Decentralized, Adaptive Resource Allocation for Sensor Networks

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Abstract

This paper addresses the problem of resource allocation in sensor networks. We are concerned with how to allocate limited energy, radio bandwidth, and other resources to maximize the value of each node's contribution to the network. Sensor networks present a novel resource allocation challenge: given extremely limited resources, varying node capabilities, and changing network conditions, how can one achieve efficient global behavior? Currently, this is accomplished by carefully tuning the behavior of the low-level sensor program to accomplish some global task, such as distributed event detection or in-network data aggregation. This manual tuning is difficult, error-prone, and typically does not consider network dynamics such as energy depletion caused by bursty communication patterns.

We present *Self-Organizing Resource Allocation (SORA)*, a new approach for achieving efficient resource allocation in sensor networks. Rather than manually tuning sensor resource usage, SORA defines a virtual market in which nodes sell *goods* (such as sensor readings or data aggregates) in response to *prices* that are established by the programmer. Nodes take actions to maximize their profit, subject to energy budget constraints. Nodes individually adapt their operation over time in response to feedback from payments, using reinforcement learning. The behavior of the network is determined by the price for each good, rather than by directly specifying local node programs.

SORA provides a useful set of primitives for controlling the aggregate behavior of sensor networks despite variance of individual nodes. We present the SORA paradigm and a sensor network vehicle tracking application based on this design, as well as an extensive evaluation demonstrating that SORA realizes an efficient allocation of network resources that adapts to changing network conditions.

1 Introduction

Sensor networks, consisting of many low-power, low-capability devices that integrate sensing, computation, and wireless communication, pose a number of novel systems problems. They raise new challenges for efficient communication protocols [13, 44], distributed algorithm design [11, 24], and energy management [1, 5]. While a number of techniques have been proposed to address these challenges, the general problem of resource allocation in sensor networks under highly volatile network conditions and limited energy budgets remains largely unaddressed. Current programming models require that global behavior be specified in terms of the low-level actions of individual nodes. Given varying node locations, capabilities, energy budgets, and time-varying network conditions, this approach makes it difficult to tune network-wide resource usage. We argue that new techniques are required to bridge the gap from high-level goals to low-level implementation.

In this paper, we present a novel approach to adaptive resource allocation in sensor networks, called *Self-Organizing Resource Allocation (SORA)*. In this approach, individual sensor nodes are modeled as self-interested agents that attempt to maximize their "profit" for performing local actions in response to globally-advertised price information. Sensor nodes run a very simple cost-evaluation function, and the appropriate behavior is induced by advertising prices that drives nodes to react. Nodes adapt their behavior by learning their utility for each potential action through payment feedback. In this way, nodes dynamically react to changing network conditions, energy budgets, and external stimuli. Prices can be set to meet systemwide goals of lifetime, data fidelity, or latency based on the needs of the system designer.

Consider environmental monitoring [9, 28] and distributed vehicle tracking [23, 45], which are two oft-cited applications for sensor networks. Both applications require nodes to collect local sensor data and relay it to a central base station, typically using a multihop routing scheme. To reduce bandwidth requirements, nodes may need to aggregate their local sensor data with that of other nodes. In-network detection of distributed phenomena, such as gradients and isobars, may require more sophisticated cross-node coordination [15, 41, 47].

Two general challenges emerge in implementing these applications. First, nodes must individually determine the ideal rate for sampling, aggregating, and sending data to operate within some fixed energy budget. This rate affects overall lifetime and the accuracy of the results produced by the network. Each node's ideal schedule is based on its physical location, position in the routing topology, and changes in environmental stimuli. Many current applications use a fixed schedule for node actions, which is suboptimal when nodes are differentiated in this way. Second, the system may wish to tune these schedules in response to changes in the environment, such as the target vehicle's location and velocity, to meet goals of data rate and latency. More complex adaptations might involve selectively activating nodes that are expected to be near some

phenomenon of interest. Currently, programmers have to implement these approaches by hand and have few tools to help determine the ideal operating regime of each node.

Rather than defining a fixed node schedule, SORA causes nodes to individually tune their rate of operation using techniques from reinforcement learning [37]. Nodes receive virtual payments for taking "useful" actions that contribute to the overall network goal, such as listening for incoming radio messages or taking sensor readings. Each node learns which actions are profitable based on feedback from receiving payments for past actions. Network retasking is accomplished by adjusting prices, rather than pushing new code to sensor nodes. Network lifetime is controlled by constraining nodes to take actions that meet a local energy budget.

In this paper, we focus on a specific challenge application, vehicle tracking, which provides a rich space of problems in terms of managing latency, accuracy, communication overhead, and task decomposition. The SORA model is not specifically tailored to tracking, however, and can be readily adopted for other problem domains. We present a thorough evaluation of the SORA approach using a realistic sensor network simulator. Our results demonstrate that, using SORA, resource allocation within the sensor network can be controlled simply by advertising prices, and that nodes self-organize to take the set of actions that make the greatest contribution to the global task under a limited energy budget. This paper expands on our previous workshop paper [18] on SORA, presenting a thorough evaluation of the approach.

We show that SORA achieves more efficient allocation than static node scheduling (the most commonly-used approach currently in use), and outperforms a dynamic scheduling approach that accounts for changes in energy availability. In addition, SORA makes it straightforward to differentiate node activity by assigning price vectors that influence nodes to select certain actions over others.

The rest of this paper is organized as follows. In Section 2 we present the background for the SORA approach, specific goals, and related work. Section 3 presents the Self-Organizing Resource Allocation model in detail, and Section 4 describes the use of SORA in our vehicle tracking application. Section 5 presents our implementation of SORA in a realistic sensor network simulator, as well as evaluation in terms of network behavior and node specialization as prices, energy budgets, and other parameters are tuned. Finally, Section 6 describes future work and concludes.

2 Motivation and Background

Sensor networks consist of potentially many nodes with very limited computation, sensing, and communication capabilities. A typical device is the UC Berkeley Mica2 node, which consists of a 7.3 MHz ATmega128L processor, 128KB of code memory, 4KB of data memory, and a Chipcon CC1000 radio capable of 38.4 Kbps and an outdoor transmission range of approximately 300m. The node measures 5.7cm $\times$ 3.1cm $\times$ 1.8cm and is typically powered by 2 AA batteries with an expected lifetime of days to months, depending on application duty cycle. The limited memory and computational resources of this platform make an interesting design point, as software layers must be tailored for this restrictive environment. The Mica2 node uses a lean, component-oriented operating system, called TinyOS [16], and an unreliable message-passing communication model based on Active Messages [38].

To begin, we outline the distributed resource allocation problem that arises in the sensor network domain. We highlight several prior approaches to this problem and make the case for market-based techniques as an attractive solution.

2.1 Resource allocation in sensor networks

Sensor networks have been proposed for a wide range of novel applications. Examples include instrumenting buildings, bridges, and other structures to measure response to seismic events [8, 20], monitoring environmental conditions and wildlife habitats [9, 28], tracking of vehicles along a road or in an open area [43], and real-time monitoring of patient vital signs for emergency and disaster response [25, 33].

One of the core challenges of sensor application design is balancing the resource usage of individual nodes with the global behavior desired of the network. In general, the sequence of actions taken by a node affects local energy consumption, radio bandwidth availability, and overall quality of the results. However, tuning the resource usage of individual sensor nodes by hand is difficult and error-prone. Although TinyOS [16] and other systems provide interfaces for powering down individual hardware devices such as the radio and CPU, using these interfaces in a coordinated fashion across the network requires careful planning. For example, if a node is sleeping, it cannot receive or route radio messages.

The typical approach to scheduling sensor operations is to calculate a static schedule for all nodes in the network. For example, query-based systems such as TinyDB [26] and Cougar [46] allow the user to specify a *query epoch* that drives periodic sampling, aggregation, and data transmission. Other programming models, such as directed diffusion [12, 17], abstract regions [41], or Hoods [43], either assume periodic data collection or leave scheduling to higher-level code. However, an application that uses a fixed schedule for every node will exhibit very different energy consumption rates across the network. For example, nodes responsible for routing messages will consume more energy listening for and sending radio messages. Likewise, nodes on the network periphery may not need to route radio messages at all.

Another solution is to compute, offline, the optimal schedule for each node based on a model of radio con-

nectivity, node location, and physical stimuli that induce network activity. For example, Adlakha *et al.* [1] describe a design-time recipe for tuning aspects of sensor networks to achieve given accuracy, latency, or lifetime goals. However, this approach assumes a statically-configured network where resource requirements are known in advance, rather than allowing the network behavior to be tuned at runtime (say, in response to increased activity).

Other systems have attempted to address the node scheduling problem for specific applications or communication patterns. For example, Liu *et al.* [24] describe an approach to tracking a moving half-plane shadow through a sensor network that can be used to selectively activate nodes along the frontier of the shadow. STEM [34] is a protocol that dynamically wakes nodes along a routing path to trade energy consumption for latency. LEACH [13] is a cluster-based routing scheme that rotates the local clusterhead to distribute energy load across multiple nodes. These techniques point to more general approaches to adapting the behavior of sensor networks to maximize lifetime.

Providing application control over resource usage is often desirable when designing high-level programming abstractions for sensor networks. Abstract regions [41] focuses on the ability to tune the communication layer to trade off energy for accuracy. Likewise, TinyDB provides a *lifetime* keyword that scales the query sampling and transmission period of individual nodes to meet a user-supplied lifetime target [27]. Both of these approaches provide a means for nodes to "self-tune" their behavior to meet specific systemwide resource and accuracy targets. However, the general problem of adaptive resource allocation in sensor networks has not been adequately addressed.

2.2 AI-based approaches to resource allocation

The SORA approach draws on the areas of reinforcement learning and economic theory to yield new techniques for decentralized optimization in sensor networks. In *reinforcement learning* [37], an agent attempts to maximize its "reward" for taking a series of actions. Whether or not a node receives a reward is defined by the *success* of the action; for example, whether a radio message is received while the node is listening for incoming messages. The agent's goal is to maximize its reward, subject to constraints on resource usage, such as energy.

The reward for each successful action can be modeled as a *price* in a virtual market. By applying ideas from economic theory, SORA attempts to achieve efficient resource allocation in a decentralized fashion. Economics has been used as an inspiration for solving resource-management problems in many computational systems, such as network bandwidth allocation [35], distributed database query optimization [36], and allocating resources in distributed systems such as clusters, Grids, and peer-to-peer networks [3, 4, 7, 10, 39].

Much of this prior work has been concerned with resource arbitration across multiple *self-interested* users, which may attempt to cheat or otherwise hoard resources in the system for their own advantage. In the sensor network context, however, we assume that nodes are well-behaved and *program* them to behave as the classic economic actors of microeconomic theory. *Thus, we use markets as a programming paradigm*, not because we are concerned with self-interested behavior of sensor nodes. We need not model complex game-theoretic behavior, but can instead focus on nodes that (by design) are classic price-taking economic agents.

SORA is inspired by Wellman's seminal work on *market-oriented programming* [30, 40], which uses market equilibrium to solve statically-defined distributed optimization problems. We believe that SORA is the first serious attempt to use market-oriented methods to provide complete runtime control for a real distributed system. This systems focus leads us to consider continuous, real-time resource allocation, while Wellman's work was concerned with solving a static allocation problem. Other recent work has applied economic ideas to specific sensor network problems. For instance, market-inspired methods have been suggested for the problems of *ad hoc* routing [2] and information-directed query processing [47]. Our goal in SORA is not to provide a point solution but to address the general issue of adaptive resource allocation.

3 Self-Organizing Resource Allocation

In Self-Organizing Resource Allocation (SORA), sensor nodes are programmed to maximize their "profit" by taking actions subject to energy constraints. Actions that contribute to the network's overall goal, such as taking useful sensor readings or forwarding radio messages, result in a payment to the node taking the action. By setting the price for each action, the network's global behavior can be tuned by the system designer. Nodes continuously learn a model for which actions are profitable, allowing them to adapt to changing conditions.

3.1 Goals

The essential problem that SORA addresses is that of determining the set of local actions to be taken by each sensor node to meet some global goals of lifetime, latency, and accuracy for the data produced by the network as a whole. Each node can take a set of local actions (such as data sampling, aggregation, or routing), each with varying energy costs and differing contributions to the global task of the network. Through *self-scheduling*, nodes independently determine their ideal behavior (or *schedule*) subject to constraints on local energy consumption. Self-scheduling in SORA meets three key goals:

Differentiation: Nodes in a sensor network are heterogeneous in terms of their position in the network topology, resource availability, and proximity to phenomena of interest. Through self-scheduling, nodes *differentiate* their behavior based on this variance. For example, nodes closer

to phenomena of interest should acquire and transmit more sensor readings than those nodes that are further away.

Adaptivity: Differentiation in nodal behavior should also vary with time, as external stimuli move, nodes join and leave the network, energy reserves are depleted, and network connectivity shifts. Such adaptation permits a more efficient use of network resources. For example, nodes will consume energy only when it is worthwhile to do so based on current network conditions, rather than as dictated by an *a priori* schedule.

Control: Finally, a system designer should have the ability to express systemwide goals and effect *control* over the behavior of the network despite uncertainty in the exact state, energy reserves, and physical location of sensor nodes. For example, if the data rate being generated by the network is insufficient for the application's needs, nodes should be instructed to perform sampling and routing actions more frequently. This goal differs from internal adaptation by nodes, since it requires external observation and manipulation.

3.2 SORA overview

In the SORA model, each sensor node acts as an *agent* that attempts to maximize its profit for taking a series of *actions*. Each action consumes some amount of *energy* and produces one or more *goods* that have an associated *price*. Nodes receive payments by producing goods that contribute value to the network's overall operation. For example, a node may be paid for transmitting a sensor reading that indicates the proximity of a target vehicle, but not be paid if the vehicle is nowhere nearby. Reacting to this payment feedback is the essential means of adaptivity in SORA. Prices are determined by the *client* of the sensor network, which can be thought of as an external agent that receives data produced by the network and sets prices to induce network behavior.

The local program executed by each node is simple and avoids high communication overhead in order to operate efficiently. In the SORA approach, nodes operate using primarily *local* information about their state, such as energy availability. The only *global* information shared by nodes is the current set of prices, which are defined by the sensor network client. To minimize overhead, prices should be updated infrequently (for example, to effect large changes in the system's activity) and can be propagated to nodes through a variety of efficient gossip or controlled-flooding protocols [22].

3.3 Goods and actions

The actions that sensor nodes can take depend on the application, but typically include sampling a sensor, aggregating multiple sensor readings, or broadcasting a radio message. An action may be *unavailable* if the node does not currently have enough energy to perform the action. In addition, production of one good may have dependencies on the availability of others. For example, a node cannot aggregate sensor readings until it has acquired multiple readings.

Taking an action may or may not produce a good of value to the sensor network as a whole. For example, listening for incoming radio messages is only valuable if a node hears a transmission from another node. Likewise, transmitting a sensor reading is only valuable if the reading has useful informational content. We assume that nodes can determine locally whether a given action deserves a payment. This works well for the simple actions considered here, although more complex actions (e.g., computing a function over a series of values) may require external notification for payments.

3.4 Energy budget

A node's *energy budget* constrains the actions that it can take. We assume that nodes are aware of how much energy each action takes, which is straightforward to measure offline. The energy budget can be modeled in a number of different ways. A simple approach is to give each node a fixed budget that it may consume over an arbitrary period of time. In this case, however, nodes may rapidly deplete their energy resources by taking many energy-demanding actions, resorting to less-demanding actions only when reserves get low.

To capture the desire for nodes to consume energy at a regular rate, we opt to use a token bucket model for the budget. Each node has a bucket of energy with a maximum capacity of C Joules, filling at a rate ρ that represents the average desired rate of energy usage (e.g., 1000 J per day). When a node takes an action, the appropriate amount of energy is deducted from the bucket. If a node cannot take any action because its bucket is too low, it must *sleep*, which places the node in the lowest-possible energy state.

The capacity C represents the total amount of energy that a node can consume in one "burst." If C is set to the size of the node's battery, the node is able to consume its entire energy reserves at once. By limiting C, one can bound the total amount of energy used by a node over a short time interval.

3.5 Agent operation

Given a set of actions, goods produced by those actions, prices for each good, and energy cost for each action, each agent operates as follows. A node simply monitors its local state and the global price vector, and periodically selects the action that maximizes its *utility* for each action. Upon taking that action, the node's energy budget is reduced by the appropriate amount, and the node may or may not receive a payment depending on whether its action produced a valuable good. We define the utility function $u(a)$ for an action a to be:

$$u(a) = \begin{cases} \beta_a p_a & \text{if the action is } \textit{available} \\ 0 & \text{otherwise} \end{cases}$$

where p_a is the current price for action a, and β_a is the *estimated probability of payment* for that action, which is learned by nodes as described below. An action may be *unavailable* if either the current energy budget is too low to take the action, or other dependencies have not been met (such as lack of sensor readings to aggregate).

In essence, the utility function represents the expected profit for taking a given action. The parameter β_a is continuously estimated by nodes over time in response to the success of taking each action. This is a form of reinforcement learning [37]. After taking an action a, the new value β'_a is calculated based on whether the action received a payment:

$$\beta'_a = \begin{cases} \alpha + (1-\alpha)\beta_a & \text{if } a \text{ receives a payment} \\ (1-\alpha)\beta_a & \text{otherwise} \end{cases}$$

α represents the sensitivity of the EWMA filter (in our experiments, $\alpha = 0.2$). In this way, nodes learn which actions are likely to result in payments, leading to a natural self-organization depending on the node's location in the network or intrinsic capabilities. For example, a node that has the opportunity to route messages for other nodes will be paid for listening for incoming radio messages; nodes on the edges of the network will learn that this action is rarely (if ever) profitable.

The expected profit for an action will vary over time due to price adjustments and changing environmental conditions. Therefore, it is important that nodes periodically "take risks" by choosing actions that have a low payment probability β_a. We employ an ϵ-greedy action selection policy. That is, with probability $1-\epsilon$ (for some small ϵ; we currently use $\epsilon = 0.05$), nodes select the "greedy" action that maximizes the utility $u(a)$. However, with probability ϵ a node will select an (available) action from a uniform distribution. In effect, this ignores the value of β_a and allows a node to explore for new opportunities for profit. Such exploration prevents a node from never electing to take an action because it has not recently been paid to do so [37].

Our current reinforcement learning scheme does not take into consideration other aspects of a node's state, such as the sequence of past actions or the state of neighboring nodes, which may lead to more efficient solutions. However, these techniques involve considerable complexity, which goes against our goals of simplicity and limiting per-node state. We intend to explore alternative learning algorithms as part of future work.

3.6 Price selection and adjustment

In SORA, the global behavior of the network is controlled by the client establishing prices for each good. Prices are propagated to sensor nodes through an efficient global data dissemination algorithm, such as SPIN [14] or Trickle [22]. The client can also adjust prices as the system runs, for example, to affect coarse changes in system activity.

There is a complex relationship between prices and agent behavior. Raising the price for a good will not necessarily induce more nodes to produce that good; the dynamics of maximizing expected profits may temper a node's desire to take a given action despite a high price. Our experiments in Section 5 demonstrate the effect of varying prices. As it turns out, subtle changes to prices do not have much impact on global network behavior. This is because each node's operation is mostly dictated by its adaptation to coarse-grained changes in the local state, such as whether sampling sensors or listening for incoming radio messages is currently profitable. Prices serve to differentiate behavior only when a node has multiple profitable actions to choose between. Even when one action has a much higher price than others, nodes will still take a mixture of actions due to continual exploration of the state space through the ϵ-greedy learning policy.

Action	**Energy consumed**
sample (single sensor)	$8.41 \times 10^{-5} J$
send (single message)	$2.45 \times 10^{-3} J$
listen	$5.97 \times 10^{-3} J$
sleep	$8.25 \times 10^{-5} J$
aggregate (compute max of array)	$8.41 \times 10^{-5} J$

Figure 1: **Energy consumed for each sensor action.**

The best approach to selecting optimal price settings in SORA is still an open problem. Given the complexities of agent operations and unknown environmental conditions, analytically solving for prices to obtain a desired result is not generally possible. In a stationary system, it is possible to search for optimal prices by slowly adjusting each price and observing its effect on network behavior; this approach is used by the WALRAS system [40].

A better approach is to determine prices empirically based on an observation of the network's behavior at different price points. For example, a system designer can experiment with a testbed deployment or simulation to understand the effect of differing prices on overall behavior. Prices can be readily tuned after deployment, since broadcasting a new price vector to an active network is not expensive. This process could be automated by an external controller that observes the network behavior over time and adjusts prices accordingly.

One approach to setting prices, based on economic principles, is to establish a *competitive equilibrium*, where the supply of goods produced by the network equals the demand for those goods expressed by the client. This model is attractive when there are multiple users programming the sensor network to take different sets of actions on their behalf, since equilibrium prices ensure that network resources are shared in an optimal manner. However, computing equilibrium prices often requires continuous information on the network's supply of goods, which may lag pricing updates. A detailed discussion of this technique is beyond the scope of this paper, but we return to this problem in Section 6.

4 Application Example: Vehicle Tracking

As a concrete example of using SORA to manage resource allocation in a realistic sensor network application, we consider tracking a moving vehicle through a field of sensors. We selected vehicle tracking as a "challenge application" for SORA because it raises a number of interesting problems in terms of detection accuracy and latency, in-network aggregation, energy management, routing, node specialization, and adaptivity [6, 43, 45]. Vehicle tracking can be seen as a special case of the more general data collection problem also found in applications such as environmental and structural monitoring [20, 28].

4.1 Tracking overview

In the tracking application, each sensor is equipped with a magnetometer capable of detecting local changes in magnetic field, which indicates the proximity of the vehicle to the sensor node. One node acts as a fixed base station, which collects readings from the other sensor nodes and computes the approximate location of the vehicle based on the data it receives. The systemwide goal is to track the location of the moving vehicle as accurately as possible while meeting a limited energy budget for each node.

Each sensor node can take the following set of actions: *sample* a local sensor reading, *send* data towards the base station, *listen* for incoming radio messages, *sleep* for some interval, and *aggregate* multiple sensor readings into a single value. Each node maintains a fixed-length LIFO buffer of sensor readings, which may be sampled locally or received as a radio message from another node. Each entry in the buffer consists of a tuple containing a vehicle location estimate weighted by a magnetometer reading. The sample action appends a local reading to the buffer, and the listen action may add an entry if the node receives a message from another node during the listen interval.

Aggregation is used to limit communication bandwidth by combining readings from multiple nodes into a single value representing the "best" sensor reading. The aggregate action replaces the contents of the sample buffer with a single weighted position estimate, ignoring any sample older than a programmer-defined constant (10 sec in our simulations). The *sleep* action represents the lowest-energy state of a node which is entered when energy is unavailable for other actions, or no other action is deemed profitable. Figure 1 summarizes the energy requirements for each action, based on measurements of the Mica2 sensor node.

4.2 Routing

All radio transmissions route messages towards the base station using a multihop routing protocol. Nodes are not assumed to be within a single radio hop of the base. The choice of routing algorithm is not essential; we use a simple greedy geographic routing protocol, similar to GPSR [19] but without any face routing, although other routing algorithms can be used [44, 17]. Messages are forwarded to the neighboring node that is both physically closer to the destination (always the base station, in this case) and is currently executing the *listen* action. This protocol assumes a CTS-RTS MAC layer that allows a node to send a message to any one of its next-hop neighbors that are currently listening. In this way, as long as any closer neighbor is currently listening, the message will be forwarded. This approach meshes well with the stochastic nature of node actions in SORA and does not require explicit coscheduling of senders and receivers.

4.3 Discussion

SORA naturally leads to an efficient allocation of network resources. Individual nodes are constrained to operate within their energy budget, and the schedule for each node may vary over time depending on network conditions and external stimuli. Nodes continuously learn which actions are most profitable and thereby have the most value to the sensor network as a whole. This *emergent* behavior is more effective at allocating limited network resources than traditional schemes based on static schedules.

The SORA approach captures a number of design tradeoffs that are worth further discussion. One advantage of this model is that the nodal program is simple: nodes simply take actions to maximize their expected profit. Nodes do not reason directly about dependencies or consequences of a series of actions, ordering, or the rate at which actions are taken. Because nodes learn the payoff probabilities β_a, they adapt to changing network conditions over time, and different nodes will take different sets of actions depending on their utility functions.

Adjusting prices gives the client of the network control over the behavior of the system, allowing the network to be readily retasked simply by advertising a new price vector. However, because nodes operate to maximize their *expected* profit, an equilibrium arises that balances the actions taken by different nodes in the network. For example, increasing the price of the listen action might substantially reduce the number of nodes that choose to sample or send sensor readings. However, since listening nodes are only paid when other nodes send data, the proportion of sending and listening nodes is kept in balance. This is a valuable aspect of self-scheduling and does not require *explicit* coordination across nodes; this equilibrium arises naturally from the feedback of payments. We demonstrate this aspect of SORA in Section 5.

SORA can be viewed as a general approach to decentralized resource allocation in sensor networks, and is not specifically tailored for data collection and vehicle tracking. However, it is worth keeping in mind that many sensor network applications operate by routing (and possibly aggregating) data towards a single base station, as evidenced by much prior work in this area [5, 11, 17, 26, 46]. It seems clear that the SORA approach could be readily applied to this broad class of systems; for example, SORA could be used to control the execution of query operators

in TinyDB [26].

Extending SORA to other applications involves two basic steps: first, identifying the set of primitive actions and goods that the system should expose, and second, measuring the associated energy costs for each action. For example, exposing a complex operation such as "compute the sum-reduce of sensor readings over a node's k nearest neighborhood" [41] would be straightforward to wrap as an SORA action. One requirement for actions is that data dependencies be made explicit. For example, the send and aggregate actions depend on the sensor reading buffer being non-empty. More complex actions might have a richer set of dependencies that must be met in order to fire. This suggests that nodes should be able to reason about taking a *sequence* of actions to produce some (highly-valued) good; this is another interesting avenue for future work.

5 Experiments and Evaluation

To demonstrate the use of Self-Organizing Resource Allocation in a realistic application setting, we have implemented the SORA-based vehicle tracking system in a sensor network simulator. This simulator captures a great deal of detail, including hardware-level sensor operations and a realistic radio communication model based on traces of packet loss statistics in an actual sensor network. We have also implemented the SORA-based tracking application in TinyOS [16] using the TOSSIM [21] simulator environment. However, due to performance limitations in TOSSIM, the results below are based on our custom simulator that runs roughly an order of magnitude faster. This performance gain is accomplished primarily by eliminating the high overhead associated with the TOSSIM GUI, as well as eliding hardware-level details of node actions that are not relevant to the SORA approach. We have verified that the two simulators produce nearly identical results. The SORA code can be readily ported to run on actual sensor nodes, and we are currently planning to take measurements on our building-wide sensor network testbed [42].

Our evaluation of SORA has three basic goals. First, we show that SORA allows nodes to self-schedule their actions to achieve an efficient allocation of network resources. Second, we show that SORA achieves much greater energy efficiency than traditional scheduling techniques without sacrificing data fidelity. Third, we show that SORA allows the system designer to differentiate node actions by varying energy budgets and price vectors.

We compare the use of SORA to several other implementations of vehicle tracking that use different scheduling techniques. These include the commonly-used static scheduling technique, a dynamic energy-aware scheduling scheme, and a tracking application based on the Berkeley NEST design as described in [43]. These systems are described in detail below.

5.1 Configuration

We simulated a network of 100 nodes distributed semi-irregularly in a 100x100 meter area. The base station (to which all nodes route their messages) is located near the upper-left corner of this area. The energy cost for each action is shown in Figure 1. The simulated vehicle moves in a circular path of radius 30 m at a rate of 1.5 m/sec. Moving the vehicle through such a path causes nodes in different areas of the network to detect the vehicle and route sensor readings towards the base station. The strength of each sensor reading depends on the distance to the vehicle; sensors cannot detect the vehicle when it is more than 11 meters away.

Unless otherwise noted, the energy budget for each node is 1000 J/day, corresponding to a node lifetime of 30.7 days.[1] The prices for all actions were set to an identical value, so nodes have no bias towards any particular action. The exploration probability ϵ is set to 0.05, and the learning parameter α is set to 0.2. We demonstrate the effect of varying these parameters in Section 5.7 and 5.8.

5.2 Comparative Analysis

To compare the use of SORA with more traditional approaches to sensor network scheduling, we implemented three additional versions of the tracking system. The first employs *static scheduling*, in which every node uses a fixed schedule for sampling, aggregating, and transmitting data to the base station. This is the most common approach to designing sensor network applications, typified by fixed sampling periods in TinyDB [26] and directed diffusion [17]. The static schedule is computed based on the energy budget. Given a daily budget of B joules, a node calculates the rate for performing each round of actions (sample, listen, aggregate, transmit, and sleep) in order to meet its budget. For example, given a daily budget of 1000 J, the data collection sequence can be performed once every 0.4 sec. This schedule is conservative, since not all nodes will actually detect the vehicle or transmit data during each period. The same schedule is used for every node in the network, so nodes do not learn which actions they should perform, nor adapt their sampling rate to stimuli such as the approach of the vehicle.

The second approach employs *dynamic scheduling* in which nodes continuously adjust their processing rate based on their current energy budget. In this way, nodes that do not consume energy aggregating or transmitting data can recycle that energy to increase their sampling rate accordingly.

The third and final approach, the *Hoods tracker*, is based on the tracking system implemented using the Hoods communication model [43]. It is largely similar to the dynamically-scheduled tracker, except in the way that nodes calculate the target location. Each node that detects

[1] This assumes that a node runs at 3V with 2850 mA-hours of battery supply.

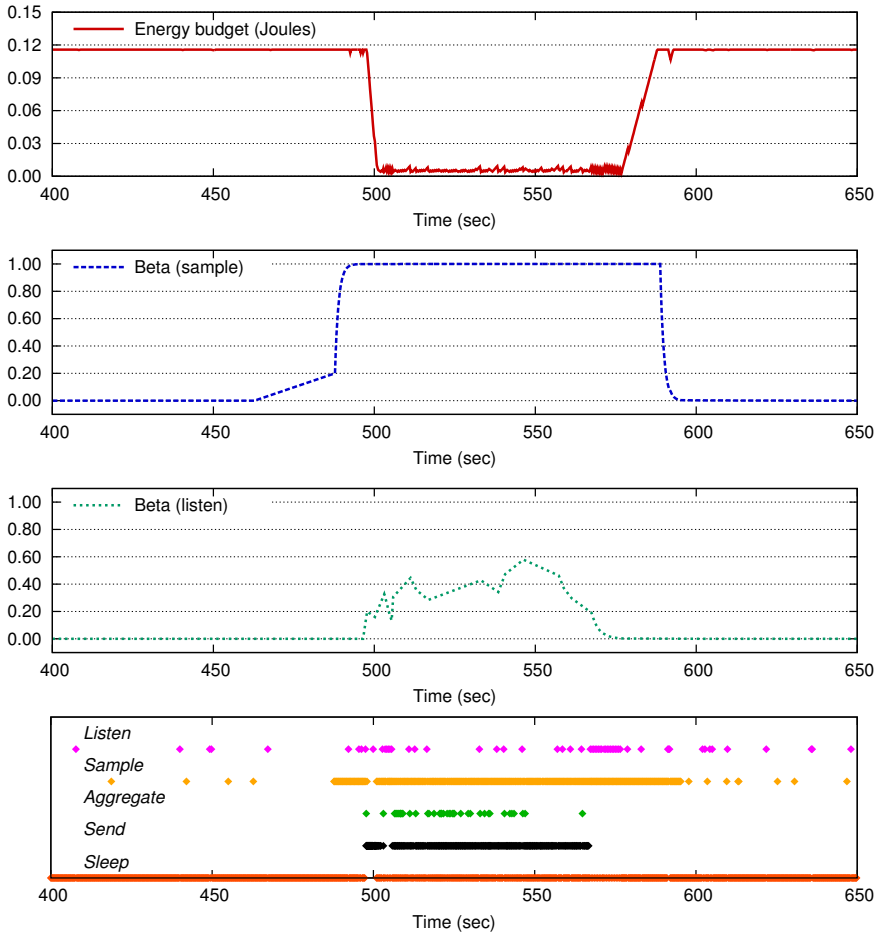


Figure 2: **Actions and energy budget for a single node.** This figure shows the actions taken, the energy budget, and the β values for the listen and sample actions for node 31, which is along the path of the vehicle.

the vehicle broadcasts its sensor reading to its neighbors. The node then listens for some period of time, and if its own reading is the maximum of those it has heard, computes the centroid of the readings (based on the known locations of neighboring nodes) as the estimated target location. This location estimate is then routed towards the base station. We implemented the Hoods tracker to emulate the behavior of a previously-published tracking system for direct comparison with the SORA approach.

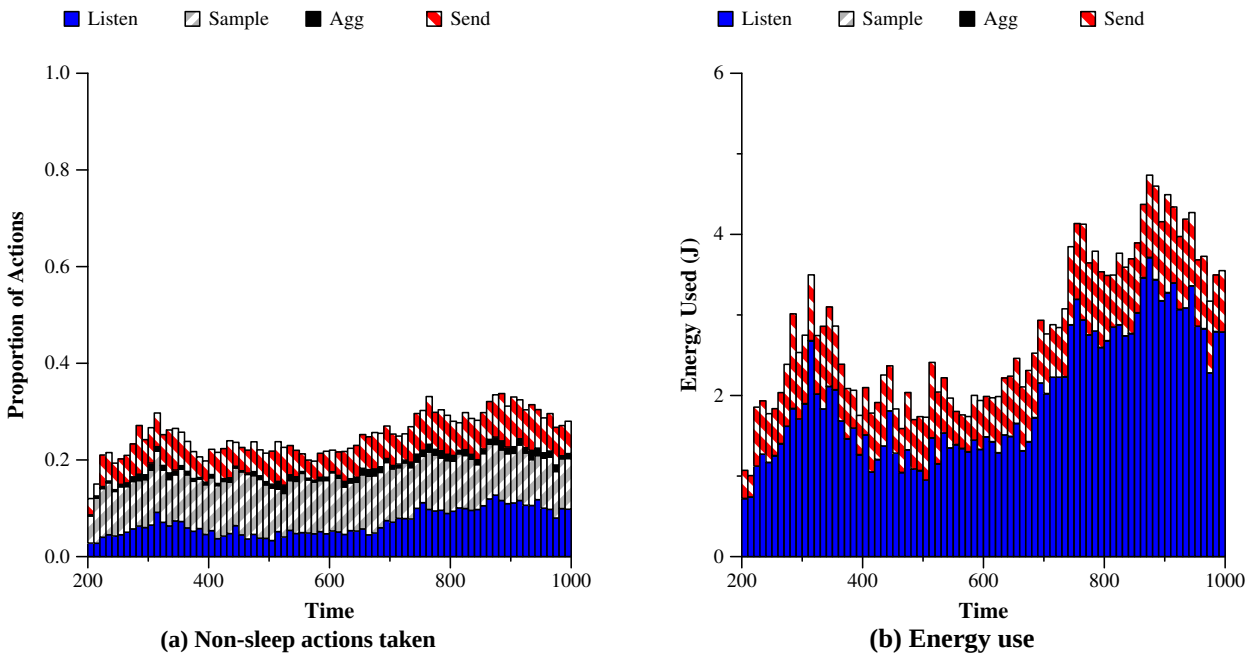
5.3 Agent operation

We begin by demonstrating the operation of the sensor network over time, as nodes learn which actions receive payments. Figure 2 depicts the actions taken, energy budget, and β values for node 31, which is along the path of the vehicle. As the vehicle approaches along its circular path at time $t = 470$, the node determines that it will be paid to sample, aggregate, and send sensor readings. As the vehicle departs around time $t = 590$, the node returns to its original behavior. At certain times (e.g., at $t = 500$ and $t = 548$), the node receives messages from other nodes and routes them towards the base station, explaining the increase in β for the listen action. When the vehicle is not nearby, the node mostly sleeps, since no interesting samples or radio messages are received. The energy bucket fills during this time accordingly; the bucket capacity C is set arbitrarily to 115 mJ, which requires the node to sleep for 20 seconds to fill the bucket entirely.

Observe that the node performs listen and sample actions even when its utility for doing so is low (even zero). This is because the node has enough energy to perform these actions, and the ϵ-greedy action selection policy dictates that it will explore among these alternatives despite negligible utility.

5.4 Network activity over time

Figure 3 shows the proportion of (non-sleeping) actions and energy use by the network over time. As the graph shows, over 60% of the actions taken by nodes during the run are *sleep*. *Listen* and *send* consume far more energy than other actions. The variation in network activity arises due to the movement of the vehicle. For example, at time $t = 600$, the vehicle is closest to the base station, so only those nodes close to the base are sampling and routing data, while the rest of the network is dormant.



(a) Non-sleep actions taken **(b) Energy use**

Figure 3: **Actions taken and energy use over time.** *This graph shows (a) the proportion of non-sleep actions taken by all nodes in the network and (b) the total energy consumed over time. Over 60% of the actions taken by the network are* sleep.

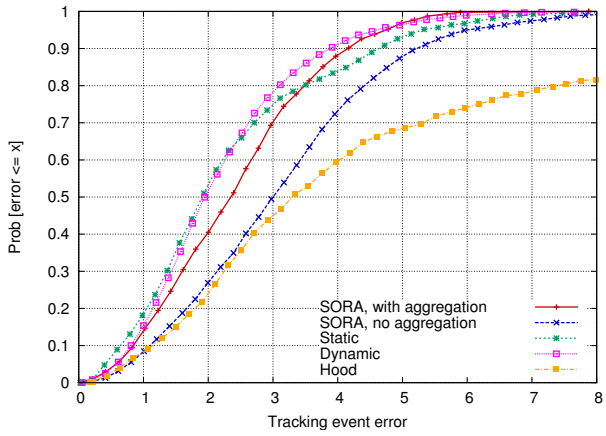


Figure 4: **Tracking accuracy.** *This figure is a CDF of the tracking position error over a run of 1000 sec for each of the tracking systems. The static and dynamic schedulers are the most accurate, since they operate periodically, while SORA has slightly higher error due to its probabilistic operation. Disabling aggregation in SORA causes accuracy to suffer since more readings are delivered to the base station. These three tracking schemes outperform the Hood-based tracker with the same energy budget.*

5.5 Tracking accuracy

To compare SORA with the other scheduling techniques, we are interested in two metrics: tracking accuracy and energy efficiency. We do not expect SORA to be more accurate than the other scheduling approaches, however, it is important that it performs in the same ballpark in order to be viable.

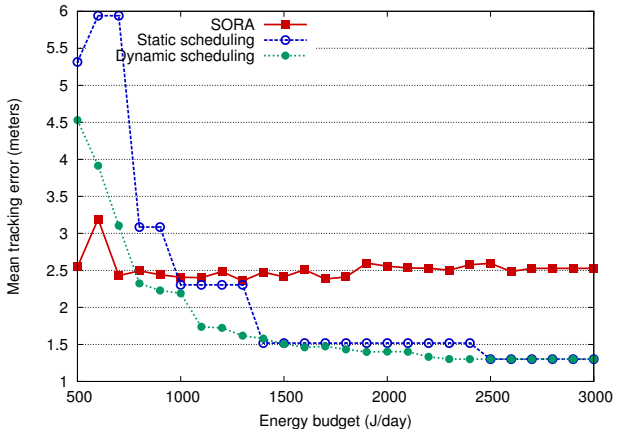
Figure 4 compares the accuracy of the SORA tracker with the other three scheduling techniques. For each position estimate received by the base station, the tracking error is measured as the difference between the estimated and true vehicle position *at the time that the estimate is received*. This implies that position estimate messages that are delayed in the network will increase tracking error, since the vehicle may have moved in the interim. As the figure shows, SORA achieves an 80th percentile tracking error of 3.5 m, only slightly higher than the static and dynamic trackers.

The Hood tracker performs poorly due to its different algorithm for collecting and aggregating sensor data. Figure 5 shows a scatterplot of position estimates received at the base station for each tracking technique. Hood delivers far fewer position estimates and exhibits wider variation in accuracy. Also, disabling aggregation in SORA (by setting the price for the *aggregate* action to 0) causes more position estimates to be delivered that exhibit greater variation than the aggregated samples.

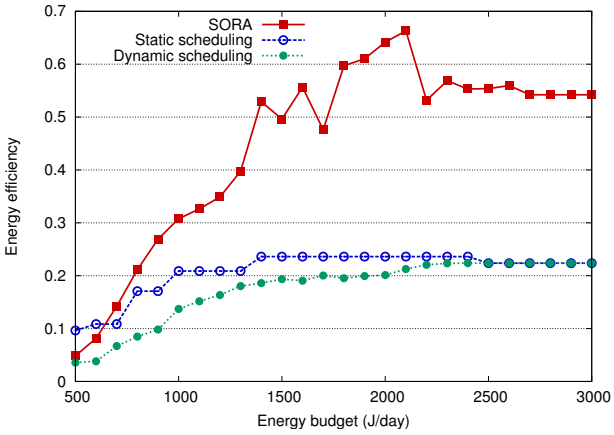
5.6 Energy efficiency

By allowing nodes to self-schedule their operation in response to external stimuli and energy availability, SORA achieves an efficient allocation of energy across the network. For each of the scheduling techniques, we measure the efficiency of resource allocation in terms of the energy cost to acquire each position estimate in proportion to the total amount of "wasted" energy in the network.

For each position estimate received by the base station, we measure the "useful" energy cost of acquiring and routing that data. This includes the sum energy cost of sampling, (optional) aggregation, radio listening, and transmission of the data along each hop. In the case of esti-



(a) Mean tracking error



(b) Energy efficiency

Figure 6: **Tracking accuracy and energy efficiency.** *This figure shows (a) the mean tracking error and (b) overall system energy efficiency as the energy budget is varied.*

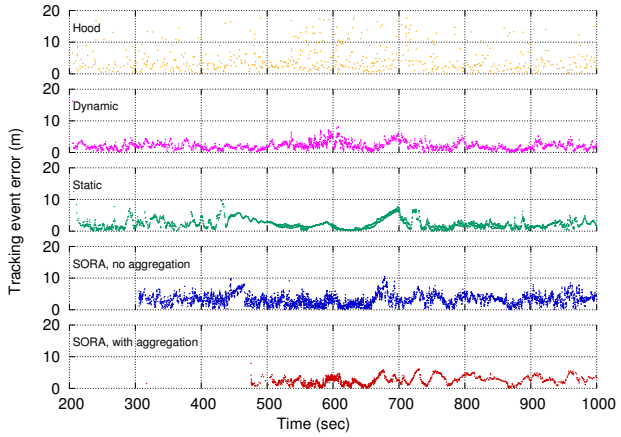


Figure 5: **Tracking accuracy scatterplots.** *These scatterplots show the set of readings delivered to the base station by each tracking system over time. Hood performs poorly and delivers far fewer vehicle position estimates. The effect of disabling aggregation in SORA can be seen clearly.*

mates with aggregated values, we count both the total energy cost for each sensor reading in the estimate, as well as the number of sensor readings represented. Because aggregation amortizes communication overhead across multiple readings, we expect aggregation to reduce the overall per-sample energy cost. The total amount of *useful energy* consumed by the network is the sum of the energy cost for all position estimates produced during a run of the tracking system.

All other energy consumed by the network is *wasted* in the sense that it does not result in data being delivered to the base. In a perfect system, with *a priori* knowledge of the vehicle location and trajectory, communication patterns, and so forth, there would be no wasted energy. In any realistic system, however, there is some amount of waste. For example, nodes may listen for incoming radio messages or take sensor readings that do not result in position estimates. We define *efficiency* as the ratio of the total useful energy consumed by the network to the total energy consumed (useful plus wasted energy).

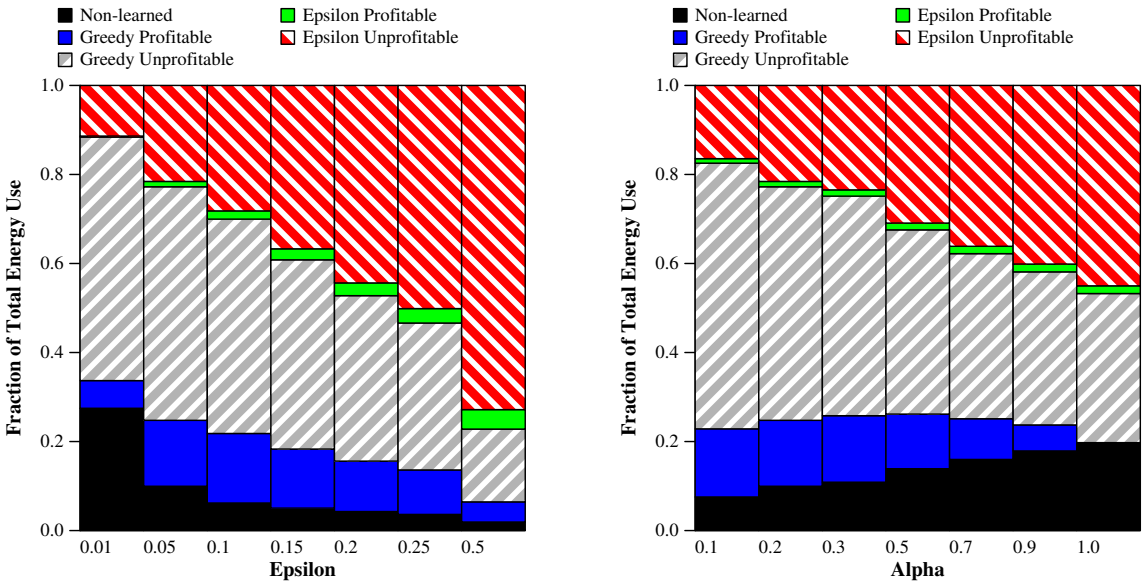
It is important to note that the statically-scheduled and dynamically-scheduled trackers do not make any attempt to save energy beyond their energy budget. Nodes are programmed to operate at a rate that consumes the local energy budget, despite local network conditions. In SORA, however, many nodes may conserve energy by sleeping when they have zero utility for any potential action (e.g., because they are in a quiescent area of the network). The use of reinforcement learning in SORA allows nodes to tune their duty cycle in response to local conditions, significantly extending lifetime.

Figure 6 summarizes the accuracy and efficiency of each scheduling technique as the energy budget is varied. Each system varies in terms of its overall tracking accuracy as well as the amount of energy used. While SORA has a somewhat higher tracking error compared to the other scheduling techniques, it demonstrates the highest efficiency, exceeding 66% for an energy budget of 2100 J. The static and dynamic schedulers achieve an efficiency of only 22%. In SORA, most nodes use far less energy than the budget allows. The ability of SORA to "learn" the duty cycle on a per-node basis is a significant advantage for increasing network lifetimes.

5.7 Varying learning parameters

Apart from the energy budgets and prices, two parameters that strongly affect node behavior in SORA are ϵ, the exploration probability, and α, the EWMA gain for learning action success probabilities. By varying ϵ, we can trade off increased energy waste (for exploring the action space) for faster response to changing network conditions. By varying α, the system reacts more or less quickly to changes in success probabilities; higher values of α cause a node to bias action selection towards more-recently profitable actions.

Figure 7(a) shows the effect of varying ϵ from 0.01 to 0.5. As the probability of taking a random action increases,



(a) Varying exploration probability ϵ **(b) Varying EWMA filter gain α**

Figure 7: **Effect of varying exploration and learning parameters.** *(a) α is held constant at 0.2 and the probability of taking a random action ϵ is varied. (b) ϵ is held constant at 0.05 and the EWMA filter gain is α is varied.*

the proportion of energy wasted taking those actions also increases. However, the proportion of energy wasted taking the "greedy" action (the action with the highest expected probability of success) decreases, since nodes learn more rapidly which actions are profitable by exploring the action space.

Figure 7(b) shows a similar result for varying α. When α is increased, nodes react very quickly to changes in action success. When $\alpha = 1.0$, if an action is successful once, the node will immediately prefer it over all others. Likewise, the node will immediately ignore a potentially profitable action the first time it is unsuccessful. As a result, the proportion of energy used on successfully choosing the greedy action decreases. Also, since the node's action selection policy is increasingly myopic, nodes spend more time sleeping. As a result, a greater proportion of energy is spent on exploratory actions since few "greedy" actions are considered worthwhile.

5.8 Heterogeneous energy budgets and prices

SORA allows nodes to be differentiated with respect to their energy budgets, as well as the prices under which they operate. For example, certain nodes may have access to a large power supply and should be able to perform more power-hungry operations than nodes operating off of small batteries. Likewise, advertising different price vectors to different nodes allows them to be customized to take certain actions.

Figure 8 shows the behavior of the tracking system where 20% of the nodes are given a large energy budget of 3000 J/day, effectively allowing them to ignore energy constraints for the purpose of selecting actions. The large energy budget nodes automatically elect to perform a greater number of listen and send actions, while the other nodes mostly perform sample actions, which consume far less energy overall. Identical prices are used throughput the network, showing that differences in energy budget have a profound effect on resource allocation.

Advertising different price vectors to different sets of nodes is another way to specialize behavior in SORA. Figure 9 shows a case where 20% of the nodes are configured as "routers" with all prices set to 0, except for listening, aggregation, and sending. The other nodes act as "sensors" with nonzero prices only for sampling and sending. As the figure shows, each group of nodes exhibits very different behavior over the run, with sensor nodes performing a large number of sampling and send actions, while router nodes primarily listen and transmit. Routers spend a great deal of time sleeping because most actions (e.g., aggregation and sending) are unavailable, and listening consumes too much energy to perform continually.

6 Future Work and Conclusions

The design of sensor network applications is complicated by the extreme resource limitations of nodes and the unknown, often time-varying, conditions under which they operate. Current approaches to resource management are often extremely low-level, requiring that the operation of individual sensor nodes be specified manually. In this paper, we have presented an technique for resource allocation in sensor networks in which nodes act as self-interested agents that select actions to maximize profit, subject to energy limitations. Nodes self-schedule their local actions in response to feedback in the form of payments. This allows nodes to adapt to changing conditions and specialize their behavior according to physical location, routing topology,

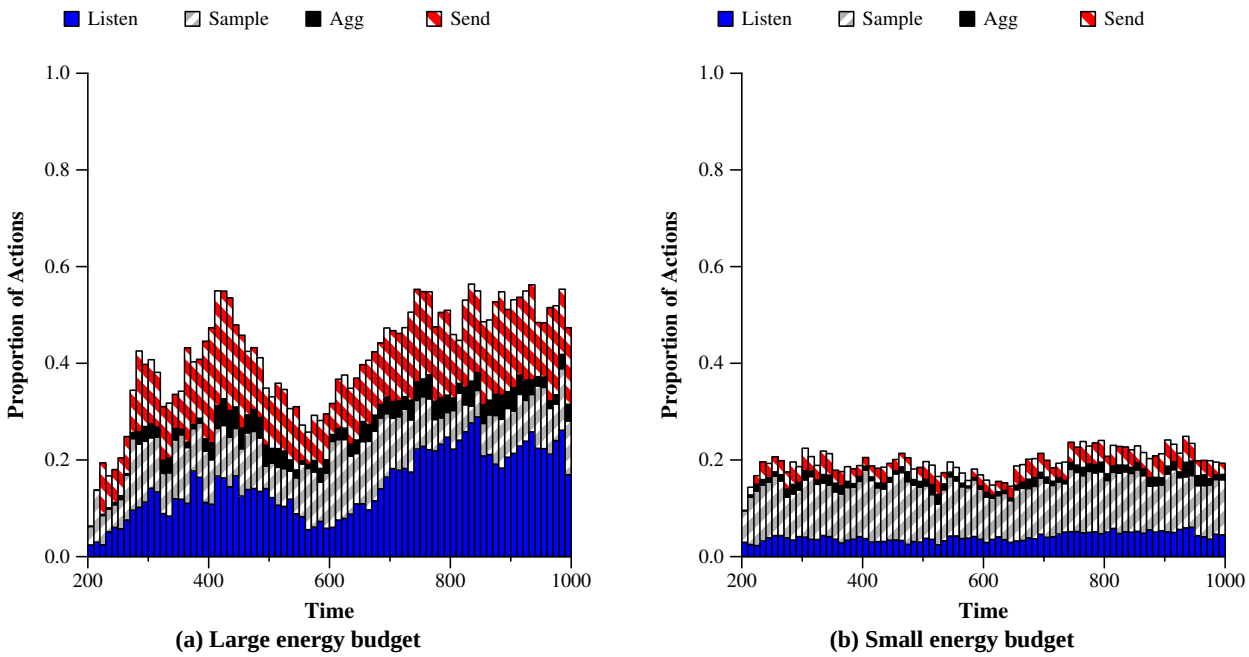


Figure 8: **Exploiting heterogeneous energy budgets.** *Here, 20% of the nodes are given a large energy budget of 3000 J/day (a), where the rest of the nodes use a smaller energy budget of 500 J/day (b). The large energy budget nodes automatically take on a greater proportion of the energy load in the system, choosing to perform a far greater number of listen and send actions than the low-energy nodes.*

and energy reserves.

Exploiting techniques from reinforcement learning and economic theory yields new insights into the allocation of scarce resources in an adaptive, decentralized fashion. Our initial work on SORA raises a number of interesting questions that we wish to explore in future work. These are described in summary below.

Equilibrium pricing: As discussed earlier, a system is in competitive equilibrium (Pareto optimal) when prices are selected such that supply of goods equals demand. This is an attractive model for allowing multiple users to allocate and share sensor network resources in an optimal fashion. However, such an approach raises a number of practical problems that must be addressed before it can be applied to sensor networks. The traditional tâtonnement approach [29] is to increase prices on undersupplied goods (and vice versa for oversupplied goods) until reaching equilibrium, and execute trade only after prices have been selected. A real system must depart from this approach in that it operates continuously. As a result, since supply and demand may lag price adjustments, true equilibrium may never be reached.

In addition, calculating equilibrium prices generally requires clients to have *global* information on the supply provided by each sensor node at the currently-proposed prices. We are exploring techniques in which aggregate supply information is collected and piggybacked on other transmissions to the base station. However, clients must then operate on incomplete and out-of-date supply information. Another approach is to collect supply information at several price points simultaneously, allowing the client to adjust prices based on the resulting gradient information.

Richer pricing models: More complex pricing schemes can be used to induce sophisticated behaviors in the network. For example, rather than pricing only those goods that result from single actions, we can price *sequences* of actions. Consider aggregating multiple sensor readings into a single value for transmission. Rather than price the final aggregate value and requiring an agent to reason about a sequence of actions to achieve that result, we can establish prices for each step in the sequence and introduce control or data dependencies between actions. Another question is that of *location-based prices*, in which goods are priced differently in different areas of the network. This can be used to establish a ring of "sentry nodes" around the perimeter of the network that wake other nodes in the interior when the entrance of a vehicle is detected.

New application domains: We intend to explore other applications for the SORA technique. As discussed earlier, this requires that nodes be programmed with new actions and corresponding energy consumption models. One application that we are actively investigating involves sensor networks for emergency medical care and disaster response [25]. This scenario involves establishing multicast communication pathways between multiple vital sign sensors worn by patients and handheld devices carried by rescuers and doctors. We envision SORA providing a mechanism for efficient bandwidth and energy allocation in this environment.

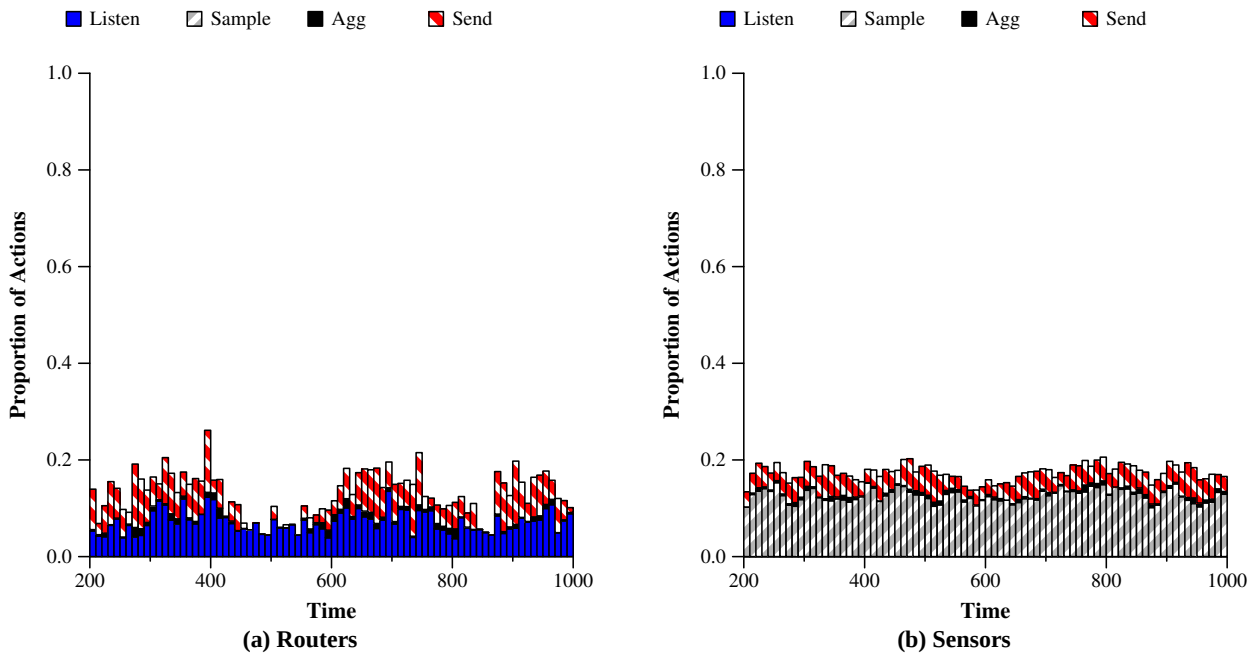


Figure 9: **Specialization through pricing.** *Here, 20% of the nodes are configured as "routers" (left) using prices for listening, aggregation, and sending. The other 80% of the nodes are configured as "sensors" (right) and only have prices for sampling and sending. As the figure shows the proportion of actions taken by each group of nodes differs greatly according to the prices.*

Integration with programming languages: Finally, our broader research agenda for sensor networks involves developing high-level *macroprogramming* languages that compile down to local behaviors of individual nodes. SORA presents a suite of techniques for scheduling node actions and managing energy that could be integrated into such a language. For example, TinyDB's SQL-based query language could be implemented using SORA to control the execution of query operators on each node, rather than the current model of relying on a static schedule. We have completed the initial design of a functional macroprogramming language for sensor networks that compiles down to a simple per-node state machine that could be readily implemented using a SORA-based model [31, 32].

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