DynaChannAl: Dynamic Channel Allocation with Minimal End-to-end Delay for Wireless Sensor Networks

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Abstract

With recent advances in wireless communication, networking, and low power sensor technology, wireless sensor network (WSN) systems have begun to take significant roles in various applications ranging from environmental sensing to mobile healthcare sensing. While some WSN applications only require a limited amount of bandwidth, new emerging applications operate with a noticeably large amount of data transfers. One way to deal with such applications is to maximize the available capacity by utilizing the use of multiple wireless channels. This work proposes \textit{DynaChannAl}, a distributed dynamic wireless channel algorithm with the goal of effectively distributing nodes on multiple wireless channels in WSN systems. Specifically, \textit{DynaChannAl} targets applications where mobile nodes connect to a pre-existing wireless backbone and takes the expected end-to-end queuing delay as its core metric. We use the link quality indicator (LQI) values provided by IEEE 802.15.4 radios white-list potential links with good link quality and evaluate such links with the aggregated packet transmission latency at each hop. Our approach is useful for applications that require minimal end-to-end delay (i.e., healthcare applications). \textit{DynaChannAl} is a light weight and highly adoptable scheme that can be easily incorporated with various pre-developed components and pre-deployed applications. We evaluate \textit{DynaChannAl} in on a 45 node WSN testbed. As the first study to consider end-to-end latency as the core metric for channel allocation in WSN systems, the experimental results indicate that \textit{DynaChannAl} successfully distributes multiple (mobile) source nodes on different wireless channels and enables the nodes to select wireless channel and links that can minimize the end-to-end latency.

Keywords: Wireless Sensor Networks, Dynamic Channel Allocation, Latency Aware Protocols

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1. Introduction

The recent advances in both sensing and wireless communication technology have motivated researchers to study the applicability of wireless sensor networks (WSNs) in various applications. Most WSN platforms use IEEE 802.15.4-based radios to achieve extremely low power consumption. While the simple design of IEEE 802.15.4 offers significantly lower power consumption compared to other wireless standards such as IEEE 802.11, their bandwidth is significantly limited to only 250 Kbps in an ideal environment. We note that in practice when using widely used software and hardware platforms, even this low rate is impossible to achieve. While early WSN applications that have low data rate requirements can properly operate even with such strict wireless capacity limitations, various emerging applications require significantly higher data rates to support the increasing amount of sensing data. One way to provide such high data rate applications with sufficient wireless channel capacity is the smart use of multiple wireless channels. Doing so extends the usable bandwidth within a system and since the Zigbee alliance defines 16 different channels for its systems in the 2.4 GHz band, we can significantly increase the capacity of a WSN system by accommodating a smart channel allocation scheme.

Previous work that propose channel allocation techniques for WSNs mainly focus on balancing the number of nodes on each channel with the assumption that all nodes generate the same amount of traffic. Also, most of the proposed schemes either target networks that consist of only stationary nodes or they perform channel allocation only during the initial phase of the deployment. Such characteristics make previously proposed schemes less appropriate for applications with dynamic traffic patterns which is common in WSN deployments. Furthermore, given that in many WSN applications the sensing or communication devices are mobile and that different devices can have different data rate requirements, a dynamic channel allocation technique should be used to utilize the use of multiple wireless channels efficiently. Moreover, some applications such as medical sensing applications require the data to be received at the gateway with minimal latency. Therefore, for such applications, the end-to-end delay should act as a core metric that determines which channel that a source node should operate on. Finally given that WSN systems incorporate many different protocols and schemes to optimize their performance for a specific application, the channel allocation scheme should be easily adaptable with minimal communication and memory overhead.

With such issues in mind, we propose DynaChannAl a distributed dynamic channel allocation scheme with the goal of effectively utilizing multiple wireless channels while minimizing the end-to-end latency of packets from mobile WSN nodes. As discussed above, since many WSN applications require soft real-time data delivery, we take the goal of minimizing end-to-end latency as DynaChannAl’s primary goal. By minimizing the end-to-end delay, we target to see fairness in packet delivery performance between multiple wireless channels as well. Our scheme also makes use of the link quality indicator (LQI)
values reported by IEEE 802.15.4-based radios to whitelist or blacklist potential links with respect to their wireless conditions before they are selected for further monitoring (e.g., latency measuring). *DynaChannAl* targets to benefit the performance of WSN systems that consist of a wireless mesh backbone network rooted at the gateway and multiple mobile source nodes that associate to such backbone network for delivering their data to the gateway using multihop connections. To our knowledge, this work is the first to propose the use of end-to-end latency as a core metric in the subject of channel allocation for WSN systems.

Specifically in this work we make the following contributions. (1) We propose *DynaChannAl*, a lightweight distributed dynamic channel allocation scheme for WSNs that takes estimated end-to-end latency as the core metric for determining the wireless channel conditions. (2) We quantify the effectiveness and show the feasibility of wireless channel allocation techniques for IEEE 802.15.4 radio-based WSN systems using a simple empirical study with real mote-class devices. (3) We validate the effectiveness of *DynaChannAl* in real testbed environments to show that it is effective in minimizing the end-to-end latency and distributing multiple nodes to different wireless channels in real WSN systems despite being extremely lightweight.

The paper is organized as follows. In Section 2 we introduce existing literature related to wireless channel allocation in the area of WSNs and discuss how the previously proposed techniques are not appropriate for the application scenarios of our interest. Next we introduce the results obtained from our empirical studies to show the feasibility of channel switching in WSNs then discuss about our metrics and propose our scheme, *DynaChannAl* in Section 3. Our evaluation results obtained from the testbed experiments are presented in Section 4 and we discuss about some interesting aspects of *DynaChannAl* in Section 5. Finally, we conclude the paper by introducing some potential future work (Section 6) and with a conclusion in Section 7.

### 2. Related Work

Until now, most of the work in channel allocation for wireless sensor networks (WSNs) have focused on evenly dividing the number of nodes on each channel without considering the amount of traffic that each node generates [8, 9]. These work hold the assumption that the traffic generated by each sensor node will remain constant over time and be equal for all nodes. However, we argue that WSNs can introduce dynamic traffic patterns for various reasons. First, because many WSN systems are event-driven [13], nodes can easily have bursty traffic patterns. Such bursty traffic can quickly degrade the performance of a channel allocation method when the nodes are distributed on multiple channels in a static manner. Second, WSN applications introduced recently can be mobile. Such applications have dynamic traffic patterns due to the mobility of end-user devices [5]. Also, such applications can support multiple types of sensors and therefore, generate different amount of traffic on each sensor.
To address such issues, some work have made attempts to perform channel allocation based on the amount of traffic each node generates. Wu et al. [10], consider traffic aware allocation by computing the estimated traffic in a channel for proper channel allocation to sensor nodes. However, their scheme is only performed in the initial stage of the system deployment and therefore, cannot be effective to tolerate dynamic channel environments.

Despite such previous work related to channel allocation for WSNs, one main drawback of such schemes is that these schemes are not flexible and therefore are not widely used. Specifically, the previous work mentioned above tried to propose a comprehensive solution for the entire system while most WSN systems are designed as a combination of multiple pre-existing components [5]. We argue that the channel allocation scheme presented in this work, DynaChannAl, is flexible enough to accommodate and coexist with protocols in different layers of the network stack. We present some examples in Section 5.

We also note that previous work on channel allocation in WSNs such as [14, 15] discuss thoroughly about the analytical aspects of WSN system’s wireless channel allocation. However their evaluation on the proposed protocols are only shown using simulation or analytical results which only partially represent real wireless environments. This work is one of the few work that propose a channel allocation scheme for WSNs and evaluate the scheme with real devices on a testbed environment.

One example of previous work that has been evaluated in realistic testbed environments is the work proposed by Le et al. [16]. Here, the authors proposed a MAC protocol for multi-channel systems which targets general WSN applications. Their scheme is a control theory based approach where the channel switching metric is directly related to the channel accessibility (e.g., the number of CCA failures that a node encounters). They optimize their protocol so that the amount of cross channel communication and channel switching fluctuation is minimized. While we see this as a notable approach with valid evaluation methods, one drawback of their scheme is that the scheme does not consider latency as a decision metric. We argue that given the numerous emerging sensing applications that require soft-real time data delivery, maintaining a maximum end-to-end latency threshold and balancing the latency on multiple wireless channels should be taken in consideration when nodes select between multiple wireless channels. Works proposed by He et al. [17, 18] deal with wireless sensor networks that have latency constraints but their schemes mostly focus on the routing side of the system while DynaChannAl discusses about channel allocation techniques for WSNs. Specifically, the SPEED protocol [17] requires that node to be aware of their physical location which is not practical for mobile nodes and AIDA [18] only focuses on maximizing the utilization for a single channel, both for making routing decisions. To our knowledge DynaChannAl is the first work that focuses on channel allocation for WSNs while taking the expected end-to-end delay as a core decision metric.
3. **DynaChannAl**

3.1. **Feasibility of Channel Switching in WSNs**

We first show the results obtained from a simple empirical study to confirm that the overhead of channel switching is minimal and therefore, channel switching is an attractive way to maximize the performance for WSN systems. We note that the main overhead of switching between multiple wireless channels is the delay overhead. The two main delay overheads that arise due to channel switching are (1) the delay required to physically “switch” the wireless channel of the radio and (2) the delay for “seeking” the channels to determine the link quality with a potential next hop node. We define the two types of delays as **channel switching delay** and **channel seeking delay**, respectively. Our empirical study is performed with CC2420 radio based Tmote Sky devices using a TinyOS 2.x based software platform. We show the results of the two types
of delay overheads in Figure 1. We note that we take at least 1000 samples for each test case.

The top part of Figure 1 shows a PDF of how long it takes to actually “switch” the channel in our experimental settings (i.e., the channel switching delay). The results indicate that most of the channel switching delays take less than 1.4 ms. Given that the number of usable wireless channels for IEEE 802.15.4 devices is 16 (see the Zigbee plot in Figure 2), changing the wireless channels from among all possible channels (i.e., worst case) can be done within ∼23 ms. This short amount of time is tolerable given that even for WSN applications that require relatively high data rates, the data generation intervals are slower than 100 ms [5].

The bottom plot in Figure 1 shows the CDFs of two different test cases. In the first experiment, a transmitter sends periodic packets with acknowledgment requests but fails in receiving an acknowledgment packet from its destination node. Therefore the transmitter waits for the maximum amount of time until it detects that the packet transmission was not successful (i.e., no Ack). The second experiment (i.e., with Ack), shows results from an experiment where an acknowledgment frame is immediately received at the transmitter after the packet is sent. In this case, instead of waiting for the maximum amount of time, the transmission process terminates as soon as the acknowledgment is received. Again, given that we have a maximum of 16 channels to seek (see Figure 2), in the worst case, the maximum idle waiting delay is ∼350 ms when no acknowledgments are received on any of the 16 channels. In other words, a source node can recognize the existence of different nodes in its communication range (potentially nodes that can forward its packets) operating on any of the 16 channels within a maximum time of ∼350 ms. We note that when acknowledgment frames are received on a subset of these channels, this channel seeking delay can be much lower. Therefore, a scheme where nodes actively probe the channel for potential relay nodes can be an effective way of determining their existence and link qualities on each wireless channel. We will describe in detail later in this work how this observation is used in DynaChannAl.

To conclude, even in the worst case where a node must seek all 16 channels and wait for the maximum amount of time on each channel, the channel seeking delay plus the channel switching delay is less than ∼400 ms. Such small delay can keep the idle listening time low and can be used as evidence that channel switching schemes are desirable for resource constraint WSN systems.

3.2. Defining the Target Scenario and System Metrics

To design an algorithm that efficiently utilizes multiple channels for WSN systems, we must first define metrics that enables a node to effectively compare the performance of potentially usable wireless channels. To suit our target

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1 On each wireless channel, multiple potential next hop nodes exist and the link qualities are different for each connection. We use the term of selecting a “link” and selecting a “channel” interchangeably in the work.
application \cite{5} (i.e., a medical sensing application), we take the expected end-to-end latency as the core metric. Additionally, we also use the link quality indicator (LQI), offered by IEEE 802.15.4 based radios, to determine the quality of potential links that connect a mobile source node and the next hop relay node (more details on why we say “relay” node is presented in the following subsection). Overall, since good quality links with high LQI will lead to less first hop retransmissions, thus reduce the first hop latency, the LQI metric is used as an indicator of how good the local network conditions are, while the expected end-to-end latency reflects the network conditions on an end-to-end perspective. We use the LQI metric over the received signal strength indicator (RSSI) given that it is well known through previous literature that the aggregate LQI is a more accurate estimate of the link quality than RSSI \cite{19, 20}. The following subsections discuss about our target usage scenario of our proposed channel allocation scheme and the two metrics (e.g., end-to-end latency and LQI) in further detail.

3.2.1. Target Scenario

Our proposed channel allocation scheme targets WSN applications that operate on a multi-tier network. Specifically, DynaChannAl targets systems where a backbone network already exists with the goal of forwarding the data from mobile source nodes to a common destination (e.g., a gateway node). The benefits of maintaining a backbone network rather than a fully ad-hoc single-tier networks have been shown in our previous work \cite{11}. Examples of such systems include previously proposed medical sensing applications such as MEDiSN \cite{5} and AlarmNet \cite{12}. In these applications the mobile source nodes associate themselves to one or more relay nodes and act as leaf nodes of the tree (or backbone) network. For such networks, the role of DynaChannAl is to balance the traffic load and latency of the WSN system by controlling the wireless channel of individual mobile source nodes in a distributed manner. In this work we as-

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**Figure 3:** Diagram of DynaChannAl's target scenario. DynaChannAl targets applications that have a wireless backbone for data relaying. Data packets are originated from mobile source nodes that connect to the backbone as leaf nodes. Specifically, the backbone collects data from mobile source nodes (via single hop communication) and forwards this data to a gateway using a multihop tree network. In the diagram the solid edges with the oval vertices represent the backbone network and the mobile source nodes are presented in rectangled vertices and dotted edges.
sume that wireless backbone infrastructure exists on multiple wireless channels that IEEE 802.15.4 systems can operate on. A diagram of our target scenario’s network hierarchy is illustrated in Figure 3.

### 3.2.2. Expected End-to-End Queuing Delay

We define our first and main metric, the expected end-to-end queuing delay as a metric that provides the source node with a global view of the wireless channel conditions within path to the gateway/destination. This metric will not only provide information on how a packet will encounter the local channel environment but also show how the wireless channel conditions will be throughout its path to the packet’s final destination in an aggregated way. We define the expected end-to-end queuing delay at node $i$ as Equation 1.

$$D_q^i = \sum_{j \in P_i} d_q^j$$  \hspace{1cm} (1)

where, $d_q^j$ is the local queuing delay at node $j$ and $P_i$ is the set of nodes on the path from node $i$ to the root of the tree (i.e., first relay node to the gateway in Figure 3). Note that set $P_i$ includes node $i$ (i.e., the source node) as well. Therefore, $D_q^i$ can be simply computed by all the nodes in the network in a distributed fashion using the following procedures.

- Each node $i$ maintains an Exponentially Weighted Moving Average (EWMA) with $\alpha = 0.5$ of its own queuing delay ($d_q^i$) for packets that it transmits. This information is propagated to its children. In our implementations the measured queuing delay has a granularity of milliseconds and therefore, can be measured with a simple timer implementation in common software platforms.

- The child node $k$ that receives this delay information from a parent node computes its own $D_q^k$ using Equation 1.

- Finally, this updated end-to-end queuing delay is propagated to $k$’s children as well. This propagation can be done using explicit control packets or by piggybacking the information on data packets.

- If a data packet requires retransmissions due to the lack of acknowledgments (when requested) or the lack of available bandwidth on node $k$’s local wireless channel, the additional time that the packet spends in the node’s queue is aggregated to $D_q^k$, and therefore implicitly includes the local congestion level of the network.

The procedure described above assures that all nodes in the network can easily compute its own $D_q$ and quickly update the queuing delay changes when dynamic traffic conditions occur (due to the fast propagation of delay values). Here, we make the assumption that the channel conditions will stay constant for $\Delta t$ seconds where $\Delta t$ is the time needed for a node to decide the wireless channel it will transmit its packet on. This is a valid assumption for two reasons. First,
Figure 4: Average LQI values with respect to the packet reception ratio of each link. The y-axis represents the packet reception ratio (PRR) collected from each link averaged over every minute.

we note that in most cases the delay values will be fairly stable. In our target applications mobile source nodes are not used to forward other source nodes’ data. Therefore, the local queuing delays of other source nodes will not affect a source node’s delay measurements. Knowing that the $D_q$ from the potential next hop node will only be affected by the latency variation introduced from the stationary backbone network, it is intuitively true that the stationary nodes will have less variance in queuing delay measurements than those of the mobile nodes. Second, as we pointed out in Section 3.1 that the time needed for channel switching and seeking is small. Such small delay will lead to a small value of $\Delta t$, making the assumption practically valid. If a list of potentially usable wireless channels is given as an input during the initialization stage or as a parameter in run-time, $\Delta t$ can be further minimized.

We note that all delay values used in $D_q^i$ can be accurately measured using resource constraint mote-class devices, by using a simple timer implementation and four bytes of memory space for each packet in its queue (when using 32 bit timestamps). Such simple computation and piggybacking techniques (mentioned in the third item above) makes the use of the $D_q^i$ measurements, feasible with minimal memory and communication overhead.

3.2.3. Link Quality Indicator (LQI)

While the measurement and estimation of end-to-end delay is a way of indicating the end-to-end network conditions, there is also a need to maintain a metric that represents the wireless channel conditions in a local network’s perspective as well. Typically in a local single-hop’s perspective, the quality of the links determine the expected number of packet retransmissions and thus can represent the expected single hop latency (i.e., more retransmissions lead to longer queuing delays). Therefore, we are interested in defining a metric that represents the conditions of each individual link that a source node can use to minimize the number of retransmissions. The link quality indicator (LQI) is a metric that is specific to IEEE 802.15.4-based radios [1]. LQIs indicate the link quality between the sender node and the receiver node pair on a per packet
basis. While the IEEE 802.15.4 standard does not specify a method to compute the LQI value, the widely used TI/Chipcon CC2420 radio [21] defines LQI as a representation of the chip error rate. Given that the CC2420 radio is used in popular WSN mote platforms (TelosB and MicaZ), we use this implementation of the LQI as our third metric.

The LQI values can be collected without any additional timing or memory overhead when using TinyOS 2.x as the software platform. As previous work shows [19], high aggregate LQI values can be an effective indicator of good quality links. We show similar results in Figure 4 where we present the relationship between average LQI values and the per minute packet reception ratio (PRR) collected from Tmote Sky devices on our testbed. While we cannot imply precise wireless channel condition estimates, we can notice that LQI can provide an indication of good, average and poor quality links. We define an aggregate LQI metric, computed for each sender-receiver pair, in Equation 2.

\[ LQI_i^n = \frac{\sum_{k=0}^{n} LQI_i^k}{n} \]  

Here, \( LQI_i^n \) represents the aggregate LQI of the link between node \( i \) and its parent for the \( n \)th packet. While the accuracy of \( LQI_i \) partially relates to the number of packet exchanges, we use findings from previous work [19] as evidence that even a small number of samples (i.e., as low as one, due to the small variance in LQI values when the link conditions are good) can roughly classify the link quality. Again, while with a small number of samples it is difficult to accurately determine the estimated PRR but can at least roughly classify the quality of a wireless link in three regions, e.g., good, fair, and poor. Results in previous work [20] support this idea and also provide evidence that a higher \( n \) (e.g., \( LQI_i \)) “will” indeed provide higher accuracy and precision in link quality estimation. Therefore, we use \( LQI_i \) to monitor the link conditions in a long-term scale and use a small \( i \) when roughly classifying link qualities when we quickly seek among different channels. We will describe how we use \( LQI_i \) for each case with greater detail in Section 3.3. Furthermore, we note that the observations from Figure 4 show that we can classify links with \( LQI > 85 \) as good links (\( PRR > 80\%) \), \( 75 < LQI < 85 \) as fair links (\( 50\% < PRR < 80\%) \) and \( LQI < 75 \) as poor quality links (\( PRR < 50\%) \).

### 3.3. Selecting Channels

With the metrics defined in Section 3.2, we describe the specific procedures of DynaChannAl in greater detail. Overall, DynaChannAl is a fully distributed scheme that consists of a channel seeking phase and a channel monitoring phase. DynaChannAl is a simple and intuitive scheme with the goal of showing that even such a simple channel allocation scheme can effectively distribute mobile WSN nodes in multiple channels with respect to the goal of minimizing the end-to-end latency. The following subsections will discuss about the role of the two phases and their transitions.
Algorithm 1 Channel Seeking Phase Procedure

1: Source node $i$ enters channel seeking phase and broadcasts a probe with its network ID $i$ on wireless channel $C$.
2: Each relay node $j$ that receives this probe message responds with a reply packet that contains its most up-to-date expected $D_q^i$ measurement and network ID $j$.
3: Source node $i$ receives the reply packet.
4: Determines quality of link using the observations in Section 3.2.3. Save the link quality classification for the link between node $i$ and $j$ (i.e., good / fair / poor).
5: Save $D_q^i$ from the reply message and associate with current node $j$.
6: Repeat steps 3-5 for all reply messages received from different nodes on a channel.
7: $C \leftarrow C + 1$.
8: If $C$ is a valid channel, repeat from step 1.

3.3.1. Channel Seeking Phase

When a source node joins the network, the channel seeking phase is initiated. The channel seeking phase is the period when a source node actively probes all possible wireless channels (or a subset when the active channels are known) to determine which link (i.e., next hop node) on which channel would be its best choice for its current location (i.e., different physical locations can have different performance on each wireless channel/link) and time instance. In this phase, the mobile source nodes send probe packets that advertise its presence on the channel and starts to classify each potential link with the information provided by the reply messages that relay nodes (i.e., the nodes on the backbone network; see Figure 3) send back. The results in Section 3.1 can be used as evidence that this phase can be done quickly, even if we seek all possible 16 channels. This short duration is desirable given that during this period, the source node is unable to transmit its data packets nor put its radio to sleep to conserve energy. Specifically, in the channel seeking phase mobile source nodes perform the procedures presented in Algorithm 1.

As a result, at the end of the channel seeking phase the source node should have a view of the link quality for each potential relay node. With this information, the source node first tries to select the node with the smallest expected delay measurements that is classified to have a good quality link connection. If no good quality connections exist, the node sequentially searches for fair and poor quality links with respect to the expected delay measurements to finally select the best possible wireless channel and associates to a relay node on that specific channel.

We note that the size of the table where we store the link and delay related information is at maximum proportional to the number of potential next hop relay nodes that are within the source node’s communication range, therefore, storage is not a major constraint in our scheme. Also note that while asym-
Figure 5: Decision tree diagram of the channel monitoring phase and its interaction with the channel seeking phase. At each channel monitoring phase the \(LQ_i\) and \(D_q^i\) values are recursively evaluated using the values that are stored at the end of the previous channel seeking phase. The channel seeking phase is re-invoked when the channel monitoring phase determines that the channel quality has degraded (e.g., in terms of LQI or delay) more than a pre-specified threshold.

Metrics in link quality is common for low power wireless networks it mostly happens for links with low quality links in the transitional region [22]. Therefore, by selecting links with good or fair quality and blacklisting poor quality links to be in the lowest priority, **DynaChannAl** is minimally affected by link asymmetries despite using LQI measurements from a single direction to infer the link quality of the other direction.

### 3.3.2. Channel Monitoring Phase

The outcome of the channel seeking phase is the best wireless channel and relay node that a source node can select in its “current” physical location and time instance. However, due to the potential mobility and the dynamic traffic patterns of the source nodes that our target applications introduce, we need a way to continuously monitor and re-evaluate the selected wireless channel conditions. This monitoring is to assure that the performance of the selected relay node and wireless channel are still the best, or at least close to what the source node expected when they were initially selected. This leads to proposing an additional phase that monitors the current status of the wireless channel and link conditions.

With this purpose, we start a channel monitoring phase as soon as the channel seeking phase terminates. In the channel monitoring phase, the source node performs the operations shown in Algorithm 2.

In the channel monitoring phase operations, the LQI value comparisons assure that the one hop link quality of the current connection has not degraded significantly compared to when the link was initially selected and the delay measurement comparison confirms that both the absolute and relative values of the current end-to-end delay estimates are still tolerable. We summarize this channel monitoring phase as a decision tree in Figure 5.
Algorithm 2 Channel Monitoring Phase Procedure

Require: Source node ID $i$
1: Set $\tau_D$ and $\tau_{LQI}$ in percentiles.
2: Set application specific end-to-end delay requirement.
3: $D_{channelInit} \leftarrow D_i$
4: $LQI_{channelInit} \leftarrow LQI_i$
5: $LQI_{classify} \leftarrow$ classification of selected link
6: Node $i$ overhears messages sent by its associated relay node $j$ and collects the updated $D_j$ along with the new LQI ($LQI_{new}$) from the packets. Compute updated $LQI_i$ with $LQI_{new}$.
7: if $LQI_i \geq (LQI_{channelInit} \times \tau_{LQI})$ then
8: if New LQI classification $\geq LQI_{classify}$ then
9: if $D_i <$ delay requirement then
10: if $D_i \geq (D_{channelInit} \times \tau_D)$ then
11: Continue on current channel
12: else
13: Begin Channel Seeking Phase
14: end if
15: else
16: Begin Channel Seeking Phase
17: end if
18: else
19: Begin Channel Seeking Phase
20: end if
21: else
22: Begin Channel Seeking Phase
23: end if
24: When new packets are overheard, repeat procedure from step 6.

We note that this monitoring phase that consists of four simple comparisons (as specified in lines 7-23 in Algorithm 2) is extremely light weight with minimal memory constraints and takes minimal processing time since there are no significant computation needed in the process. Such characteristics of the scheme make DynaChannAl desirable for resource constraint WSN systems.

4. Evaluation

4.1. Evaluation Environment and Metrics

As the sections until now discusses, DynaChannAl is a simple and light weight scheme that can be practically executed on a highly resource constraint mote-class platform. Furthermore, there is no existing work that takes the goal of channel allocation for mobile WSN nodes with the goal of end-to-end latency. Therefore, the goal of this evaluation is to show that such a simple
scheme can effectively distribute nodes on different channels. Thus we begin
the evaluation to show that this is true (Sections 4.2 - 4.3). The later part
of the evaluation (Section 4.4) will confirm that the achieved throughput of
DynaChannAl does not degrade the maximum throughput that is achievable by
our hardware and software platforms in our target indoors environment. Our
evaluations are based on experiments performed using real mote-class devices
deployed in an indoor testbed. The testbed consists of 45 Tmote Sky motes
deployed in various locations on a single floor hallway (see Figure 6) which act
as the source nodes. We deploy eight additional Tmote Sky devices to form the
backbone network for our two different channels of interest. The tree network
is formed using the collection tree protocol (CTP) [23], the de-facto standard
tree routing protocol for TinyOS 2.x applications. In our tests we use Zigbee
channels 25 and 26 to minimize the effect of IEEE 802.11 WiFi interference (see
Figure 2). To experiment and monitor the effect of mobile source devices, two
volunteers carry five Tmote Sky devices at walking speed in the hallway where
our testbed and backbone network is deployed. We note that DynaChannAl is
implemented in TinyOS 2.1.

To quantify the performance of DynaChannAl, we define the following per-
formance metrics. First we take the distribution of nodes on different channels to
see how effectively DynaChannAl distributes nodes on different wireless chan-
nels. Second, we use the end-to-end latency of the packets generated at the
source nodes on each channel. This second metric is an important metric that
indicates whether DynaChannAl successfully achieves its primary goal of mini-
Figure 7: Distribution of 45 nodes on each of the two operating channels over time with steady-periodic traffic. The left plot shows the case when packets are generated at an interval of 1024 ms and the right plot shows the case for traffic with 128 ms interval at each source node. The distribution of nodes on the two channels is uneven in the beginning of the experiment due to the fact that the relay nodes cannot provide the source nodes with sufficient information related to the expected end-to-end channel delay. However shortly after the experiment begins, nodes self-distribute themselves evenly on channels 25 and 26. We can see that the distribution of the nodes are fair between the two wireless channels.

mizing the end-to-end latency of all generated packets. Finally, using the total network throughput at the root nodes, we show that DynaChannAl effectively uses the available wireless bandwidth.

In our experiments we set parameters as the following. First, for the LQI metric we set \( n = 1 \) during the channel seeking phase and \( n = 10 \) in the channel monitoring phase. Second, \( D_q^i \), as described in Section 3.2, is computed in runtime on a per packet basis using packet overhearing techniques. The channel seeking phase in DynaChannAl is executed every 30 seconds to tolerate dynamic channel environments. Finally, we set both delay and LQI thresholds, \( \tau_D \) and \( \tau_{q_i} \) as 90% (details in Section 3.3.2) and the application specific end-to-end delay threshold as 500 ms.

4.2. Channel Selection of Mobile and Stationary Source Nodes

The first set of results that we present aims to show that DynaChannAl effectively distributes multiple source nodes on the two different channels that we use in our experiments. We use three types of traffic patterns and two types of traffic loads for all of our experiments. We define our three traffic patterns of interest as the following:

- **Steady and Stationary Traffic**: Each source node generates packets at a fixed interval with no mobility in the environment.

- **Dynamic and Stationary Traffic**: Each source node begins by generating steady traffic but a subset of the source nodes are switched off and then back on during the experiment. There are no mobile source nodes in the experiment.
Figure 8: Distribution of 45 nodes on each of the two operating channels over time with dynamic traffic patterns. The left plot shows the case when packets are generated at an interval of 1024 ms and the right plot shows the case for traffic with 128 ms interval at each source node. To generate dynamic traffic environments, we randomly turn off approximately half of the source motes (23 nodes) at time $t = 30$ minutes. We can see that the nodes fairly re-distribute themselves within a short period of time when a significant change in the network traffic occurs. When all nodes become active again at time $t = 45$ minutes, the original behavior is recovered quickly as well.

- **Mobile Traffic:** Each source node generates steady traffic throughout the experiment and a subset of the source nodes are mobile at human walking speed.

For each of the traffic patterns described above we experiment with two different traffic loads, low data rates (i.e., 1024 ms packet generation interval at each source node) and high data rates (i.e., 128 ms packet generation interval).

We first present the results for steady and stationary traffic with the two types of traffic loads in Figure 7. Both the left (packet interval 1024 ms) and right (packet interval 128 ms) plots indicates that *DynaChannAl* successfully distributes nodes fairly. Each point in the plots represent the average number of nodes in each channel per minute. The small yet consistent changes in the nodes’ channel distributions are caused by variances introduced in the wireless channel (e.g., non-deterministic human movement within the testing environment). In the initial stage of all our experiments, nodes select their channels based on only a small number of previous samples (or even none in some cases), and therefore, there is a noticeable difference in the number of nodes on the two channels.

We generate dynamic traffic patterns by randomly turning off approximately half of the source nodes (23 nodes) from our testbed. We make this change 30 minutes after the beginning of the experiment. These nodes are re-activated after 15 minutes of node blackout (i.e., 45 minutes in to the experiment). Both left (low data rate) and right (high data rate) plots of Figure 8 show that with *DynaChannAl* nodes can discover and position themselves on an effective wireless channel regardless of the amount of traffic in the network. We can notice that the fairness of node distribution on the two channels break slightly at the beginning of a major traffic pattern changes (e.g., when nodes are turned off or when they are suddenly turned on). This fluctuation is relaxed as soon
as nodes notice the changes in traffic conditions and adapt to such changes. According to Figure 8 this process takes $\sim 1 \text{ minute}$.

Finally, since source nodes can be mobile in applications such as healthcare WSN systems [5], we observe how the mobility of nodes affect the distribution of nodes on multiple wireless channels. For this, we take five nodes from our testbed to act as mobile nodes (specified as blue circles in Figure 6) and generate mobile traffic. Two volunteers each carry two and three nodes respectively for 20 minutes and perform continuous walks on the hallway shown in Figure 6. The experiments are performed with all source nodes (both mobile and stationary) generating eight packets each second (i.e., high data rate). We show that the number of stationary and mobile nodes on each of our two channels of interest with respect to experiment duration in Figure 9. One can notice that the source nodes change their wireless channels more frequently when a subset of the nodes are mobile compared to the case where all the nodes are stationary (compare

Figure 9: Distribution of nodes on each of the two operating channels over time with mobile nodes’ traffic. 40 nodes stay stationary on the testbed and two volunteers each carry two and three nodes respectively on the hallway for 20 minutes as the mobile devices. All nodes in the experiment transmit one packet each 128 ms. While the distribution of the nodes are not as stable as the results observed in the experiments when all nodes are stationary, the distribution of the nodes are comparably fair among the two channels.

Figure 10: End to end latency of packets generated from nodes on different channels with steady traffic at a packet interval of 1024 ms. Nodes connected to different hops on the backbone tree network have different average latency values.
Figure 11: End to end latency of packets generated from source nodes on different channels with steady traffic at a packet interval of 128 ms. The higher data rates lead to more packets on each relay node and therefore, longer packet latencies compared to the low traffic rates presented in Figure 10.

Figure 12: End to end latency of packets generated from nodes on different channels with mobile nodes. The five mobile nodes and the other 40 stationary nodes generate steady traffic with an interval of 128 ms. The latency observed at the mobile devices are comparable with the latency of the packets generated from stationary nodes (see Figure 10 and Figure 11).

with right figure of Figure 7. Such increased amount of channel switches result from more frequent execution of the channel seeking phase. We argue that the link quality fluctuations of the links connecting the mobile nodes with the backbone network causes the mobile nodes to initiate the channel seeking phase more frequently (mostly due to the LQI comparison in Figure 5). Therefore this opens the possibility of more frequent channel switching. This, in turn, fluctuates the delay on the backbone network, causing additional stationary nodes to start the channel seeking phase as well. In any case, Figure 9 indicates that despite continuously having node mobility in the wireless network, DynaChannAl successfully distributes nodes on the two channels effectively.

4.3. End to End Queuing Latency

During our experiments, we also collect the amount of end-to-end queuing latency encountered for each packet received at the root of the tree network. Using these latency measurements we determine if the delay on the two channels
Figure 13: Node distribution (left) and latency with respect to the hop count of the source node (right). Even when a higher number of wireless channels are available for the source nodes, the distribution of nodes over multiple channels are fair and the latency is fairly distributed over the four different wireless channels of our interest. Similar to the results in Figure 9, we experiment with the dynamic traffic patterns with high data rates (i.e., half of the nodes are switched off at $t = 30$ and turned back on at $t = 45$).

are fairly distributed and minimized. We point out that given a specific amount of traffic, the most efficient way to distribute nodes on multiple channels (when end-to-end latency of the packets is the core consideration point) is to balance each channel with the same end-to-end latency. Therefore, an optimal scheme will show even latency on all used wireless channels. We present the results with steady traffic (explained in Section 4.2) for both low and high data rates in Figures 10 and 11, respectively. In the figures, we plot the average end-to-end delay observed by packets generated from nodes connected to different hops in the backbone tree network. Results indicate that the latency is (as expected) lower with low data rates and increases with increasing amount of traffic. Also, as the number of hops increases, the end-to-end latency grows as well. While these observations are intuitive, one interesting point to notice from Figures 10 and 11 is the differences in the increasing slopes of the latency as the number of hops increase. We notice that while the latency increases gradually with hop count in the low data rate experiments, a significant amount of end-to-end latency is seen even at the source nodes that are connected to the first hop nodes of the backbone network in the high data rate experiments. We speculate that such behavior is due to the significant amount of packets that are “stacked up” at the relay nodes close to the gateway (i.e., first hop relay nodes) when the amount of traffic in the network is significantly high. Such traffic congestion increases the queue size at specific relay nodes and thus, this increases the packets’ queuing delays. In any case, despite the unavoidable higher end-to-end latency in such cases, we can observe that the latency is almost equal on the two active wireless channels. This indicates that DynaChanAl achieves semi-optimal node distribution with respect to minimizing the end-to-end delay with stationary nodes.

The delay results obtained from the experiment with mobile source nodes are presented in Figure 12. Since the traffic patterns that the source nodes generate
Seeking 2 Active Channels | 63.76 ms
Seeking All 16 Possible Channels | 353.37 ms

Table 1: Latency introduced by channel seeking phase with different number of channels that are seeked within the phase. The measurements are gathered experimentally from our tests.

are the same as the high traffic rate experiments (packet interval of 128 ms) the results look similar to Figure [11] with only slightly higher latency values. We conjecture that such higher latencies despite the same number of source nodes and traffic are caused by the overhead introduced from the increased number of channel seeking phases and the fluctuating wireless channel selections. Still the latency distribution on the two active channels are highly correlated, thus, DynaChannAl is achieving the minimal possible latency on both wireless channels.

Finally, we note that each channel seeking phase (channel seeking delay + channel switching delay) took an average 63.76 ms when only channels 25 and 26 were part of the channel seeking phase. This was done by pre-configuring the source nodes with the active channels. When all 16 channels were probed during the channel seeking phase (i.e., no pre-configuration) the average channel seeking delay was 353.37 ms. These results, summarized in Table 1 show that DynaChannAl indeed effectively selects channels with minimal channel seeking overhead and these experimental results match what we expected in the empirical studies shown in Section 3.1.

4.4. Throughput of DynaChannAl

To see how efficient DynaChannAl performs in terms of end-to-end network throughput, we compare the amount of data received at the root node (gateway) in our experiments with the optimal throughput value of IEEE 802.15.4-based networks. First, while the IEEE 802.15.4 standard [1] states that the maximum throughput is 250 Kbps for 2.4 GHz radios, we take an experimental approach to see how much throughput can actually be achieved when using TinyOS 2.1 and Tmote Sky nodes. For this, we set one receiver and place five transmitter nodes within a single communications range. The transmitter nodes sent back-to-back packets (i.e., as fast as possible) with each packet size being 114 bytes. When a carrier sense multiple access with collision avoidance (CSMA/CA) based medium access control (MAC) protocol is fully used (TinyOS 2.1 implements the B-MAC [24] as the default MAC protocol), we observed a throughput of 38.92 Kbps and the maximum throughput was 49.19 Kbps when we disabled the clear channel assessment (CCA) checks in the MAC. For a single transmitter with back to back packet transmissions, the maximum throughput achieved was 42.61 Kbps. This indicates that the throughput of 38.93 Kbps for multiple nodes is a result of channel saturation. We will compare the throughput achieved by DynaChannAl with the saturated throughput since the amount of traffic that the nodes in our experiments generate easily saturates a 802.15.4 wireless medium. Such low throughput values with the hardware and software
platform that we use (e.g., TelosB motes and TinyOS 2.x) is also observed in previous work such as [3, 25]. We conjecture that the overhead introduced by TinyOS' software stack with the speed limitations of the serial interfaces in the hardware are the main causes of the performance degradation (e.g., memory copy operations to/from the radio’s buffer, receive pointer reservations until the received process is terminated from the upper most layer, cross layer communications, etc.). These experimental values represent the maximum possible throughput at a single receiver node when all transmitting nodes are connected via singlehop links. In the experiments performed for DynaChannAl, we incorporate a multihop tree network of relay nodes which mobile user nodes connect for transmitting their data to the root of the tree. Such network architectures can potentially decrease the throughput of the wireless network due to its multihop nature. In any case, for our testing environments we observed an average throughput of 33.67 Kbps per wireless channel. Given that the gateway issues acknowledgment packets to all packet receptions and all nodes perform full CSMA/CA (including CCA checks), this throughput is 86.51% of the maximum achievable performance in a saturated environment. Despite the multihop network architecture, since the main bottleneck of the throughput performance is the data flow within TinyOS and the local device, the performance degradation compared to the optimal case (maximum singlehop throughput) is not significant. We conjecture that the small performance difference that we see is mainly caused by the communication and computational overhead introduced by the Collection Tree Protocol (CTP) [23] that we use to form the tree relay network. Overall, for both channels we observed an aggregate throughput of 67.34 Kbps.

4.5. Performance with Increasing Number of Usable Wireless Channels

To confirm that DynaChannAl performs effectively as we predicted in the previous subsections even with increasing number of usable wireless channels, we perform a simple experiment on the testbed in Figure 6 with the backbone infrastructure installed for four different wireless channels (i.e., Zigbee channels 23, 24, 25 and 26). In this setting, we generate dynamic/stationary traffic (as described in Section 4.2) with high data rates. Again at \( t = 30 \) minutes we turn off 23 nodes and switch them back on at \( t = 45 \) minutes to emulate dynamic traffic patterns. We present the results of the nodes’ distribution on multiple channels (left) and the end-to-end delay with respect to the source node’s hop count with error bars that indicate the minimum and maximum values (right) in Figure 13. The results indicate that both the distribution of nodes and the distribution of end-to-end latency are fair over the four active wireless channels. These results provide evidence that DynaChannAl is scalable with increasing number of wireless channels.

5. Notable Aspects of DynaChannAl
Applicability with Different Protocols. DynaChannAl is a fully distributed scheme that is suitable for WSN systems with multihop connections and incorporate a wireless backbone architecture. In such networks, systems combine different schemes to optimize the performance of the WSN system as a whole (i.e., network protocols, medium access control (MAC) protocols, etc.). Examples of such WSN systems include [5, 20, 27]. We point out that DynaChannAl is lightweight both in terms of memory usage and computational power. Therefore, DynaChannAl can be used along with other algorithms with minimal additional overhead. First, our scheme is mainly dependent on the packets and decisions of the mobile source nodes while being less dependent on the infrastructure nodes (i.e., only require reply messages). Therefore, DynaChannAl minimally interacts with the protocols that relay nodes use. Second, the metrics collected for DynaChannAl can be used to combine with other metrics to make improved decisions for pre-existing protocols as well (e.g., low power MAC protocols that could benefit from minimizing the delay or routing protocols that can use the latency information to select latency effective paths).

Minimizing Energy Consumption. Finally in terms of minimizing idle listening times, we show in this work that channel seeking delays can be minimal (i.e., < 400 ms). In DynaChannAl we can further minimize the idle waiting times by pre-specifying the active wireless channels. As seen in the results obtained from Section 4.3 seeking only a subset of active channels instead of all 16 can reduce the seeking delay by up to 81.97%. This potentially leaves room for extending the nodes’ lifetime. On the other hand we note that trying to overhear the next hop’s packets to gather the updated LQI and $D_q$ values can increase idle listening at the resource limited source nodes. In such cases, explicitly transmitting the parameters in a separate data packet can decrease the total energy consumption, given that for CC2420 radios the energy spent on idle listening is greater than that for transmitting. In this case, the lower energy consumption is a tradeoff with a small amount of communication overhead. Another way of minimizing the idle listening time while keeping the communication overhead low, is synchronizing the source nodes with the next hop node. By learning the transmission patterns of the next hop node, the source node can perform radio duty cycling with respect to this transmission pattern to conserve energy and overhear the updated piggybacked parameters simultaneously.

6. Limitations and Future Work

The current proposal of DynaChannAl requires a pre-deployed backbone network on multiple channels which should be carefully deployed with considerations on the estimated network capacity usage. While this is a realistic case in applications such as MEDiSN [5] where the positions of the backbone network nodes and the network capacity usage is carefully monitored and engineered, removing the requirement of a pre-deployed backbone network on multiple channels would significantly increase the number of applications that DynaChannAl can support. For this, DynaChannAl should invade other layers of the network.
stack including the routing and MAC layers. We should think as future work what the tradeoffs are in keeping DynaChannAl as an independent layer (i.e., higher portability to applications but less optimized) or as part of a system as a whole (i.e., highly optimized with less portability).

7. Conclusion

In this work we propose and evaluate DynaChannAl, a distributed channel allocation scheme for WSN systems with the goal of minimizing end-to-end queuing latency on multiple wireless channels. DynaChannAl experimentally measures the queuing delay at each hop of a multihop network and aggregate these measurements to assure that a mobile source nodes can make accurate estimates of the expected end-to-end queuing latency. DynaChannAl also incorporates link quality indicator (LQI) values to classify the quality of the local wireless channel environments. Our evaluation is based on experimental results from a 45 node indoor testbed to demonstrate the effectiveness of such a simple and light-weight scheme in actual mote-class platforms. Our results show that DynaChannAl effectively distributes multiple nodes on different wireless channels with steady, dynamic and mobile traffic patterns. The channel selection of DynaChannAl also assures that the end-to-end queuing delay is minimal on all active channels, which is the end goal of our protocol. To our knowledge this work is the first work to consider the expected end-to-end queuing delay as a main design metric for wireless channel allocation in WSN systems research.

[1] IEEE Standard for Information technology – Telecommunications and information exchange between systems – Local and metropolitan area networks. Specific requirements – Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (LR-WPANs), Available at http://www.ieee802.org/15/pub/TG4.html (May 2003).

[2] IEEE Standard for Information technology-Telecommunications and information exchange between systems-Local and metropolitan area networks-Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications (2007).

[3] M. Petrova, J. Riihijarvi, P. Mahonen, S. Labella, Performance study of ieee 802.15. 4 using measurements and simulations, in: Proceedings of IEEE WCNC, 2006, pp. 487–492.

[4] R. Musăloiu-E., A. Terzis, K. Szlavecz, A. Szalay, J. Cogan, J. Gray, Life Under your Feet: A Wireless Sensor Network for Soil Ecology, in: Proceedings of the 3rd EmNets Workshop, 2006.

[5] J. Ko, J. H. Lim, Y. Chen, R. Musaloiu-E., A. Terzis, G. M. Masson, T. Gao, W. Destler, L. Selavo, MEDiSN: Medical Emergency Detection in Sensor Networks, ACM Transactions on Embedded Computing Systems, Special Issue on Wireless Health Systems.
[6] C. Liang, J. Liu, L. Luo, A. Terzis, F. Zhao, RACNet: A High-Fidelity Data Center Sensing Network, in: Proceedings of ACM Sensys, 2009.

[7] ZigBee Alliance, ZigBee Specification, Available at: http://www.zigbee.org (2006).

[8] Y. Wu, J. A. Stankovic, T. He, S. Lin, Realistic and efficient multi-channel communications in wireless sensor networks, in: Proceedings of INFOCOM, 2008.

[9] G. Zhou, C. Huang, T. Yan, T. He, J. Stankovic, MMSN: Multi-Frequency Media Access Control for Wireless Sensor Networks, in: Proceedings of INFOCOM, 2006.

[10] Y. Wu, M. Keally, G. Zhou, W. Mao, Traffic Aware Channel Assignment in Wireless Sensor Networks, in: Proceedings of International Conference on Wireless Algorithms, Systems an Applications, 2009.

[11] J. Ko, T. Gao, A. Terzis, Empirical Study of a Medical Sensor Application in an Urban Emergency Department, in: Proceedings of the ICST 4th international conference on Body area networks (BodyNets), 2009.

[12] A. Wood, J. Stankovic, G. Virone, L. Selavo, Z. He, Q. Cao, T. Doan, Y. Wu, L. Fang, R. Stoleru, Context-Aware Wireless Sensor Networks for Assisted Living and Residential Monitoring, IEEE Network.

[13] T. H. Hane Suda Krishnamurthy, J. A. Stankovic, T. F. Abdelzaher, L. Luo, R. Stoleru, T. Yan, L. Gu, J. Hui, B. Krogh, An Energy-Efficient Surveillance System Using Wireless Sensor Network, in: Proceedings of the Second International Conference on Mobile Systems, Applications, and Services (MobiSys), 2004.

[14] K. Chowdhury, N. Nandiraju, P. Chanda, D. Agrawal, Q. Zeng, Channel allocation and medium access control for wireless sensor networks, Ad Hoc Networks 7 (2) (2009) 307–321.

[15] H. Salameh, T. Shu, M. Krunz, Adaptive cross-layer MAC design for improved energy-efficiency in multi-channel wireless sensor networks, Ad Hoc Networks 5 (6) (2007) 844–854.

[16] H. Le, D. Henriksson, T. Abdelzaher, A Practical Multi-Channel Medium Access Control Protocol for Wireless Sensor Networks, in: Proceedings of the Seventh International Conference on Information Processing in Sensor Networks (IPSN), 2008.

[17] T. He, J. Stankovic, C. Lu, T. Abdelzaher, SPEED: A Stateless Protocol for Real-Time Communication in Sensor Networks, in: Proceedings of the 23rd International Conference on Distributed Computing Systems, IEEE Computer Society, 2003, p. 46.
[18] T. He, B. Blum, J. Stankovic, T. Abdelzaher, AIDA: Adaptive application-independent data aggregation in wireless sensor networks, ACM Transactions on Embedded Computing Systems (TECS) 3 (2) (2004) 426–457.

[19] J. Polastre, R. Szewczyk, D. Culler, Telos: Enabling Ultra-Low Power Wireless Research, in: Proceedings of the Fourth International Conference on Information Processing in Sensor Networks: Special track on Platform Tools and Design Methods for Network Embedded Sensors (IPSN/SPOTS), 2005.

[20] K. Srinivasan, P. Levis, RSSI is Under Appreciated, in: Proceedings of the 3rd Workshop on Embedded Networked Sensors (EmNets), 2006.

[21] Texas Instruments, 2.4 GHz IEEE 802.15.4 / ZigBee-ready RF Transceiver, Available at http://www.ti.com/lit/gpn/cc2420 (2006).

[22] N. Zamolloa, Marco Zú B. Krishnamachari, An analysis of unreliability and asymmetry in low-power wireless links, ACM Trans. Sen. Netw. 3 (2) (2007) 7. doi:http://doi.acm.org/10.1145/1240226.1240227.

[23] O. Gnawali, R. Fonseca, K. Jamieson, D. Moss, P. Levis, Collection Tree Protocol, in: Proceedings of the 7th ACM Conference on Embedded Sensor Systems (SenSys), 2009.

[24] J. Polastre, J. Hill, D. Culler, Versatile Low Power Media Access for Wireless Sensor Networks, in: Proceedings of the 2nd ACM Sensys Conference, 2004.

[25] S. Kim, R. Fonseca, P. Dutta, A. Tavakoli, P. L. David Culler, S. Shenker, I. Stoica, Flush: A Reliable Bulk Transport Protocol for Multihop Wireless Networks, in: Proceedings of 5th ACM SenSys Conference, 2007.

[26] D. Malan, T. Fulford-Jones, M. Welsh, S. Moulton, CodeBlue: An Ad Hoc Sensor Network Infrastructure for Emergency Medical Care, in: Proceedings of the MobiSys 2004 Workshop on Applications of Mobile Embedded Systems (WAMES 2004), 2004.

[27] N. Xu, S. Rangwala, K. K. Chintalapudi, D. Ganesan, A. Broad, R. Govindan, D. Estrin, A Wireless Sensor Network for Structural Monitoring, in: Proceedings of SenSys 2004, 2004.