers may refuse to make the payment, while sellers may provide fake results, more robust transaction protocols, including more strict authentication and certification mechanisms, will be needed. Previous research work has proposed various techniques to detect and avoid misbehavior. For example, Byzantine-General-based protocols [31] can be used to catch misbehaving sellers—each buyer signs contracts with multiple contractors concurrently and compares the multiple received computation results to detect invalid results and refuses payment to punish misbehaving sellers. Sometimes, efficient verification algorithms are also available to verify the correctness of the result of complicated computation tasks; NP-hard problems have verification algorithms with polynomial complexity. In order to compel buyers to fulfill their payment obligations, previous works, such as DigiCash [32] and NetBill [33], propose the following scheme–contractors can first send an encrypted result to the buyers and send the decryption key after receiving the payment. Digital signatures [32] can be used to provide unforgeable credentials. A trustable third party may be required, which may not be available during online transactions. However, authentication can be done offline and misbehaving buyers and sellers can be punished in the future. All of these techniques can be applied in conjunction with DESP. Generally, these mechanisms may degrade the energy efficiency of network transaction protocols, which is the trade off that needs to be made under a malicious environment. How to adapt DESP to a malicious environment, while maintaining an energy-efficient transaction protocol, is an interesting extension of our current work that can be addressed in the future.

4 Network Simulator

We have implemented a network simulator, ESIM, which is designed to model the behavior of mobile devices in ad hoc wireless networks. It is implemented in C++ and runs under Linux. ESIM simulates a wireless network. Mobile devices dynamically enter and leave the network. These devices move and trade energy with each other using the transaction policies described in Section 3. In ESIM, there are a number of parameters associated with each device.

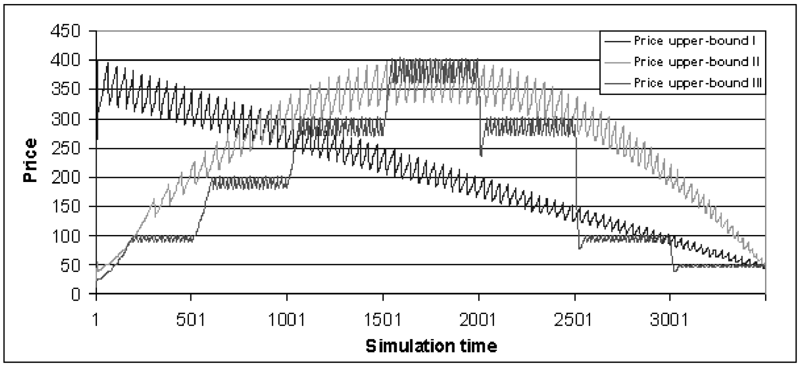


Fig. 7. Dynamic pricing policy in Scenario 1.

Each device starts with an energy budget, a monetary budget, and a two-dimensional position. Independent Poisson processes with randomly selected, device-dependent average rates control the motion and task arrival times of each device. The ratio between distance-dependent communication energy and computation energy randomly varies from task to task. Each device has an initial advertising distance that is adjusted during transactions, using the algorithms described in Section 3.2.

5 Simulation Results

In this section, we present experimental results to evaluate the performance of DESP. We focus on the behavior of our dynamic pricing strategies in the presence of different price-demand curves. In addition, we examine the energy allocation effectiveness of DESP in competitive and co-operative scenarios.

5.1 Dynamic Pricing of Competitive Sellers

In this section, we evaluate the dynamic pricing strategies of competitive sellers in two different market scenarios. In the first scenario, the relationship between price and energy demand is a step function. When a seller's price is less than a buyer-defined upper-bound, the energy demand is a positive constant; otherwise, the energy demand drops to zero. Fig. 7 contains the simulation results for dynamic pricing of competitive sellers in this scenario. The simulation period is 3,500 seconds. In this figure, three different market configurations are studied. In the first configuration, the buyer-defined upper-bound on price is a continuous function that decreases from 400 to 50 during the simulation. In the second configuration, the upper-bound on price is a concave function. Its initial value is 50, it increases to 400, and then decreases to 50. In the third configuration, the upper-bound price is a step function that starts at 100, changing to 200 at time 501, 300 at time 1,001, 400 at time 1,501, 300 at time 2,001, 100 at time 2,501, and 50 at time 3,001.

From the simulation results, it is clear that, in each configuration, sellers using DESP dynamically adjust their prices to reach the buyer-defined upper-bound on price, thereby maximizing their total profits. Similarly, they dynamically adapt their prices to changes in the buyer-defined upper-bound on price. The slight oscillations around the optimal prices result from continuously probing the market conditions.

In the second scenario, the relationship between price and energy demand is a continuous nonincreasing function. The relationship between price and profit is a concave function in which profit is maximal at price 400. Fig. 8 contains the simulation results for dynamic pricing of competitive sellers in this market. The simulation results show that using DESP allows a seller to adjust its price to maximize its total profit.

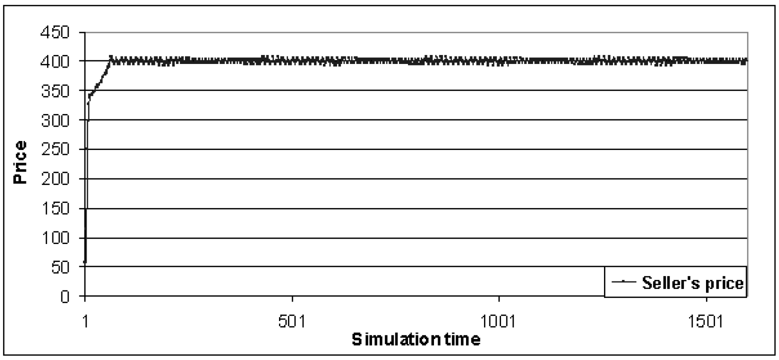


Fig. 8. Dynamic pricing policy in Scenario 2.

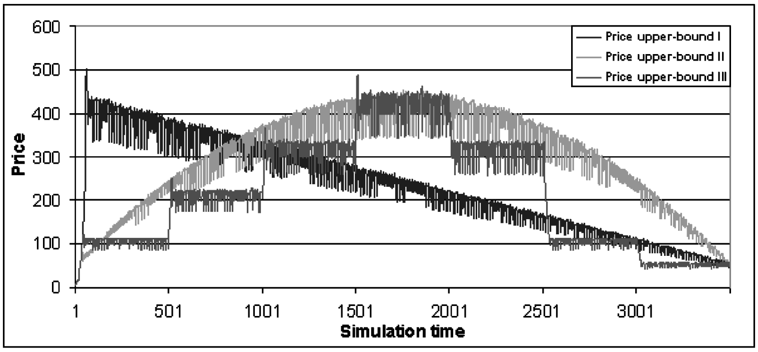


Fig. 9. Dynamic pricing of cooperative sellers.

5.2 Dynamic Pricing of Cooperative Sellers

In this section, we evaluate the dynamic pricing strategies of cooperative sellers. First, we examine these strategies when energy demand exceeds supply. We use a setup similar to that in Section 5.1. As shown in Fig. 9, the prices offered by cooperative sellers vary around the buyer upper-bound on price. This results in sellers expending the last of their energy as they exit the market. Second, we examine the fairness of energy allocation in this scenario. As described in Section 3.3.2, in a fair market, the quantity of energy that a rational decision maker receives is proportional to the amount of money it spends. We examined the amount of energy allocated to buyers with different monetary budgets. Table 1 shows the network setup. In this table, the *funding ratio* column contains the ratio between the starting money held by three different classes of buyers. The *finished task energy ratios* column shows, for the three classes of buyers, the ratios between the amounts of energy used for task execution. As we can see from the table, cooperative sellers allocate their energy in a manner that approximates their funding ratios, i.e., they achieve fair energy allocation. The deviations of the energy allocation ratios from the funding ratios are caused by numerous factors, e.g., the uneven spatial and temporal distributions of energy and well as the discrete nature of transactions.

5.3 Effectiveness in Cooperative Markets

Network *effectiveness* is the proportion of task volume that the network is able to execute. To determine the impact of subcontractors on effectiveness, we consider two scenarios. In the first, subcontracting is allowed; in the second, it is forbidden. In addition, we examine the effect of varying the ratio between computation and communication energy. We simulate an ad hoc network composed of 100 buyers and 1,000 sellers. The average speed of each device is 5 meters per second. The average distance between neighboring devices is 50 meters. We vary the ratio of computation to communication energy, for devices separated by this average distance, in a range from 1 to 100.

TABLE 1
Fair Energy Allocation

	Finished task energy ratios		
Funding ratios	3 buyers	30 buyers	100 buyers
1:1:1	1:0.99:1	0.97:1:1	0.97:0.97:1
3:2:1	2.94:1.98:1	2.90:1.97:1	2.90:1.96:1
10:5:1	9.57:4.87:1	9.36:4.75:1	8.98:4.60:1

Fig. 10 shows the simulation results for DESP under four different market conditions: advertising distances (adv.) of 30 m and 50 m, with and without subcontractors (sub.). These results indicate that DESP made good trade offs between energy demands and communication energy. When the computation energy to communication energy ratio is high, DESP allocates energy resources from sellers outside a buyer's local market. As the ratio decreases, the energy overhead associated with subcontractor collaboration also increases. As a result, subcontractors are used less frequently. As shown in Fig. 11, this causes a decrease in the average number of subcontractors used in the chain from the initial buyer to the final seller. When the ratio reaches one, communication energy has the same cost as computation energy. In this case, buying energy from sellers is not beneficial. In this case, the subcontractor chain length is greater than 0 because the energy ratio sometimes deviates from the average due to nonuniform and varying device positions.

An increase in advertising distance allows a buyer to directly negotiate with more distant sellers that would otherwise have required a contractor intermediary to reach. However, a large increase in advertising distance results in a large increase in advertising energy. Further experiments indicate that using DESP results in a significant improvement in network effectiveness when compared with a network protocol that does not allow subcontractors. A network protocol without subcontractors requires an advertising range of 106 meters (without considering the communication overhead for buyers) in order to execute the same task volume as a DESP network with an advertising range of 50 meters. As indicated by the energy model in Section 2.2, increasing advertising distance from 50 to 106 meters, with $n = 2$, results in a 4.5-fold increase in advertising energy.

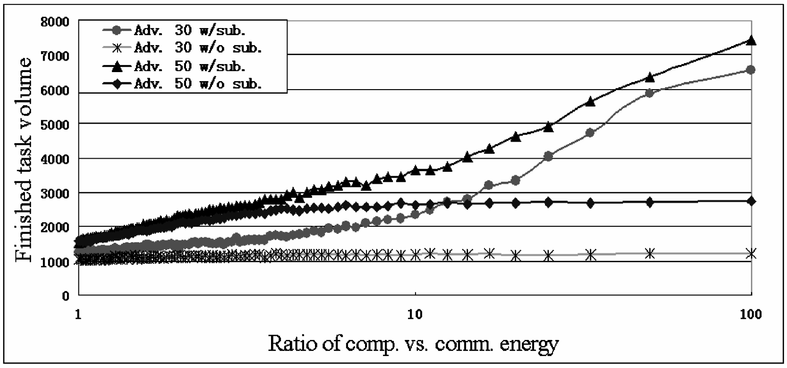


Fig. 10. Effectiveness of energy allocation.

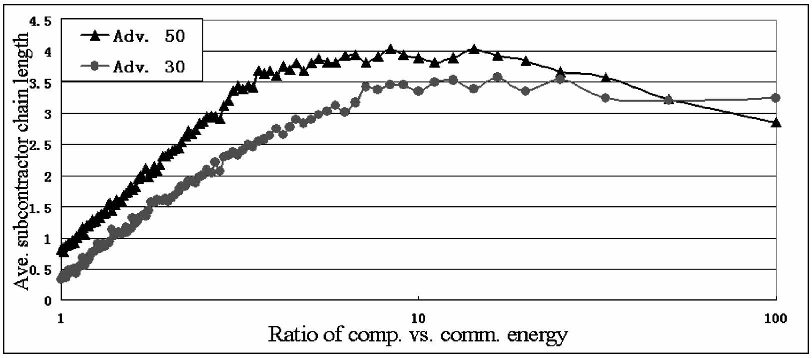


Fig. 11. Average subcontractor chain length.

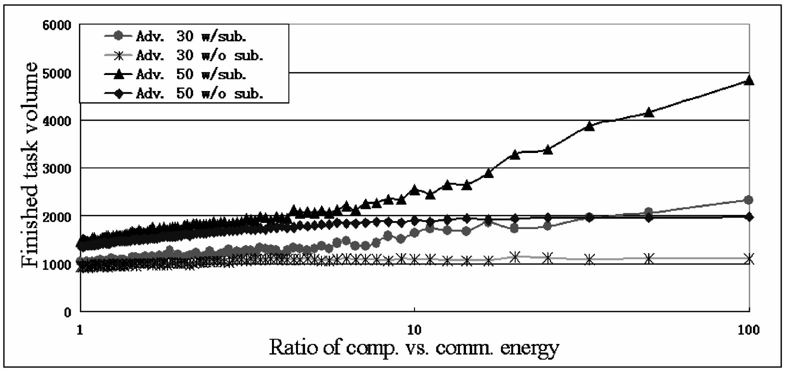


Fig. 12. Effectiveness of energy allocation.

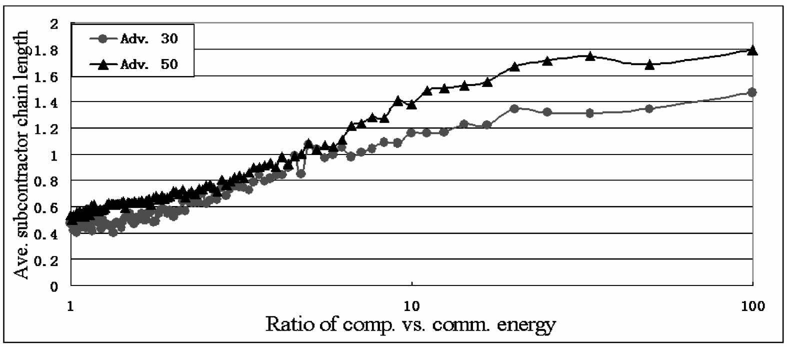


Fig. 13. Average subcontractor chain length.

5.4 Effectiveness in Competitive Markets

Figs. 12 and 13 show the effectiveness of DESP in competitive markets. In such markets, each seller tries to maximize its total profit. DESP allows better allocation of spare energy resources to buyers, and higher seller profits than a market without subcontractors because sellers outside a local market are sometimes willing to provide their energy at lower prices than contractors. Therefore, when a contractor's energy level is low, it can increase its profit by collaborating with subcontractors.

6 Conclusions

We presented a novel economics-based protocol, called DESP, that dynamically allocates energy resources in ad hoc wireless mobile networks. DESP is a scalable, distributed approach: It requires no central coordinator. We have provided and analyzed buyer and seller decision strategies for cooperative and competitive scenarios. Experimental results indicate that DESP fairly and effectively allocates energy resources to devices in mobile ad hoc networks. Security is an important issue in the design of such networks. In our current work, we assumed that the mobile devices are well-behaved. In scenarios in which misbehaving devices can be present, stricter security is necessary. This is part of future work.

Acknowledgments

This work was supported by the US Defense Advanced Research Projects Agency (DARPA) under contract no. DAAB07-02-C-P302.

References

[1] C.E. Perkins, *Ad Hoc Networking.* Addison Wesley, 2000.

[2] J.L. da Silva Jr., J. Shamberger, M.J. Ammer, C. Guo, S. Li, R. Shah, T. Tuan, M. Sheets, J.M. Rabaey, B. Nikolic, A. Sangiovanni-Vincentelli, and P. Wright, "Design Methodology for Picoradio Networks," *Proc. Design, Automation and Test in Europe Conf.,* pp. 314-323, Mar. 2001.

[3] D. Carman, B. Matt, P. Kruus, D. Balenson, and D. Branstad, "Key Management in Distributed Sensor Networking," *Proc. DARPA Sensor IT Workshop,* Apr. 2000.

[4] M. Othman and S. Hailes, "Power Conservation Strategy for Mobile Computers Using Load Sharing," *Mobile Computing and Comm. Rev.,* vol. 2, no. 1, pp. 19-26, Jan. 1998.

[5] U. Kremer, J. Hicks, and J.M. Rehg, "A Compilation Framework for Power and Energy Management on Mobile Computers," *Proc. Workshop Compilers and Operating Systems for Low Power,* Oct. 2000.

[6] A. Rudenko, P. Reiher, G. Popek, and G. Kuenning, "The Remote Processing Framework for Portable Computer Power Saving," *Proc. ACM Symp. Applied Computing,* pp. 365-372, Feb. 1999.

[7] J. Flinn, D. Narayanan, and M. Satyanarayanan, "Self-Tuned Remote Execution for Pervasive Computing," *Proc. Eighth Workshop Hot Topics in Operating Systems,* pp. 61-66, May 2001.

[8] A. Rudenko, P. Reiher, G.J. Popek, and G.H. Kuenning, "Saving Portable Computer Battery Power through Remote Process Excution," *Mobile Computing and Comm. Rev.,* vol. 2, no. 1, pp. 19-26, Jan. 1998.

[9] A. Vahdat, A. Lebeck, and C.S. Ellis, "Every Joule Is Precious: The Case for Revisiting Operating System Design for Energy Efficiency," *Proc. ACM SIGOPS European Workshop,* pp. 31-36, Sept. 2000.

[10] R.G. Smith, "The Contract Net Protocol: High-Level Communication and Control in a Distributed Problem Solver," *IEEE Trans. Computers,* vol. 29, no. 12, pp. 1104-1113, Dec. 1980.

[11] T.W. Malone, R.E. Fikes, and M.T. Howard, "Enterprise: A Market-Like Task Scheduler for Distributed Computing Environments," *The Ecology of Computation,* pp. 177-206, 1988.

[12] C.A. Waldspurger, T. Hogg, B.A. Huberman, J.O. Kephart, and W.S. Stornetta, "Spawn: A Distributed Computational Economy," *IEEE Trans. Software Eng.,* vol. 18, no. 2, pp. 103-117, Feb. 1992.

[13] O. Regev and N. Nisan, "The Popcorn Market—An Online Market for Computational Resources," *Proc. Int'l Conf. Information and Computational Economies,* pp. 148-157, Oct. 1998.

[14] J.F. Kurose and R. Simha, "A Microeconomic Approach to Optimal Resource Allocation in Distributed Computer Systems," *IEEE Trans. Computers,* vol. 38, no. 5, pp. 705-717, May 1989.

[15] J.S. Chase, D. Anderson, P. Thakar, A. Vahdat, and R. Doyle, "Managing Energy and Server Resources in Hosting Centers," *Proc. ACM Symp. Operating Systems Principles,* pp. 103-116, Oct. 2001.

[16] V. Shah, N.B. Mandayam, and D.J. Goodman, "Power Control for Wireless Data Based on Utility and Pricing," *Proc. IEEE Int'l Symp. Personal, Indoor, Mobile Radio Comm.,* vol. 3, pp. 1427-1432, Sept. 1998.

[17] A.B. Machkenzie and S.B. Wicker, "Game-Theory in Communications: Motivation, Explanation, and Application to Power Control," *Proc. GlobeCom,* Nov. 2001.

[18] M. Stonebraker, P.M. Aoki, A. Pfeffer, A. Sah, J. Sidell, C. Staelin, A. Yu, "Mariposa: A Wide-Area Distributed Database System," *VLDB J.: Very Large Data Bases,* vol. 5, no. 1 pp. 48-63, Jan. 1996.

[19] D. Reininger, D. Raychaudhuri, and M. Ott, "Market Based Bandwidth Allocation Policies for QoS Control in Broadband Networks," *Proc. Int'l Conf. Information and Computation Economies,* pp. 101-110, Oct. 1998.

[20] L. Buttyán and J.-P. Hubaux, "Stimulating Cooperation in Self-Organizing Mobile Ad Hoc Networks," *ACM/Kluwer Mobile Networks and Applications,* vol. 8, no. 5, Oct. 2003.

[21] J. Byers and G. Nasser, "Utility-Based Decision-Making in Wireless Sensor Networks," *Proc. IEEE MobiHoc Conf.,* pp. 143-144, Aug. 2000.

[22] E.M. Royer and C.-K. Toh, "A Review of Current Routing Protocols for Ad Hoc Mobile Wireless Networks," *IEEE Personal Comm.,* pp. 46-55, Apr. 1999.

[23] C.E. Jones, K.M. Sivalingam, P. Agrawal, and J.-C. Chen, "A Survey of Energy Efficient Network Protocols for Wireless Networks," *Wireless Networks,* vol. 7, no. 4, pp. 343-358, July 2001.

[24] D.M. Kreps, *A Course in Microeconomic Theory.* Princeton Univ. Press, 1990.

[25] T.S. Rappaport, *Wireless Communication: Principles and Practice,* pp. 69-122, pp. 139-196. Prentice Hall, 1996.

[26] V. Rodoplu and T.H. Meng, "Minimum Energy Mobile Wireless Networks," *IEEE J. Selected Areas Comm.,* vol. 17, no. 8, pp. 1333-1344, Aug. 1999.

[27] J.J. Caffery and G.L. Stüber, "Overview of Radiolocation in CDMA Cellular Systems," *IEEE Comm. Magazine,* pp. 38-45, Apr. 1998.

[28] S. Capkun, M. Hamdi, and J.-P. Hubaux, "GPS-Free Positioning in Mobile Ad Hoc Networks," *Cluster Computing J.,* vol. 5, no. 2 Apr. 2002.

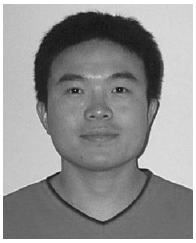
[29] S. Ravi, A. Raghunathan, N. Potlapally, and M. Sankaradass, "System Design Methodologies for a Wireless Security Processing Platform," *Proc. Design Automation Conf.,* pp. 777-782, June 2002.

[30] N. Potlapally, S. Ravi, A. Raghunathan, and G. Lakshminarayana, "Optimizing Public-Key Encryption for Wireless Clients," *Proc. IEEE Int'l Conf. Comm.,* pp. 1050-1056, May 2002.

[31] L. Lamport, R. Shostak, and M. Pease, "The Byzantine Generals Problem," *ACM Trans. Programming Language and System,* vol. 4, no. 3, pp. 382-401, July 1982.

[32] D. Chaum, "Achieving Electronic Privacy," *Scientific Am.,* pp. 96-101, Aug. 1992.

[33] B. Cox, J.D. Tygar, and M. Sirbu, "NetBill Security and Transaction Protocol," *Proc. First USENIX Workshop Electronic Commerce,* pp. 77-88, July 1995.



Li Shang (S'99) received the BE and ME degrees from Tsinghua University in 1997 and 1999. He is currently a graduate student at Princeton University's Department of Electrical and Computer Engineering. His research has focused on system-level power analysis and optimization in distributed embedded systems, specialized in hardware/software cosynthesis, power analysis, and optimization of reconfigurable devices and interconnection networks. Currently, his research is in the area of power-aware interconnection networks. He received Princeton University's Wallace Memorial Honorific Fellowship. Such fellowships are awarded only to the university's top 20 senior graduate students. He won the best paper award at the 14th IASTED International Conference on Parallel and Distributed Computing and Systems (PDCS '02). He is a student member of the IEEE.

Robert Dick (S'95-M'02) received the BS degree in computer engineering from Clarkson University and recently completed the PhD degree at Princeton University's Electrical Engineering Department. He is currently an assistant professor at Northwestern University's Department of Electrical and Computer Engineering. He was previously a visiting professor at Tsinghua University's Department of Electronic Engineering. He received Princeton University's George Van Ness Lothrop Honorific Fellowship. He also worked as a visiting researcher at NEC Computers and Communication Research Laboratories. His publications have focused on the multiobjective optimization of embedded system designs. In addition, he has published in the areas of real-time operating system power consumption analysis, wireless ad hoc network protocols, and multiobjective evolutionary algorithms. In addition to these topics, he is interested in the impact of tightly coupling low-level and high-level design automation software upon algorithm design. He is a member of the IEEE.

Niraj K. Jha (S'85-M'85-SM'93-F'98) received the BTech degree in electronics and electrical communication engineering from Indian Institute of Technology, Kharagpur, India, in 1981, the MS degree in electrical engineering from the Sate University of New York at Stony Brook in 1982, and the PhD degree in electrical engineering from University of Illinois, Urbana-Champaign in 1985. He is a professor of electrical engineering at Princeton University. He has served as an associate editor of the *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing*. He is currently serving as an editor of the *IEEE Transactions on Computer-Aided Design*, *IEEE Transactions on VLSI Systems*, *Journal of Electronic Testing: Theory and Applications (JETTA)*, and *Journal of Embedded Computing*. He has served as the guest editor for the *JETTA* special issue on high-level test synthesis. He has also served as the program chairman of the 1992 Workshop on Fault-Tolerant Parallel and Distributed Systems. He is the director of the Center for Embedded System-on-a-Chip Design funded by New Jersey Commission on Science and Technology. He was the recipient of the AT&T Foundation Award and the NEC Preceptorship Award for research excellence and NCR Award for teaching excellence. He has coauthored three books titled *Testing and Reliable Design of CMOS Circuits* (Kluwer,1990), *High-Level Power Analysis and Optimization* (Kluwer, 1998), and *Testing of Digital Systems* (Cambridge University Press, 2003). He has also authored three book chapters. He has authored or coauthored more than 230 technical papers. He has coauthored six papers which have won best paper awards at ICCD'93, FTCS'97, ICVLSID'98, DAC'99, PDCS'02, and ICVLSID'03. Another paper of his was selected for the "The Best of ICCAD: A Collection of the Best IEEE International Conference on Computer-Aided Design Papers of the Past 20 Years." He has received 11 US patents. His research interests include low power hardware and software design, computer-aided design of integrated circuits and systems, digital system testing, and distributed computing. He is a fellow of the IEEE.