

# A Hierarchical Transport Architecture for Wireless Sensor Networks

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**Abstract**—For practical applications, wireless sensor networks (WSNs) with diverse sensor types and that run heterogeneous applications are becoming increasingly important. Our motivation in this work is to, for this sort of heterogeneous WSNs, devise a flow control and resource allocation algorithm (with respect to both wireless channel usage and sensor node energy), that allow data to be gathered in the fairest manner, while still respecting the needs of different sensing tasks. A two-layer hierarchical transport architecture is designed to guarantee a certain measure of optimality in rate allocation, addressing the balance between fairness and performance. In essence, utility max-min fairness is achieved among upper-layer cluster heads, whereas utility proportional fairness is achieved within each lower-layer cluster. The proposed architecture is to be applied to a real marine sensor network on the Great Barrier Reef.

## I. INTRODUCTION

Sensor nodes nowadays possess a multitude of sensing modalities including simple scalar data (e.g., temperature, infra-red, acoustic, humidity) and high dimensional multimedia (e.g., audio, video). The consequence of this technological development is that WSNs are becoming an ideal interface for the environment to the world community. Current and potential applications range from environmental monitoring and conservation, home automation, health-care services, business inventory, to control and manufacturing [1].

When diverse sensor nodes with their own characteristics are involved, the objective of WSNs is no longer to simply maximize the sum of data rates from all the nodes, subject to certain constraints. The research community is in general agreement that there exists a severe bias in the rate allocation among sensor nodes of different types [2], [3] – in particular, a node with low demand is usually allocated a high bandwidth. To solve this problem, a flow control or resource allocation algorithm should be devised to cater for a variety of performance metrics depending on the type of the sensors. Here, we model node performance as a generic utility function over the available bandwidth. In order to discriminate different applications or tasks according to sensor types, we relax the utility function conditions, such that the function is only required to be strictly increasing with the data rate, but may not be strictly concave. This relaxation has a significant effect on real-time applications.

In most scenarios, sensor nodes are scattered in a geographical area. Due to the nature of convergecast traffic, the

nodes near the sink favor the transmission rates over the ones far away [4]. This causes the fairness issue associated with the network coverage problem. Ideally, the flow control algorithm needs to allocate bandwidth fairly among all sensor nodes so that the sink can obtain a fair amount of data from the entire network. Our contribution in this work is a two-layer hierarchical transport architecture that achieves the aforementioned two goals.

Additionally, since the majority of sensor nodes have limited power and irreplaceable batteries, energy remains the primary concern in WSNs. To address this concern, we propose a power dissipation model, and based on this model, we make our algorithms energy-aware by incorporating energy constraints in them.

The remainder of the paper is organized as follows. In Section II, we describe the layered network structure and system models concerning both the channel capacity constraint and the energy constraint. Section III compares the differences between utility (bandwidth) max-min fairness and utility (bandwidth) proportional fairness, and then presents two transmission algorithms, one for the cluster-head layer and the other for the cluster-member layer. Following that, a practical implementation of the hierarchical transport architecture on the Great Barrier Reef is proposed in Section IV. Finally, Section V concludes this paper and points out some future work.

## II. SYSTEM MODELING

We consider a wireless sensor network with a layered structure [3]. Fig. 1 shows the physical topology and a hierarchical view of the sensor network. There are three types of nodes in the network, i.e., *Sensor Node* (SN), *Cluster Head* (CH) and *Base Station* (BS). The SNs are application-specific sensor nodes such as temperature sensor nodes, hydrological sensor nodes and video sensor nodes. They are usually deployed in clusters (groups), which we call Lower-Layer Clusters (LLCs), and form the lower layer of the network architecture.

For each cluster of sensor nodes, there is one cluster head, which is more powerful in terms of communications, computational capability, and energy level. The primary functions of a cluster head are: 1) *aggregating* data flows from the SNs within its local cluster, and 2) *forwarding* the aggregated traffic to the next-hop CH towards the base station. Though provisioned

with much more energy than a SN, a CH is still energy-constrained because of higher energy consumption rate (due to high transmission rate and large communication distance). The last component of the two-layer architecture is the base station (or *sink* node), which is supposed to have sufficient energy resource. In Fig. 1, all the CHs and the BS form an Upper-Layer Cluster (ULC).

Let  $\mathcal{H} = \{1, 2, \dots, H\}$  denote the set of cluster heads in the sensor network and  $\mathcal{D}$  denote the single base station. Each cluster  $h$  consists of a set  $\mathcal{S}_h = \{S_{h1}, S_{h2}, \dots, S_{hS}\}$  of sensor nodes and each particular sensor node  $s$  is the source that senses and delivers data to the local CH, possibly over multiple hops. There are in total  $N = H + S_1 + S_2 + \dots + S_H$  nodes in the network. A node  $n$ , either a CH or an SN, is characterized by five parameters  $\{r_n, x_n, m_n, M_n, U_n(x_n)\}$ .  $r_n$  is a unique path from node  $n$  to the local CH if node  $n$  is an SN; or from node  $n$  to the BS if node  $n$  is a CH. The feasible routes are assumed to be known and can be obtained from a network-layer routing protocol [5].  $x_n$  is the source rate satisfying  $0 \leq m_n \leq x_n \leq M_n < \infty$ , where  $m_n$  and  $M_n$  are the minimum and maximum bandwidth requirements of the node  $n$  respectively.  $U_n(x_n) : \mathcal{R}^+ \mapsto \mathcal{R}$  is a continuously increasing and bounded utility function which indicates the performance of node  $n$ .

#### A. Channel Capacity Constraint

Assuming the entire sensor network adopts orthogonal link transmissions which could be FDMA-based link layer transmissions or spread spectrum-based link layer transmissions using orthogonal codewords. These schemes successfully avoid the interference from neighboring nodes. Therefore, node interference is not considered in this paper.

Denote the whole set  $\mathcal{L} = \{1, 2, \dots, L\}$  of links which are a part of at least one route. In our model, due to the nature of the underlying physical and MAC layers, it is safe to assume the link capacity  $c_l$  of link  $l$  is a constant. Moreover, it is equivalent to the allocated free-space channel capacity. Let  $x = [x_1, x_2, \dots, x_N]^T$ . For each link  $l$ , define  $\mathcal{S}_l = \{n \in \mathcal{S} | l \in r_n\}$ , which is the set of sources that go through link  $l$ . Then for any  $l \in \mathcal{L}$ , the channel capacity constraint (1) must be satisfied

$$\sum_{n \in \mathcal{S}_l} x_n \leq c_l. \quad (1)$$

Sometimes it is more convenient to represent the information  $r_n$  and  $\mathcal{S}_l$  in terms of a routing matrix  $R \in \{0, 1\}^{L \times N}$  whose  $(l, n)$ th entry is  $R_{ln} = 1$  if and only if  $l \in r_n$  or  $n \in \mathcal{S}_l$ , and 0 otherwise. The channel capacity constraint (1) now can be represented more compactly as

$$Rx \leq \mathbf{c} \quad (2)$$

where  $\mathbf{c} \in \mathcal{R}_+^L$  is the vector of link capacities.

In the context of sensor networks, besides the channel capacity constraint of each link, a node itself is energy-constrained. Typical node operations, such as sensing, transmitting, and receiving data, consume a fair amount of energy.

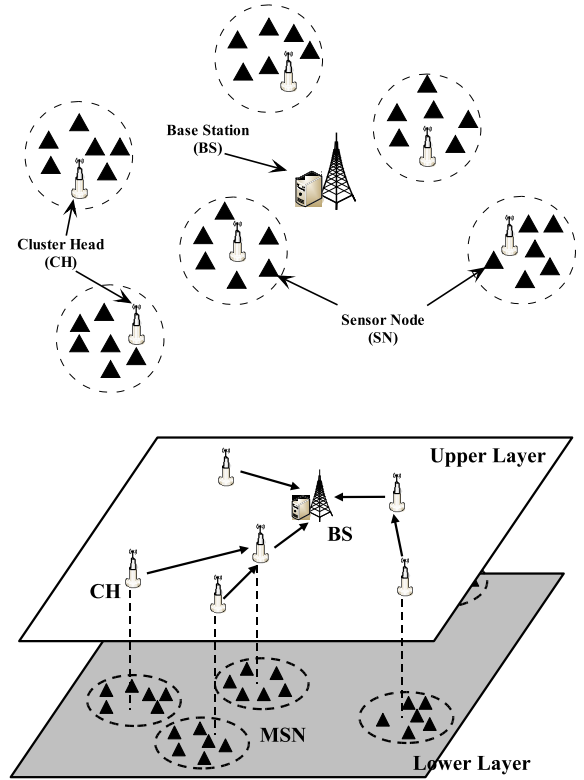


Fig. 1. Reference Architecture for two-layer wireless sensor networks. (Above) Physical topology; (Below) a hierarchical view.

In the next section, we will introduce the power dissipation model and impose the corresponding energy constraint.

#### B. Power Dissipation Model and Energy Constraint

Let  $e_s$ ,  $e_t$  and  $e_r$  be the energy consumption per bit incurred by data sensing, transmitting and receiving respectively.  $e_t$  includes radiated energy per bit. Define a matrix  $E \in \mathcal{R}_+^{N \times N}$  according to

$$E_{jn} = \begin{cases} e_s + e_t & \text{if node } j \text{ is the starting node of route } r_n \\ e_t + e_r & \text{if node } j \text{ is an intermediate node of } r_n \\ 0 & \text{if node } j \text{ is not belonging to route } r_n \end{cases} \quad (3)$$

and let  $E_n$  be the  $n$ th row of the matrix  $E$ . Note that the energy consumption of computation is typically much smaller and is hence neglected. Thus, for a given network flow  $x$ , the total power dissipation  $P_n$  of node  $n$  is  $P_n = E_n x$ .

Next, let  $I_n$  denote a limited amount of initial energy available at node  $n$ . We define the network lifetime  $T$  as the time until the first cluster head in the network runs out of energy as in [3]. Upon depletion of energy at a CH, we expect that the *coverage* of the entire cluster is lost, although some of the SNs within the cluster may still have remaining energy (the SN is assumed only to forward data to the local CH for processing). By denoting  $T_h$  the lifetime of CH  $h$ , the network lifetime is  $T = \min_{h \in \mathcal{H}} T_h$ .

Let  $T_d$  be the designed network lifetime guarantee. The maximum energy consumption per unit time, or equivalently the maximum power consumption, allowed at node  $n$  is then equal to

$$P_n^{\max} = \frac{I_n}{T_d}. \quad (4)$$

To ensure the required network lifetime  $T_d$ , the power consumption of each node  $n$  should not be more than the maximum allowed power consumption. It leads to the energy constraint for all nodes

$$Ex \leq \mathbf{p} \quad (5)$$

where  $\mathbf{p} \in \mathcal{R}_+^N$  is the vector of maximum node power consumption.

In order to formulate the flow control problem for the sensor network, we need to define the notion of feasible (or attainable) source rate allocation.

*Definition 1:* A particular source rate allocation  $x = [x_1, x_2, \dots, x_N]^T$  is *feasible* or *attainable* if and only if  $x_n \in [m_n, M_n]$ , and in the sensor network no link is saturated and no node is energy depleted, i.e.:

$$\begin{aligned} Rx &\leq \mathbf{c} \\ Ex &\leq \mathbf{p} \end{aligned}$$

Throughout the paper, we assume that a minimum allocation  $x = [m_1, m_2, \dots, m_N]^T$  is attainable in the sensor network.

The major task of the flow control is to guide data flow to a feasible source rate allocation, in such a way that the base station can obtain a fair amount of data from all the sensor nodes regardless the geographical locations [4]. Also within the cluster, each type of sensor application is treated in a fair manner and guaranteed high application performance. When the resource (channel capacity and node energy) is abundant, there is no difficulty in satisfying the above requirement, i.e., if  $x = [M_1, M_2, \dots, M_N]^T$  is attainable within the sensor network. If the resource is not sufficient (or even worse, is scarce), then there arises the problem of how to allocate the existing resource fairly among competing nodes that have completely different behaviors.

### III. HIERARCHICAL TRANSPORT ARCHITECTURE

In this section, we will address the problem formulated in Section II and build the hierarchical transport architecture. Before proceeding, some fundamental flow control design objectives are covered first.

#### A. Utility Max-Min Fairness and Utility Proportional Fairness

Generally in computer networks, flow control is designed to allocate bandwidth resource fairly and maximally among competing users without incurring network congestion. There are three types of common fairness criteria that are being widely used. They are *max-min fairness* [6], *proportional fairness* [7] which is the result of network utility maximization, and *TCP friendly fairness* [8] which also has an alternative notion of “potential minimum delay fairness” [9]. The difference among

these three types of fairness is illustrated by the following example.

Consider a linear network consisting of links  $1, 2, \dots, 9$  in tandem, each with a bandwidth capacity of 1 unit. The network is shared by sources (connections)  $0, 1, 2, \dots, 9$ . Source 0 traverses all the links, while source  $i$ ,  $i \geq 1$ , traverses link  $i$  only. If the aim is to maximize the overall throughput, then each short connection should receive a rate of 1 while the access of long connection (source 0) is blocked. On the other hand, *max-min fairness* results in a fair resource allocation which allocates each connection equally with a bandwidth of 0.5. In *proportional fairness*, the length of each connection is taken for granted, this yields an allocation of 0.9 to each short connection and 0.1 to long connection. In between, *TCP friendly fairness* provides a good balance and allocates 0.75 to each source  $i \geq 1$ , and 0.25 to source 0. In that regard, long connection neither uses too much network resource as in max-min fairness, nor suffers from a serious bandwidth shortage as in proportional fairness.

In sensor networks, however, since sensor nodes are application-specific, application performance measured by the utility is often a more important factor than bandwidth allocation. Referring to our architecture, a LLC consists of SNs of different types and that exhibit different utility functions; a ULC possibly employs different data aggregation or fusion techniques and produces different output satisfaction levels.

As such, it may be undesirable to allocate source rates simply according to conventional criteria such as max-min fairness and proportional fairness. Instead, the sensor network should have the ability to allocate sensor source rates to various applications, addressing their real utility requirements. This has been the motivation for a new concept of utility max-min fairness suggested by Cao and Zegura [10].

*Definition 2:* A sensor source rate allocation  $x^* = [x_1^*, x_2^*, \dots, x_N^*]^T$  is utility max-min fair, if it is feasible and for each node  $n$ , the utility  $U_n(x_n^*)$  cannot be increased while still maintaining feasibility, without decreasing the utility  $U_{n'}(x_{n'}^*)$  for some node  $n'$  with a lower utility  $U_{n'}(x_{n'}^*) \leq U_n(x_n^*)$ . Max-min fair allocation is recovered with

$$U_n(x_n) = x_n, \quad n = 1, \dots, N.$$

Another newly proposed criterion for utility-based fairness is utility proportional fairness [11].

*Definition 3:* A sensor source rate allocation  $x^* = [x_1^*, x_2^*, \dots, x_N^*]^T$  is utility proportionally fair, if it is feasible and for any other feasible allocation  $x$ ,

$$\sum_{n \in N} \frac{x_n - x_n^*}{U_n(x_n^*)} \leq 0, \quad (6)$$

and the traditional proportional fairness is recovered if

$$U_n(x_n) = x_n.$$

The difference between utility max-min fairness and utility proportional fairness is analogous to the difference between (bandwidth) max-min fairness and (bandwidth) proportional

fairness. Now we are ready to describe in detail our transmission (flow control) algorithms and hierarchical transport architecture.

### B. Transmission Algorithms

We propose a set of transmission algorithms for Lower-Layer Clusters (LLC) and Upper-Layer Cluster (ULC) respectively.

1) *Flow control within an LLC*: The flow control algorithm within an LLC uses a similar flow control structure as the optimal flow control approach [12] does, with the help of pricing scheme. There are two price vectors  $\alpha \in \mathcal{R}_+^{L_h}$ ,  $\beta \in \mathcal{R}_+^{S_h}$  associated with links and nodes in the cluster  $h$ . A link algorithm is deployed at each link<sup>1</sup> to update the link price depending on the saturation of channel usage, and a node algorithm is deployed at each SN to update the node price depending on the depletion rate of energy. Each SN runs a source algorithm which adapts the sensor source rate based on these two prices.

Both the link algorithm and node algorithm are iterative. At time  $t + 1$ , each link  $l$  updates its link price  $\alpha_l$  according to:

$$\alpha_l(t + 1) = [\alpha_l(t) + \gamma(x^l(t) - c_l)]^+ \quad (7)$$

where  $\gamma > 0$  is a small step size, and  $x^l(t) = \sum_{s \in S_l} x_s(t)$  is the aggregate source rate at link  $l$ . Equation (7) implies that if the aggregate source rate at link  $l$  exceeds the channel capacity  $c_l$ , the link price is increased; otherwise it is decreased. The projection  $[z]^+ = \max\{0, z\}$  ensures that the link price is always non-negative.

Similarly, each sensor node  $s$  updates its node price  $\beta_s$  at time  $t + 1$  according to:

$$\beta_s(t + 1) = [\beta_s(t) + \gamma(E_s x(t) - P_s^{\max})]^+ \quad (8)$$

where  $\gamma > 0$  is the same step size as equation (7), and  $E_s x(t)$  is energy consumption at sensor node  $s$ . Equation (8) also implies that if energy consumption at sensor node  $s$  exceeds the maximum rate allowed, the node price will be increased; otherwise it will be decreased.

Given these two prices, each SN adopts the following source algorithm to update the source rate:

$$x_s(t + 1) = U_s^{-1} \left( \left[ \frac{1}{p^s(t)} \right]_{U_s(m_s)}^{U_s(M_s)} \right) \quad (9)$$

where

$$p^s(t) = \langle \alpha^T R_h + \beta^T E_h \rangle_s \quad (10)$$

is  $s$ th element of  $\alpha^T R_h + \beta^T E_h$ , or namely the aggregate price of sensor node  $s$ ,  $[z]_a^b = \max\{a, \min\{b, z\}\}$ , and  $U_s^{-1}$  is the inverse of  $U_s$  over the range  $[U_s(m_s), U_s(M_s)]$ . According to the definition of utility function, it is clear that  $x_s(p^s)$  given by equation (9) is decreasing over the aggregate price  $p^s$ . When  $p^s \geq 1/U_s(m_s)$ , sensor node  $s$  is required to transmit at the minimum rate  $m_s$ . When  $p^s \leq 1/U_s(M_s)$ , sensor node

<sup>1</sup>In practice, it is the transmitting node to update the link algorithm, other than the free-space link in a wireless environment.

$s$  transmits at the maximum rate  $M_s$ . In between, sensor node  $s$  attains a utility factor of  $1/p^s$ . Combining (7), (8), (9) and (10), the flow control algorithm within LLC is summarized as follows:

**Algorithm:** At time  $t = 1, 2, \dots$ ,

- 1) Update source rate: Each sensor node  $s$  calculates the source rate based on the aggregate price of links and nodes along its route  $r_s$  to the local CH

$$x_s(t + 1) = U_s^{-1} \left( \left[ \frac{1}{p^s(t)} \right]_{U_s(m_s)}^{U_s(M_s)} \right)$$

where

$$p^s(t) = \sum_{l \in r_s} \alpha_l(t) + \sum_{j \in K(s)} \beta_j(t) E_{j_s}$$

$K(s)$  denotes the set of nodes along route  $r_s$ .

- 2) Update link and node prices: Using the aggregate data flow passing through it, each sensor node  $s$  updates the outgoing link price  $\alpha_l$  and node price  $\beta_s$

$$\alpha_l(t + 1) = [\alpha_l(t) + \gamma(x^l(t) - c_l)]^+$$

$$\beta_s(t + 1) = [\beta_s(t) + \gamma(\sum_{j \in R(s)} E_{s_j} x_j(t) - P_s^{\max})]^+$$

$R(s)$  denotes the set of routes passing node  $s$ .

- 3) Deliver message towards the local CH: Sensor node adapts the updated source rate  $x_s(t + 1)$ , aggregates all the data and propagates towards the CH.
- 4) Feedback message from the CH: The CH feedbacks the updated link price  $\alpha_l(t + 1)$  and node price  $\beta_s(t + 1)$  by aggregating them at intermediate nodes along each reverse route.

The above algorithm has an important feature that only the aggregate variables, instead of individual one, are exchanged in the cluster. The total number of messages passing towards and from the local CH is  $S$ , which can be piggy-backed on the destined data and returned by acknowledgement. In this sense, the overhead of the algorithm is a minor issue.

2) *Flow control within ULC*: For each cluster head  $h$ , if the aggregate price is redefined as

$$p^h(t) = \max\{\max_{l \in r_h} \alpha_l(t), \max_{h \in K(h)} \beta_h(t)\} \quad (11)$$

which is the maximum of the outgoing link prices and node prices along the route, then the similar flow control algorithm (7), (8) and (9) will provide a utility max-min fair allocation within ULC.

Mathematically, the optimization and convergence of the set of transmission algorithms can be found separately in [2] and [13], including a plethora of numerical simulation examples with performance analysis. In summary, the LLC transmission algorithm aims to balance the performance of different sensors and maximize the ‘‘pseudo utility’’ within a cluster [11]. On the other hand, the ULC transmission algorithm aims to give each cluster head the fairest share of the available resource regardless whether it is near or far away

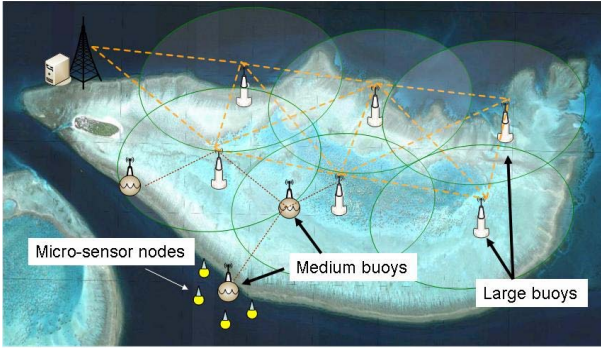


Fig. 2. Schematic sensor network deployment in Heron Island, GBR Australia.

from the base station. In this way, the overall performance of the sensor network is optimal in terms of both local information utility and global coverage.

#### IV. IMPLEMENTATION PROPOSAL ON THE GREAT BARRIER REEF

Based on the theory developed above, in this section, we propose to implement our hierarchical architecture on the Great Barrier Reef (GBR) sensor network. The environmental dynamics of marine systems such as GBR are complex and require a good understanding, for the anthropogenic stresses to be managed effectively [14]. With over 3,200 reefs extended over  $280,000 \text{ km}^2$  [15], the scale of the fluctuations range from kilometer oceanic mixing to millimeter inter-skeletal currents. The strategic collection of data at appropriate scales is critical for effective environmental monitoring and analysis [16]. With 20% of coral reef already damaged and 50% under threat, the timely collection of information is essential for understanding the impact of climate change. Wireless sensor networks comprising of low-cost intelligent sensors provide a powerful platform for effective monitoring of the harsh marine environment.

The Australian Institute of Marine Science (AIMS) has planned to deploy a sensor network deployment in Heron Island during latter part of 2008. We (ISSNIP group) have mapped the layered structure to this physical topology. Fig. 2 shows the deployment diagram, depicting heterogeneous nodes that cover the whole island for collecting oceanographic parameters [17]. Initially large buoys (CHs) equipped with solar panels and medium buoys (SNs) will be deployed in the water. At a later stage, sensor nodes (SNs) will be deployed around each medium buoy to collect temperature and salinity data at a much finer spatial resolution. These sensor nodes will be smaller, cheaper, and will communicate with the local CH that is housed in the large buoys via single or multiple hops through medium buoys. Meanwhile, the AIMS autonomous weather station is the sink (BS). Fig. 3 shows the pictures for the station tower and actual buoy. It will be an ideal testbed for validating and verifying our hierarchical transport architecture.



Fig. 3. Base Station and Sensor Node buoy.

#### V. CONCLUSION AND FUTURE WORK

In this paper, we have developed a two-layer hierarchical transport architecture for heterogeneous wireless sensor networks. A set of transmission algorithms have been proposed for LLC and ULC respectively, where channel capacity and node energy are constrained. The incorporated energy constraint serves as a network lifetime guarantee. We have shown mathematically that utility proportional fairness is achieved within an LLC and utility max-min fairness is achieved among CHs. Therefore, the overall performance is optimal in terms of both local information utility and global coverage. Moreover, we have fitted the architecture to a real marine sensor network on the GBR and an implementation proposal is provided as well. Future work includes the realization of the theory in the GBR and the consideration of practical constraints like reliability and latency etc.

#### ACKNOWLEDGMENTS

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