Energy Efficiency of Centralized and Distributed Computation in Unattended Multi-hop Wireless Sensor Networks for Battlefield Monitoring

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Abstract

The energy efficiency trade-offs available between centralized and distributed solutions in unattended wireless sensor network deployments such as those that support remote battlefield monitoring remain an open research question. In this paper, we compare the relative energy efficiency of these two approaches in multi-hop wireless sensor networks. We develop a framework that includes both total and per node energy efficiency expressions and apply it to the beamforming class of unattended battlefield monitoring solutions using Mica2, MicaZ and the latest generation Telos sensor motes. A performance threshold is shown to exist between these approaches which can be exploited through the use of preamble sampling.

1. Introduction

Researchers have focused on the military application of wireless sensor networks since the introduction of these networks in the late 1990’s and it continues to be a topic of significant interest [1],[2],[3]. Unattended battlefield monitoring is a particularly challenging subset of these applications because the nodes cannot be replaced and/or serviced and the communication distance to the collection point can be large. A solution to this latter problem was proposed in [1] in which the nodes collaborate to perform beamforming to an overhead UAV that is capable of providing a link back to the command and control point. This beamforming operation is computationally intensive, though, and is difficult to implement in energy-constrained networks. Initial proposals suggested a centralized, cluster-based solution [4] while follow-on work proposed energy-efficient distributed solutions [5],[6]. As we will demonstrate, these solutions do not fully account for the energy consumption of the multi-hop network and the choice of a centralized versus a distributed solution remains an open research question for these types of military applications.

With the increasing need for bandwidth and processing efficient solutions for wireless sensor networks, many energy efficient applications have been proposed. Wireless sensor network performance in general is characterized by a number of common constraints that include the size of the sensors and the limited power available [7]. Extending battery life presents a fundamental energy challenge that impacts both sensor node processing and communication solutions, particularly among a group of unattended sensor nodes participating in a collaborative environment. Preamble sampling [8] is a well-known medium access technique that is often employed to address this challenge. This technique minimizes energy consumption spent on receiving packets that are not destined for the node of interest by allowing a node to enter a sleep mode and periodically “wake-up” to sample the headers of arriving packets. Preamble sampling can be incorporated into many energy efficient applications proposed in literature including a number of distributed approaches to signal processing [9],[10] and collaborative beamforming [11],[12],[13],[14].

The objective of this work is to determine the relative energy efficiency of centralized and distributed solutions for multi-hop wireless sensor networks. A mathematical framework is developed and applied to produce a system level analysis of the energy trade-offs between the two approaches in unattended battlefield monitoring applications implemented using Mica2, MicaZ and the latest generation Telos sensor motes [15]. An energy performance threshold point is found between these centralized and distributed solutions which can be exploited through the use of preamble sampling.

The outline of the paper is as follows. A mathematical framework for energy consumption that includes expressions for both centralized and distributed algorithms is developed in Section 2 and compared in Section 3. In Section 4, we analyze the
energy efficiency of centralized and distributed beamforming solutions for unattended battlefield monitoring and highlight the efficiency gains that can be achieved by preamble sampling.

2. Energy consumption of centralized and distributed computation in wireless sensor networks

In this section, we derive the energy expressions for both centralized and distributed computation in multi-hop wireless sensor networks. We begin with a set of definitions and then develop generalized expressions for the centralized and distributed approaches.

A number of metrics have been proposed to capture energy consumption in a wireless sensor network [16],[17]. For the purposes of this work, we will focus on the total network energy consumption and the maximum per node energy consumption. The former reflects the overall energy cost of a computation, but does not capture the fact that a single node may be disproportionately overburdened. Thus, we use the latter, per node, metric to capture this. This per node metric, when combined with current battery level information, can be used to estimate time to node failure for a given node and, when appropriate, time to network partition [16].

2.1. Definitions

The total energy, \( E_{\text{total}} \), consumed in the computation effort can be classified into the energy consumed in computation, \( E_{\text{comp}} \), and the energy consumed in communication, \( E_{\text{comm}} \). The computation energy consumption is proportional to the number of operations required, \( N_{\text{ops}} \), and can be expressed as

\[
E_{\text{comp}} = N_{\text{ops}} R_{\text{comp}} P_{\text{comp}} \tag{1}
\]

where \( R_{\text{comp}} \) is the data computation rate in operations per second and the computation power, \( P_{\text{comp}} \), is the product of the processor current draw, \( i_{\text{comp}} \), and the supply voltage, \( V \). The energy consumption due to communication, \( E_{\text{comm}} \), is a function of the energy consumption due to reception, \( E_{\text{rx}} \), and the energy consumption due to transmission, \( E_{\text{tx}} \), where

\[
E_{\text{rx}} = t_{\text{rx}} P_{\text{rx}} = \frac{L_{\text{rx}}}{R} i_{\text{rx}} V, \tag{2}
\]

\[
E_{\text{tx}} = t_{\text{tx}} P_{\text{tx}} = \frac{L_{\text{tx}}}{R} i_{\text{tx}} V, \tag{3}
\]

\( t_{\text{rx}} \) and \( t_{\text{tx}} \) are the reception and transmission time, respectively, \( L_{\text{rx}} \) and \( L_{\text{tx}} \) are the reception and transmission packet sizes (in bits), \( R \) is the data rate in bits per second and \( P, i, \) and \( V \) are defined as in above. The superscripts \( R, P, \) and \( D \) will be used in conjunction with the energy terms to indicate the energy consumption associated with the raw, processed and distributed packets, respectively (e.g., \( E_{\text{rx}}^R \) is the energy consumption required for reception of a raw data packet).

To facilitate our analysis, we define \( \eta_{\text{comp}} \) as the ratio of the energy consumption for computation in the distributed approach to that in the centralized approach which can be expressed as

\[
\eta_{\text{comp}} = \frac{N_{\text{ops}}^{\text{dist}}}{N_{\text{ops}}^{\text{cent}}} \tag{4}
\]

where \( N_{\text{ops}}^{\text{dist}} \) and \( N_{\text{ops}}^{\text{cent}} \) are the number of operations per node for the distributed and centralized approaches, respectively.

We also define \( \eta_c \) as the ratio of the transmission energy to the reception energy. Assuming \( L_{\text{rx}} = L_{\text{tx}} \),

\[
\eta_c = \frac{t_{\text{tx}}}{t_{\text{rx}}} \tag{5}
\]

To capture the energy associated with preamble sampling, we define

\[
E_{\text{ps}} = t_{\text{ps}} P_{\text{ps}} \quad \text{and} \quad \eta_{\text{ps}} = \frac{E_{\text{ps}}}{E_{\text{rx}}} = \frac{L_{\text{ps}}}{L_{\text{rx}}} \tag{6}
\]

where \( t_{\text{ps}} \) is the time spent receiving the preamble and \( L_{\text{ps}} \) is the size of the preamble in bits. The case when \( \eta_{\text{ps}} = 1 \) equates to the situation when preamble sampling is not implemented. Finally, we define

\[
\eta_x = \frac{L_x}{L_R} \quad \text{and} \quad \eta_p = \frac{L_p}{L_R} \tag{7}
\]

to capture the relationship between the size (in bits) of a raw data packet, \( L_R \), and the size of a processed packet in both the centralized and distributed schemes, \( L_p \) and \( L_D \), respectively.

A summary of the terms used in this paper is included in Table 1.
2.2. Energy consumption in a centralized approach

In a centralized implementation, all nodes forward raw data to a central node where the computation is accomplished and the results are then transmitted back to the network nodes. The total communication energy consumption for a centralized computation approach can be divided into three parts. The first is the energy required to transmit and forward the raw packets to the central node. The second is the energy required to transmit and forward the processed packets back to the network nodes. The third component captures the energy consumed due to overhearing (i.e., the energy associated with the preamble sampling required at nodes that are not the destination node for a particular packet). We include the energy consumption due to computation and quantify these results in the following theorem.

Theorem: For a network comprised of \( N \) nodes with mean degree of \( D \) and a mean hop count of \( H \) to the central node (\( N, D, \) and \( H \) are topology-specific), the average total energy consumption for a centralized approach to computation in a wireless network can be expressed as

\[
E_{\text{total}} = H (N-1)\left[1 + \eta_p + \eta_s \eta_r + \eta_c \right] + 2(D-1) \eta_{ps} R_{\text{ps}} + N_{\text{ops}} R_{\text{comp}} P_{\text{comp}}.
\]  

(8)

Proof: We begin by calculating the energy consumption due to communication. The energy required to deliver the raw packets from the individual nodes to the central node includes both the energy consumed in packet transmission and the energy consumed in packet reception. The former is comprised of the initial transmissions from the source nodes and the subsequent retransmissions of all of the relay nodes. It is a function of both the number of nodes in the network and the mean number of hops to the central node as in

\[
E_{\text{comm}}[\text{xmsn of raw pkts to central node}] = H (N-1) E_{r}^R.
\]  

(9)

The energy consumed in reception of these packets includes reception by the relay nodes and the central node as well as reception by the nodes that overhear the transmissions. The packets are not destined for these latter nodes, but these nodes will consume energy listening to the packet preamble. This energy consumption can be found by multiplying the number of transmissions by the mean number of neighbors (the mean degree) less the destination node for each transmission as in

\[
E_{\text{comm}}[\text{overhearing raw pkts fwd'd to central node}] = H (N-1)(D-1) E_{p}^R.
\]  

(10)

Bringing these together, the result for the energy consumption due to reception of the raw packets is then

\[
E_{\text{comm}}[\text{reception of raw pkts fwd'd to central node}] = H (N-1) E_{r}^R + H (N-1)(D-1) E_{p}^R.
\]  

(11)

Thus, combining (9) and (11), the energy consumption required to deliver the raw packets to the central node is

\[
E_{\text{comm}}[\text{delivery of raw pkts to central node}] = H (N-1) E_{r}^R + H (N-1) E_{r}^R + H (N-1)(D-1) E_{p}^R.
\]  

(12)

Again accounting for both packet transmission and reception, the energy consumption for delivery of the processed packets back to the source nodes can be found in a similar manner to be
\[ E_{\text{comm}}^{\text{cent}} = H(N-1)E^p_{\text{tx}} + H(N-1)E^p_{\text{rx}} + 2H(N-1)(D-1)E_{\text{ps}}. \] (13)

Combining (12) and (13), the total energy consumption due to communication for the centralized approach is

\[ E_{\text{comm}}^{\text{cent}} = H(N-1)E^p_{\text{tx}} + H(N-1)E^p_{\text{rx}} + 2H(N-1)(D-1)E_{\text{ps}}. \] (14)

The computational energy consumption of processing the raw packets at the central node is given by

\[ E_{\text{comp}}^{\text{cent}} = N_{\text{ops}}^c R_{\text{comp}} P_{\text{comp}}. \] (15)

Combining (14) and (15) and rearranging terms, the average total energy consumption for a centralized approach to computation in a wireless network is

\[ E_{\text{total}}^{\text{cent}} = E_{\text{comm}}^{\text{cent}} + E_{\text{comp}}^{\text{cent}} = H(N-1)[E^p_{\text{tx}} + E^p_{\text{rx}} + 2E_{\text{ps}}] + N_{\text{ops}}^c R_{\text{comp}} P_{\text{comp}}. \] (16)

which, after making the appropriate substitutions, is equivalent to (8). \(Q.E.D.\)

In Figure 1, we plot the relative communication energy consumption (normalized by \(E^p_{\text{tx}}\)) as a function of the number of nodes in the network for various values of mean hop count and \(\eta_{ps}\). While the energy consumption increases linearly with the mean hop count as expected, what is interesting is the effect of \(\eta_{ps}\). The limiting case where \(\eta_{ps} \to 0\) shows more than an order of magnitude improvement over the case when preamble sampling is not employed \((\eta_{ps} = 1)\).

We can gain insight into the effect of the communication range on the energy consumption of the centralized solution by utilizing the findings of [18] and [19] to relate communication range to mean number of neighbors (node degree) and the mean hop count. Assuming that the nodes are distributed homogenously over the 2-D plane according to a Poisson process with intensity \(\lambda\), the node degree can be shown to be [19]

\[ D = \lambda \pi r^2 e^{-\frac{\lambda}{8}} \] (17)

where \(h = \frac{\ln 10}{10}\), \(\delta\) is the path loss exponent, and the fading is assumed to be log-normally distributed with mean of zero and variance of \(\sigma^2\). A minimum bound for the mean hop count can be arrived at if we ignore the effect of fading (set \(\sigma = 0\) ) and assume that there is always a relay node at distance \(r\) in the direction of the destination node. For a rectangular area of size \(a \times b\), this bound can be shown to be [18]

\[ H \geq \frac{1}{15r} \left[ \frac{a^3}{b} + \frac{b^3}{a} + \sqrt{a^2 + b^2} \left( 3 - \frac{a^2}{b^2} - \frac{b^2}{a^2} \right) \right] + \frac{b^3}{a} \arccosh \left( \frac{a^2 + b^2}{b} \right) + \frac{a^3}{b} \arccosh \left( \frac{a^2 + b^2}{a} \right) \] (18)

where \(\arccosh(x) = \ln \left( x + \sqrt{x^2 - 1} \right)\). For a square area of size \(a \times a\), this reduces to \(H \geq 0.5124 \left( \frac{a}{r} \right)\). Using these results, we plot the energy consumption as a function of communication range for several values of \(\eta_{ps}\) in Figure 2. Again, it can be seen that preamble sampling significantly reduces energy consumption for the centralized approach. For the limiting case where \(\eta_{ps} \to 0\), energy consumption actually decreases as a function of increasing communication range. This occurs because no energy is spent receiving packets for which a node is not the intended destination in this limiting case.

\[ E_{\text{comp}}^{\text{cent}} = \text{delivery of processed pkts to source nodes} \]

\[ E_{\text{total}}^{\text{cent}} = E_{\text{comm}}^{\text{cent}} + E_{\text{comp}}^{\text{cent}} \]
We can provide a lower bound for the maximum per node energy consumption of the centralized approach by assuming it occurs at the central node. This is a lower bound because energy consumption due to forwarding may result in higher energy consumption at an intermediate node (which is topology specific). This lower bound is comprised of the computation energy and the energy required to receive the raw data packets and transmit the processed data packets. Thus, the maximum per node energy for the centralized approach is bounded as

$$E_{\text{max}}^\text{cent} \geq (N-1)E_{\text{rx}}^R + (N-1)E_{\text{tx}}^R + N_{\text{ops}}^\text{cent} R_{\text{comp}} P_{\text{comp}}$$

(19)

which is equivalent to

$$E_{\text{max}}^\text{cent} \geq (N-1)[1 + \eta_\text{r}] E_{\text{rx}}^R + N_{\text{ops}}^\text{cent} R_{\text{comp}} P_{\text{comp}}.$$  

(20)

2.3. Energy consumption in a distributed approach

In a distributed approach, nodes share the computational burden through local processing and information exchange and conduct a series of iterations to converge to a global solution. The energy required for communication in the distributed approach is the energy required in each iteration to transmit and receive the locally processed packets within each one-hop neighborhood.

We can provide a lower bound of the maximum per node energy consumption of the distributed approach by assuming it occurs at the central node. This is a lower bound because energy consumption due to forwarding may result in higher energy consumption at an intermediate node (which is topology specific). This lower bound is comprised of the computation energy and the energy required to receive the raw data packets and transmit the processed data packets. Thus, the maximum per node energy for the distributed approach is bounded as

$$E_{\text{max}}^\text{dist} \geq (N-1)E_{\text{rx}}^R + (N-1)E_{\text{tx}}^R + N_{\text{ops}}^\text{dist} R_{\text{comp}} P_{\text{comp}}$$

(21)

which is equivalent to

$$E_{\text{max}}^\text{dist} \geq (N-1)[1 + \eta_\text{r}] E_{\text{rx}}^R + N_{\text{ops}}^\text{dist} R_{\text{comp}} P_{\text{comp}}.$$  

(22)

The computational energy consumption for a single iteration at a single node is

$$E_{\text{comp}}^\text{dist} \text{[single iteration at a single node]} = N_{\text{ops}}^\text{dist} R_{\text{comp}} P_{\text{comp}}.$$  

(23)

Accounting for all nodes in (23) and combining it with (22), we see that average total energy consumption for a distributed approach to computation in a wireless network for a single iteration is

$$E_{\text{comm}}^\text{dist} \text{[single iteration]} = N\left(E_{\text{tx}}^D + D E_{\text{rs}}^D\right).$$  

(24)

As the computation and communication load is spread out among all network nodes in the distributed approach, the maximum per node energy is nominally the same at all nodes and is therefore given by

$$E_{\text{max}}^\text{dist} = K\left(E_{\text{tx}}^D + D E_{\text{rs}}^D\right) + N_{\text{ops}}^\text{dist} R_{\text{comp}} P_{\text{comp}}.$$  

(25)

which is equivalent to

$$E_{\text{max}}^\text{dist} = K \eta_\text{r} (\eta_\text{r} + D) E_{\text{rx}}^R + \eta_{\text{comp}}^\text{dist} E_{\text{comp}}^\text{dist}.$$  

(26)

In Figures 3 and 4, we plot the relative energy consumption due to communication for the distributed approach with multiple iterations as a function of the number of nodes and the communication range, respectively. As expected, the energy consumption grows linearly with both.
We compare the energy efficiency performance of the centralized and distributed approaches using the results of the previous section. For this work, we focus on the relative energy consumption due to communication which has been shown to dominate the total energy consumption [7]. As in the previous sections, we normalize the energy consumption by the energy consumption due to reception of a raw data packet, $E_{rx}$. 

In Figure 5, we plot the energy consumption as a function of the number of nodes for multiple values of the hop count to the central controller in the centralized case and number of iterations required for convergence in the distributed case. It can be seen that when preamble sampling is not utilized ($\eta_{ps} = 1$), the distributed approach outperforms the centralized approach. However, in the limiting case where $\eta_{ps} \to 0$, the centralized approach will outperform the distributed approach for reasonable values of hop count to the central controller.

To examine this result closer, we plot the energy consumption as a function of $\eta_{ps}$ in Figure 6. The energy consumption of the distributed approach is not a function of $\eta_{ps}$ and appears as a constant in the plot, while the performance of the centralized approach, on the other hand, varies dramatically with the implementation of preamble sampling. This is because the broadcast transmissions in the distributed approach are targeted at all nodes within communication range of the transmitter while the transmissions in the centralized approach are only intended for the next hop node in the routing paths to and from the central controller. It can be seen in Figure 6 that preamble sampling significantly improves the energy efficiency of the centralized algorithms and there exists a threshold below which the centralized approach will outperform the distributed approach. This threshold is a function of the number of hops to the central controller in the centralized case and the number of iterations required for convergence in the distributed case.

4. Energy efficiency of centralized and distributed beamforming solutions for unattended battlefield monitoring

We now return to the beamforming solution for unattended battlefield monitoring and analyze the relative energy efficiency of the distributed and centralized algorithms of [5] and [6]. In this analysis, we demonstrate the efficiency gains that can be achieved by incorporating preamble sampling. To support the weight calculations required in beamforming, [5] and [6] propose distributed solutions to the least squares problem in which the QR factorization of the steering matrix is accomplished through the use of Householder transformations [20],[21].
In the baseline centralized approach of [4] (labeled “centralized” in the following plots), all nodes transmit their location information to the central controller which then calculates the weights and returns them to the nodes. The total number of operations performed by the central controller can be shown to be

\[
N_{\text{ops}}^{\text{cont}} = 2N^2 \left( \frac{m}{3} - \frac{N}{3} \right) + mN + N^2
\]  

(27)

where \( m \) is the number of rows in the beamforming steering matrix and \( N \) is the number of nodes. We can substitute (27) into (8) and (20) to calculate the energy consumption of this centralized approach.

In the distributed approach of [5] (labeled “distributed” in the following plots), the columns of the steering matrix are distributed among the nodes and the QR factorization is performed for each column locally at the appropriate node and shared among all nodes. The weights are then calculated through back substitution and the results for each node are again broadcast to the other nodes. It can be shown that the total number of operations remain the same as in the centralized solution of (27) [5]. The total number of messages transmitted in this approach is [5]

\[
M_{\text{dist}} = \left( m + 4 - \frac{N}{2} \right)(N-1).
\]  

(28)

We will make use of (21) and (26) to calculate the energy consumption of this distributed approach. Although there is only one iteration identified in the published algorithm, the number of messages in (28) must be accounted for by recognizing that these messages, in effect, constitute one iteration while a second iteration is required to then transmit the locally calculated solution. For this first iteration, we replace \( N \) with \( M_{\text{dist}} \) in (21).

In the distributed approach of [6] (labeled “distributive, iterative” in the following plots), the columns are again distributed among the nodes, but the weight calculation is done in an iterative fashion. The total number of operations are shown to be [6]

\[
N_{\text{ops}}^{\text{dist}} = N \left[ 2 \left( 1 - \frac{1}{3}m \right) + K(3m+1) \right]
\]  

(29)

where \( K \) is the number of iterations required to reach convergence. In [6], it is suggested that a nominal value for \( K \) is three. We again substitute these into (21) and (26) to calculate the energy consumption of this distributed, iterative approach.

Using the framework outlined in the previous sections and the sensor node operating parameters in Table 2, we now compare the energy efficiency of the two distributed approaches to that of the centralized solution for implementations using Mica2, MicaZ, and Telos sensor motes [15]. For the purposes of this analysis, we assume that the centralized algorithm produces one processed packet that is the same size as the sum of the raw data packets from each of the nodes (\( \eta_c = N - 1 \)) and that the packets in the distributed algorithms are the same.

![Figure 5](image)

**Figure 5.** A comparison of relative energy consumption (normalized by \( E_{\text{rx}}^a \)) of the centralized (blue) and distributed (green) approaches plotted as a function of the number of nodes in the network for various mean hop count values and iteration values with \( \eta_c = \eta_a = 1 \).

![Figure 6](image)

**Figure 6.** A comparison of relative energy consumption (normalized by \( E_{\text{rx}}^a \)) of the centralized (blue) and distributed (green) approaches plotted as a function of \( \eta_{ps} \) for various mean hop count values and iteration values with \( \eta_c = \eta_a = 1 \).
Focusing our attention on the energy consumption due to communication, we provide a comparison of the energy efficiency of the three approaches as a function of the number of nodes in Figure 7. The distributed, iterative approach of [6] can be seen to outperform both the distributed approach of [5] and the centralized approach for the majority of multi-hop cases. Of interest, though, is that the centralized approach is more efficient in terms of total energy consumption than the distributed approach. This highlights the trade-off between total energy consumption and per node energy consumption. Here, the distributed algorithm results in larger overall energy consumption in its attempt to distribute the computational load and realize smaller per node consumption. In contrast, the distributive, iterative approach achieves both reduced overall energy consumption and reduced per node energy consumption. As expected, the energy consumption rises linearly with the increasing number of nodes.

The effect of implementations with different sensor motes is shown in Figure 8 where we compare the energy efficiency as a function of the number of nodes for the Telos motes. The newer generation Telos sensor motes are seen to only slightly outperform the older generation Mica2 motes. This is because the relative performance improvement is impacted by the increased reception energy consumption of the Telos mote.

Finally, in Figure 9, we examine the impact of the use of preamble sampling in the proposed solutions and see that, for effective preamble sampling schemes where $\eta_{ps}$ is low, the centralized approach is capable of outperforming even the distributed, iterative approach. This is an important finding and suggests the implementation of

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<th>Mica2</th>
<th>MicaZ</th>
<th>Telos</th>
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<td>$i_{rx}$</td>
<td>15.1 mA</td>
<td>23.3 mA</td>
<td>21.8 mA</td>
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centralized computational algorithms coupled with preamble sampling energy efficiency techniques to reduce overall energy consumption in the wireless sensor network. A clustering approach, such as that proposed in [4] can be utilized in conjunction with the centralized approach to distribute the processing load among the member nodes as desired.

5. Conclusion

In this paper, we compared the relative energy efficiency of centralized and distributed solutions for multi-hop wireless sensor networks. We developed a mathematical framework and applied it to a class of beamforming solutions designed to support unattended battlefield monitoring applications using Mica2, MicaZ and the latest generation Telos sensor motes. We demonstrated the existence of a performance threshold point between these centralized and distributed solutions which can be identified and exploited through the use of preamble sampling. The results of this work can be extended to any collaborative wireless sensor network application.

6. References