Real-World Empirical Studies on Multi-Channel Reliability and Spectrum Usage for Home-Area Sensor Networks

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***Abstract*—Home area networks (HANs) consisting of wireless sensors have emerged as the enabling technology for important applications such as smart energy. These applications impose unique network management constraints, requiring low data rates but high network reliability in the face of unpredictable wireless environments. This paper presents two in-depth empirical studies on wireless channels in real homes, providing key design guidelines for meeting the network management constraints of HAN applications. The *spectrum study* analyzes spectrum usage in the 2.4 GHz band where HANs based on the IEEE 802.15.4 standard must coexist with existing wireless devices. We characterize the ambient wireless environment in six apartments through passive spectrum analysis across the entire 2.4 GHz band over seven days in each apartment. We find that the wireless conditions in these residential environments are much more complex and varied than in a typical office environment. Moreover, while 802.11 signals play a significant role in spectrum usage, there also exists non-negligible noise from non-802.11 devices. The *multi-channel link study* measures the reliability of different 802.15.4 channels through active probing with motes in ten apartments. We find that there is not always a persistently reliable channel over 24 hours, and that link reliability does not exhibit cyclic behavior at daily or weekly timescales. Nevertheless, reliability can be maintained through infrequent channel hopping, suggesting dynamic channel hopping as a key tool for meeting the network management requirements of HAN applications. Our empirical studies provide important guidelines and insights in designing HANs for residential environments.**

***Index Terms*—Empirical study, home-area sensor networks, spectrum, multi-channel.**

I. Introduction

In recent years, there has been growing interest in various wireless sensing applications in residential environments. For example, smart energy systems provide fine-grained metering and control of home appliances in residential settings. Similarly, assisted living applications such as vital sign monitoring and fall detection leverage wireless sensors to provide continuous health monitoring in homes. Wireless sensor networks offer a promising platform for home automation applications because they do not require a fixed wired infrastructure. Hence, home area networks (HANs) based on wireless sensor network technology can be used to easily and inexpensively retrofit existing apartments and households without the need to run dedicated cabling for communication and power [1]. HAN applications have increasingly adopted the IEEE 802.15.4 wireless personal area network standard to provide wireless communication among sensors and actuators. 802.15.4 radios are designed to operate at a low data rate and be inexpensively manufactured, making them a good fit for residential applications where energy consumption and manufacturing costs are often at a premium. Industry standards such as ZigBee Smart Energy have adopted 802.15.4 technology for use in residential automation applications. The IETF has promoted efforts to standardize IPv6 on top of 802.15.4 for integrating wireless sensors into the Internet.

However, HANs pose unique challenges in network management due to their low-power radios and uncontrolled residential environments. HANs typically feature low data rates but require high network reliability in uncontrolled residential environments. Our study shows that low-power IEEE 802.15.4 channels are highly susceptible to external interference beyond user control, such as Wi-Fi access points, Bluetooth peripherals, cordless phones, and numerous other devices prevalent in residential environments that share the unlicensed 2.4 GHz ISM band with IEEE 802.15.4 radios.

Figure 1 illustrates this challenge with raw spectrum usage traces collected from the 2.4 GHz spectrum in six apartments and an office building (described in more detail in Section III). The office environment provides a relatively clean and predictable wireless environment, with only two major sources of noise: a campus-wide 802.11g network in the middle of the spectrum, and a 802.15.4 sensor network testbed at the upper end. In contrast, the residential settings present a much noisier and more varied environment; for example, apartments 4 and 5 show sporadic interference across the entire 2.4 GHz spectrum (represented by blue shapes spanning nearly the entire X axis) which could complicate finding a persistently reliable communication channel. These results highlight a fundamental challenge of residential deployments: while the wireless devices in industrial and office settings are typically centrally managed, resulting in more predictable noise patterns, residential settings present numerous sources of environmental noise due to a lack of spectrum management. This challenge is compounded by the fact that wireless signals may traverse multiple neighboring residences, subjecting neighbors' networks to interference beyond their control. For example, in just one apartment in our dataset, a deployed

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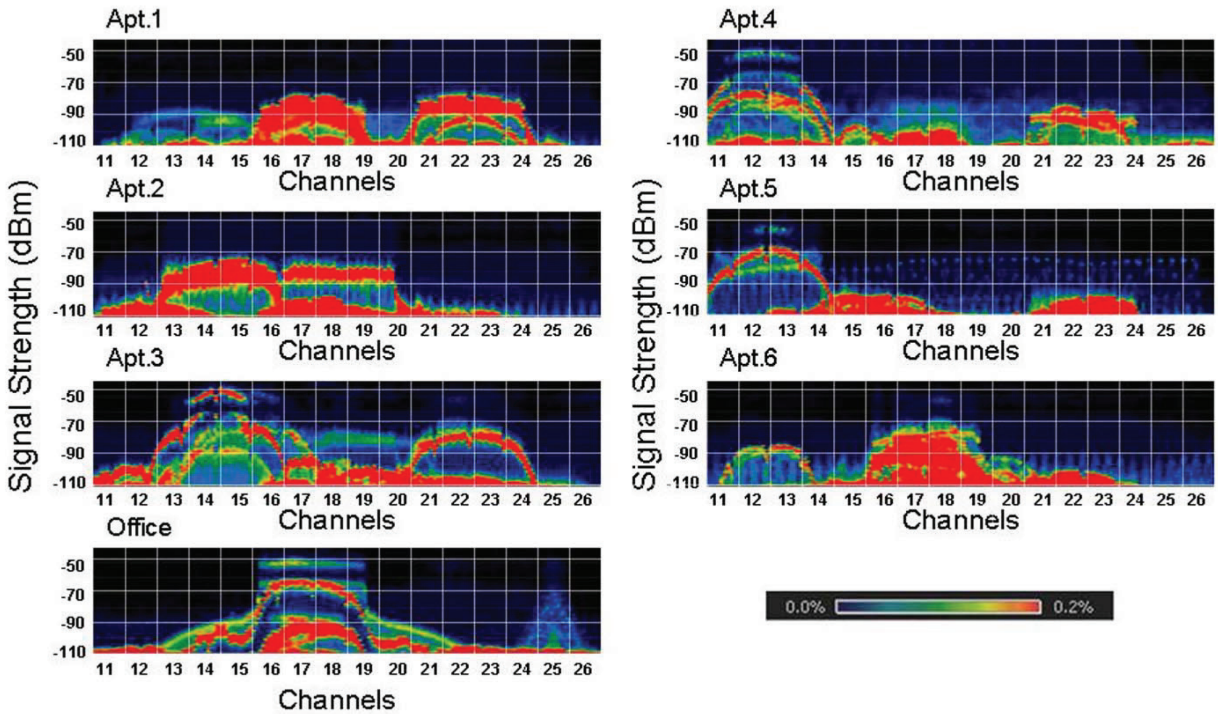


Fig. 1. Histogram over seven days' raw energy traces. X axis indicates 802.15.4 channels, Y axis indicates power, and color indicates how often a signal was detected at x GHz with an energy level of y dBm.

laptop was able to decode beacons from 28 distinct Wi-Fi access points.

In this paper, we present a two-part empirical study which aims to characterize the real-world network performance of HANs, focusing specifically on devices based on the 802.15.4 standard. Our study is divided into two major parts. First, we carry out an analysis over spectrum analyzer traces collected in six apartments. This spectrum study of ambient wireless conditions in homes illustrates the challenge of finding a "clean" part of the shared 2.4 GHz spectrum in such settings. Our analysis demonstrates that the wireless environments in these apartments are much more crowded and more variable than an office setting. Moreover, while 802.11 WLANs contribute a significant fraction of the spectrum usage, we also identified signals across the 2.4 GHz band indicating non-negligible noise from non-802.11 devices.

Second, we explore how these challenging environments may directly affect applications' QoS, through an active probing study of wireless link reliability across all 16 channels in ten apartments. This second study focuses on packet reception ratio (PRR), which is both a direct indicator of link reliability and closely related to other important QoS metrics such as latency and energy consumption. From this active study, we make several more key observations which could greatly impact the QoS of wireless sensor networks deployed in residential environments: (1) Link reliability varies significantly from channel to channel and over time. (2) In a typical apartment environment, there may not be a single channel which is persistently reliable for 24 hours. (3) Retransmissions alone are insufficient for HANs due to the burstiness of packet losses. (4) Exploiting channel diversity by infrequent channel hopping at runtime can effectively maintain long-term reliable communication. (5) Channel conditions are not cyclic. (6) Reliability is strongly correlated across adjacent channels; channel-hopping should move as far away as possible from a failing channel. (7) Increasing transmission power may be effective for maintaining channel reliability, but is potentially expensive. Combining channel diversity with transmission power control is a promising strategy for controlling energy consumption while maintaining network reliability.

These findings reveal the characteristics of wireless channels and 2.4 GHz spectrum in residential environment, highlight the importance of channel diversity in managing HANs, and provide ground truth and findings as a foundation for developing network management approaches for HANs. For example, it highlights the importance of dynamic channel selection in managing HANs. Devices cannot be deployed with a factory-set default channel as no channel can consistently achieve long-term reliability in all the apartments we studied. Neither will a channel selected based on measurements at deployment time suffice either because of the time-varying nature of channel conditions. On the other hand, sustained reliability can be achieved by changing the channel only a few times a day. This observation motivates the design of HAN management tools with dynamic channel management functions that are not typically needed in Wi-Fi network management. Our study also provides insights for managing the co-existence of HANs with other wireless technology such as Wi-Fi. While co-existence of HANs and Wi-Fi has received attention in the literature [2], we found that other devices can also be non-negligible sources of interference. Therefore, co-existence solutions tailored specifically for Wi-Fi may not be effective in all residential environments. Instead, general solutions agonistic to specific co-existing wireless technology will be more effective in residential environments with diverse sources of interference.

The rest of the paper is organized as follows. Section II reviews related work. Section III discusses the findings of our passive spectral study. Section IV then presents our active probing study. Finally, we conclude in Section V by highlighting the implications of our findings on HAN design.

II. Related Work

Several recent studies have aimed to characterize the impact of interference on wireless networks through controlled experiments [3]–[7]. [8]–[10] present theoretical analysis based on simulation study. Gummadi *et al.* [11] presents an empirical study on the impact of ZigBee and other interferers' impact on 802.11 links, proposing to alleviate interference with rapid channel-hopping in conjunction with 802.11b's existing support for Direct-Sequence Spread Spectrum (DSSS). Srinivasan *et al.* [12] examines the packet delivery behavior of two 802.15.4-based mote platforms, including the impact of interference from 802.11 and Bluetooth. Liang *et al.* [2] measures the impact of interference from 802.11 networks on 802.15.4 links, proposing the use of redundant headers and forward error correction to alleviate packet corruption. In contrast to these controlled studies, our own study examines the performance of HANs subject to normal residential activities and diverse interference sources. Due to the co-existence of diverse interference sources in these uncontrolled environments, our study considers ambient wireless conditions as a whole, rather than analyzing specific sources of interference. For example, our spectrum study showed that, while Wi-Fi is a significant source of interference in residential environments, non-Wi-Fi devices can also be non-negligible sources of interference. This result indicates that solutions tailored specifically for one type of co-existing wireless technology may not be effective in all residential environments.

Bahl *et al.* [13] presents a study of UHF white space networking, while Chen *et al.* [14] presents a large-scale spectrum measurement study followed by a 2-dimensional frequent pattern mining algorithm for channel prediction. These studies focus on supporting wide-area networks based on white space networking and the GSM band, respectively. Our own study focuses on the reliability of static, indoor wireless sensor networks designed for home environments, and on the unlicensed 2.4 GHz band used by IEEE 802.15.4 and shared by other wireless devices prevalent in residential environments. Accordingly, our study provides new insights into the reliability of HANs, including the high variability of residential wireless environments, the lack of persistently reliable wireless channels, the diverse sources of interference (including the non-negligible impact of non-Wi-Fi devices), and the effectiveness of infrequent channel hopping in maintaining link reliability.

Papagiannaki *et al.* [15] performed an empirical study of home networks based on 802.11 technology. Our study considers devices based on the 802.15.4 standard, which operate at a much lower transmission power than 802.11 devices and hence are significantly more susceptible to interference. Our study therefore leads to a different set of observations that underscores the impact of spectrum usage on these low-power 802.15.4 networks.

TABLE I
The settings and dates where the spectrum data was collected

Name	Begin Date	End Date
Apt. 1	2:00pm, Apr. 4, 2010	3:30pm, Apr. 19, 2010
Apt. 2	6:50pm, June 30, 2010	6:50pm, July 7, 2010
Apt. 3	9:05pm, May 12, 2010	11:29pm, May 20, 2010
Apt. 4	11:40am, June 6, 2010	12:40pm, June 13, 2010
Apt. 5	12:25pm, Apr. 20, 2010	10:50am, Apr. 28, 2010
Apt. 6	7:00pm, July 7, 2010	9:00pm, July 14, 2010
Office	1:15pm, July 16, 2010	1:20pm, July 23, 2010

Ortiz *et al.* evaluates the multi-channel behavior of 802.15.4 networks in a machine room, a computer room, and an office testbed. Ortiz's study finds path diversity to be an effective strategy to ensure reliability. Our own study in residential environments provides many different insights on low wireless characteristics compared with what is observed in Ortiz's study. The residential settings in our study exhibit more complex noise patterns and higher variability than the environments studied by Ortiz. This difference may be attributed to homes being open environments with no centralized control on spectrum usage; many 2.4 GHz devices are used in homes, and the physical proximity of some residences means that strong interferers (such as 802.11 APs, Bluetooth devices, and cordless phones) may even affect the wireless conditions in other homes. Accordingly, our active study in Section IV finds exploiting channel diversity to be an attractive strategy for ensuring reliability in residential environments. We note that channel and path diversity are orthogonal strategies; the two could be used together in particularly challenging wireless environments.

Hauer *et al.* [16] discusses a multi-channel measurement of Body Area Networks (BANs) and proposes a noise floor-triggered channel hopping scheme to detect and mitigate the effects of interference. Hauer's study features controlled indoor experiments along with outdoor experiments carried out during normal urban activity. Shah *el al.* [17] performed a controlled experiment to study the effect of the human body on BANs. Shah's study measures the effects of various activities (sitting, standing, and walking) and node placements (ear, chest, waist, knee, and ankle) on 802.15.4 radio performance. Instead of body-area networks, our own study focuses on HANs designed for smart energy, which feature significantly different setups and wireless properties. Moreover, our study is performed under normal home activities, providing a realistic setting to evaluate HAN performance.

III. Wireless Spectrum Study

In this section, we present a study of the ambient wireless conditions in real-world residential environments. For this study, we collected 7 days' energy traces in the 2.4 GHz spectrum from six apartments in different neighborhoods. A detailed description of the experimental settings may be found in Table I.

As a baseline for comparison, we also collected energy traces from an office in Bryan Hall at Washington University in St. Louis. We note that this baseline is meant to illustrate how controlled testbed settings within an office environment may potentially be very different from real home environments; it is not meant to be a comprehensive study of office environments.

Specifically, this study addresses the following questions. (1) Is there a common area of the 2.4 GHz spectrum which is free in all apartments? (2) Does spectrum usage change with time? (3) Do residential settings have similar spectrum usage properties as office settings? (4) Is Channel Occupancy Temporally Correlated? (5) Is 802.11 the dominant interferer in residential environments?

A. Experimental Methodology

We are primarily interested in the spectrum usage between 2.400 GHz and 2.495 GHz, which are the parts of the spectrum used by the 802.15.4 standard for wireless sensor networks. To analyze this part of the spectrum, we collected energy traces using a laptop equipped with a Wi-Spy 2.4x spectrum analyzer [18]. The Wi-Spy sweeps across the 2.4 GHz spectrum approximately once every 40 ms, returning a signal strength reading (in dBm) for each of 254 discrete frequencies. We continuously collected energy traces for 7 days in each apartment during the residents' normal daily activities, as well as in an office in Bryan Hall. The resulting traces contained 15,120,000 readings for each of the 254 frequencies, resulting in a data set of approximately 2.5 GB per location. Figure 1 presents a histogram of the raw spectrum usage data in all seven datasets.

For the purposes of analysis, we apply a thresholding process like that employed in [14] to convert signal strength readings into binary values, with 0 denoting a channel being idle and 1 denoting a channel being busy. We found experimentally that a receive signal strength of -80 dBm is needed to create a high-quality link between a pair of Chipcon CC2420 radios; however, a noise level of -85 dBm or higher would be enough to induce packet drops on such a link. We discuss this experiment in more detail in Appendix B. Hence, throughout our analysis, we use -85 dBm as our threshold value to denote a busy channel. Using a constant threshold allows for a fair comparison across different apartments. While the specific numerical results of our analysis are dependent on the threshold, the trends and observations we make from these results should generally apply to other threshold values.

To assess the impact of ambient wireless signals on HANs, we aggregate the data from the Wi-Spy's 254 channels into the 16 channels used by the 802.15.4 standard; i.e., an 802.15.4 channel is deemed busy if any of its corresponding Wi-Spy channels are busy.

B. Is There a Common Idle Channel in Different Homes?

We first considered whether any 802.15.4 channel can be considered "clean" in all the tested residences. If such a channel exists, it could be used as a default, factory preset channel for HANs. For example, channel 26 is often assumed as a good default channel, because it does not overlap with the spectrum used by 802.11 in North America.

To determine this, we calculate the channel occupancy rate — i.e., the proportion of samples that exceeded the -85 dBm threshold — over all channels in the six apartments and the office building. High occupancy rates correspond to a large proportion of samples where interference could have caused packet loss on an otherwise high-quality link.

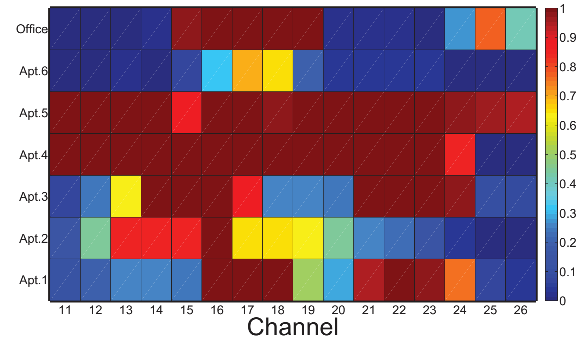


Fig. 2. Channel occupancy rate. X axis designates channels, Y axis designates experimental settings, and color represents the proportion of readings above the occupancy threshold.

Figure 2 plots the occupancy rate of each channel in each location. If we compare Figures 1 and 2, we can note various phenomena that prevent finding a common idle channel. For example, apartment 5 has a channel occupancy rate above 95% for 15 of its 16 channels. Notably, even channel 26 has a channel occupancy rate as high as 95.04%, contradicting the commonly-held assumption that channel 26 will be open. The uniformly high occupancy rate across channels is likely caused by a relatively high-power spread-spectrum signal across the whole 2.4 GHz spectrum, which appears in Figure 1 as a series of thin blue arches. Devices with such wireless footprints include Bluetooth transmitters, baby monitors, wireless speaker systems, and game controllers [19]. (Unfortunately, by the very nature of residential environments lacking central management of wireless devices, there is no way to be certain about the sources of some of these phenomena.)

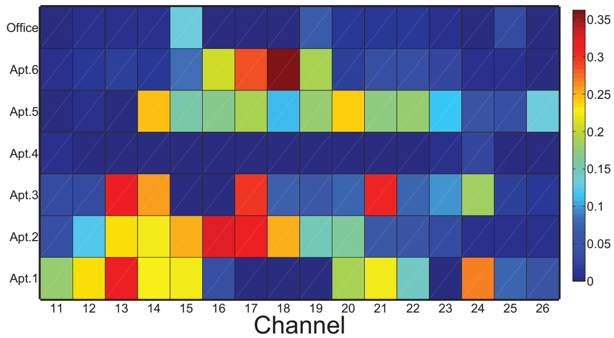
The only channel in apartment 5 with an occupancy rate below 95% is channel 15, which in contrast has an occupancy rate of 100.0% in apartments 3 and 4; thus, there is no common good channel in these apartments. In the case of apartment 3, channel 15 is unusable due to it intersecting with the middle of multiple 802.11 APs, represented as superimposed arcs on the left side of apartment 3's energy trace. For apartment 4, we see that only channels 25 and 26 have low occupancy rates; this phenomena is likely caused by the tall blue shape across most of apartment 4's energy trace, corresponding to some sporadic but high-power interferer.

Observation S1*: There may not exist a common idle channel across different homes, due to significant diversity in their spectrum usage patterns.*

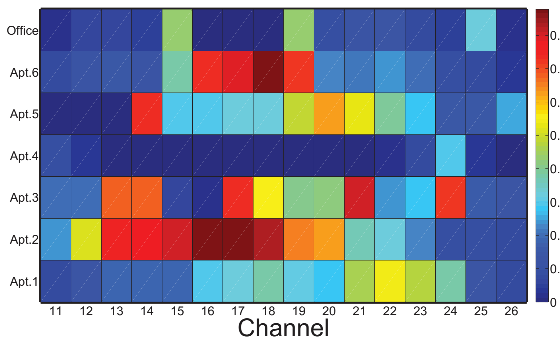
C. Does Spectrum Usage Change with Time?

We next explored whether the spectrum was stable in these residential settings. If spectrum is stable within a given apartment, it would be possible for a technician to pick a single "best" channel for the HAN at deployment time and expect it to work well over a long time period.

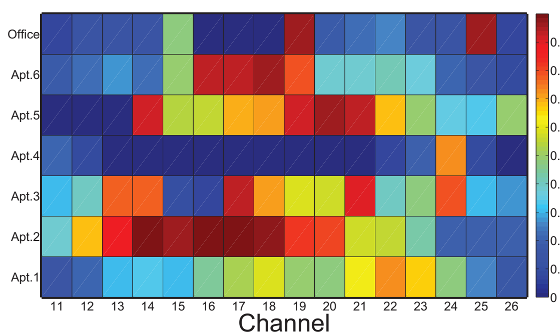
To determine this, we calculated the standard deviation in occupancy (σ) for each apartment and each channel. Figure 3



(a) Daily standard deviation



(b) Hourly standard deviation



(c) 5-minute standard deviation

Fig. 3. The standard deviation in channel occupancy rate at different timescales.

plots the standard deviation from day-to-day, from hour-to-hour, and for every 5 minutes. We see that channel conditions in most apartments can be quite variable, regardless of the timescale used. Except for apartment 4, σ ranges from 24.0%–36.2% for the worst channel at a daily timescale, from 27.4%–43.9% at an hourly timescale, and 36.4%–50.0% at a 5-minute timescale. Apartment 4 is stable across the spectrum on a day-to-day basis, with $\sigma \leq 2.5\%$ for all channels. However, even for this apartment, some variability emerges at shorter timescales, with channel 24 featuring a $\sigma = 14.9\%$ on an hourly timescale and $\sigma = 36.0\%$ at a 5-minute timescale.

We also note that the office had much lower variability than all but apartment 4. For example, at a daily timescale, 10 of the 16 channels had $\sigma < 1.0\%$, and the most highly-variable channel had σ of only 13.7%. Indeed, even at a 5-minute timescale, only three channels reveal significant variability; these three channels are at the edge of the campus 802.11g network (15), at the center of the same network (19), and at the center of the building's 802.15.4 testbed (25).

***Observation S2**: Spectrum occupancy in homes can exhibit significant variability over time, whether looking at timescales of days, hours, or minutes.*

D. Is Channel Occupancy Temporally Correlated?

Although channel occupancy is highly variable even on a timescale of minutes, there may nevertheless be temporal correlations in channel usage on even shorter time scales (e.g., packet-to-packet). To determine if such a correlation exists, we computed the conditional channel usage function ($CCUF$) for each channel in each apartment. For $k > 0$, $CCUF(k)$ is the conditional probability that k consecutive busy readings are followed by another busy reading; for $k < 0$, $CCUF(k)$ is the conditional probability that $|k|$ consecutive idle readings are followed by another idle reading.

Figure 4 plots the $CCUF$ for three apartments and four channels; results for other apartments and other channels are similar but omitted for space. For all channels and all apartments, $CCUF$ rapidly stabilizes to $\geq 80\%$ within 10 minutes, indicating that a small channel-assessment window is sufficient to estimate channel condition with high probability. Moreover, the CCUF curve remains relatively flat after increasing to $\geq 80\%$. This indicates that longer windows (of 20 to 40 minutes) have minimal benefit for predicting channel conditions.

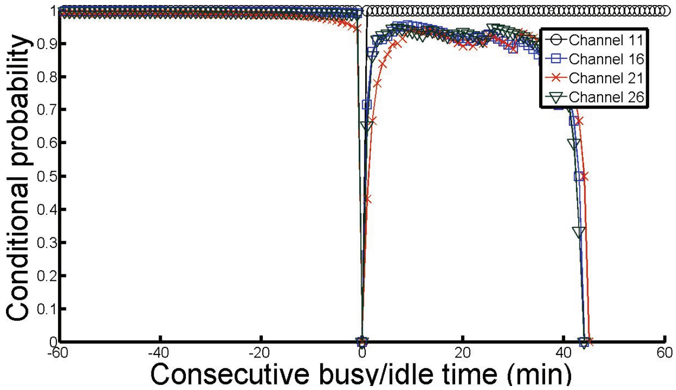
***Observation S3**: A short ($\leq$ 10 minute) channel assessment window is sufficient for estimating channel conditions with high probability; larger time windows provide minimal benefit.*

E. Is Wi-Fi the Dominant Source of Spectrum Usage?

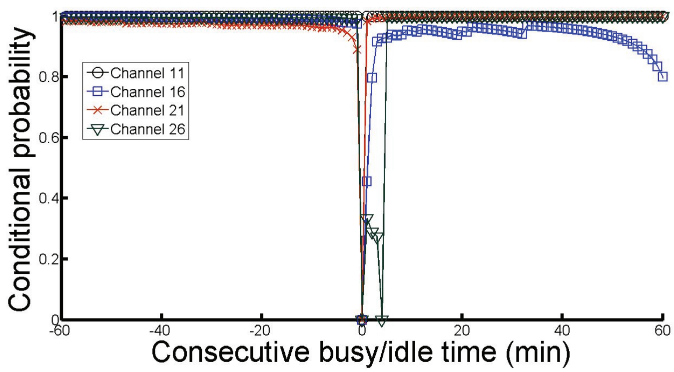
Because of Wi-Fi's ubiquity and relatively high transmission power, it is often treated as a dominant interferer. Thus, our final analysis of our passive spectrum data is to identify whether there are other significant sources of interference. If Wi-Fi is indeed the dominant interferer in residential settings, then HANs could leverage solutions which are specifically designed to avoid interference from Wi-Fi networks (e.g., [2]).

A visual inspection of Figures 1 and 2 suggests other important interferers besides Wi-Fi. Wi-Fi APs have a distinctive radiation pattern that manifests in Figure 1 as arcs the width of several 802.15.4 channels. For example, the energy traces for apartment 3 show two distinct arcs that are likely caused primarily by 802.11 APs configured to two different channels. Referring to Figure 2, we see that these areas of the spectrum are indeed highly occupied. However, looking at the energy trace for apartment 5, we see evidence of Wi-Fi APs on only part of the spectrum; nevertheless, the channel occupancy rate is above 95% for nearly the entire spectrum. This phenomena can be explained by the series of blue arcs across the 2.4 GHz spectrum, which indicate sporadic but high-powered spread-spectrum transmissions. (Again, by the nature of the environment, we cannot be certain about the source of this noise pattern.)

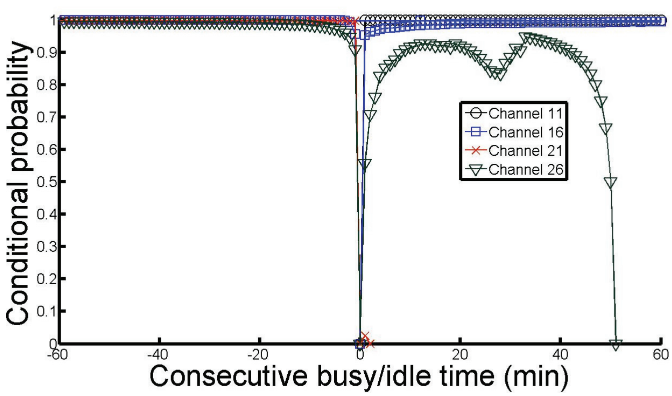
To quantify the relative impact of Wi-Fi, we leverage a feature of the Wi-Spy which logs the service set identifier



(a) Apartment 1



(b) Apartment 3



(c) Apartment 5

Fig. 4. Conditional channel usage functions ($CCUF$s) in three different apartments. The X axis indicates consecutive busy or idle readings, where negative values represent consecutive idle readings and positive values represent consecutive busy readings. The Y axis provides the probability that the channel is currently idle/busy given x prior time slots which were all idle/busy.

(SSID) and 802.11 channel of all visible 802.11 access points (APs)[1]. Based on this data, we are able to divide the 802.15.4 channels in each apartment into two groups: those that overlap with 802.11 APs detectable from the corresponding apartment, and those that do not. We then calculated the average channel occupancy rate for each of the two groups in each apartment, as shown in Figure 5.

In most of the apartments, there is a clear distinction between the overlapping and non-overlapping channels. For

[1]Although many APs may be configured not to broadcast their SSID, we have observed that the Wi-Spy software can still identify these "hidden" access points in practice.

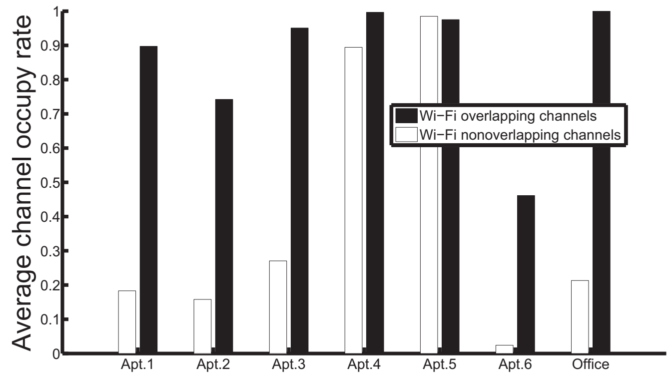


Fig. 5. A comparison of the average channel occupancy rate between channels that overlap with Wi-Fi and channels that do not.

example, apartment 1 has an average occupancy rate of 89.7% for the overlapping channels compared to 18.3% for the non-overlapping ones. But strikingly, we find that the non-overlapping channels are not *always* significantly more idle than those which overlap with Wi-Fi APs. In apartments 4 and 5, the channel occupancy rates of the non-overlapping channels are similar to the overlapping ones; indeed, in apartment 5, the non-overlapping channels are slightly more occupied on average than the overlapping ones. This observation can have important implications on the design of HANs, in that solutions specifically designed to deal with Wi-Fi interference may not be effective in all residential environments.

Observation S4*: While Wi-Fi is an important source of interference in residential environments, other interferers can also be non-negligible contributors to spectrum occupancy.*

IV. Multi-Channel Link Study

In this section, we present a multi-channel link study in homes. The spectrum study presented in Section III focuses on characterizing the ambient wireless environment in homes. While link quality can be significantly influenced by interference from existing wireless signals, other factors such as signal attenuation and multi-path fading due to human activities can also impact the reliability of low-power wireless links. Our link study *directly* evaluates the multi-channel behavior of HANs by actively sending packets between motes equipped with 802.15.4 radios.

Specifically, this study addresses the following questions. (1) Can a HAN find a single persistently reliable channel for wireless communication? (2) If a good channel cannot be found, are packet retransmissions sufficient to deal with packet loss? (3) If no single channel can be used for reliable operation, can the network exploit channel diversity to achieve reliability? (4) Do channel conditions exhibit cyclic behavior over time? (5) Is reliability strongly correlated among different channels? (6) How effective is increasing transmission power for improving link reliability?

A. Experimental Methodology

For this active study, we carried out a series of experiments in ten real-world apartments in different neighborhoods, as listed in Table II. (Due to the participating residents moving,

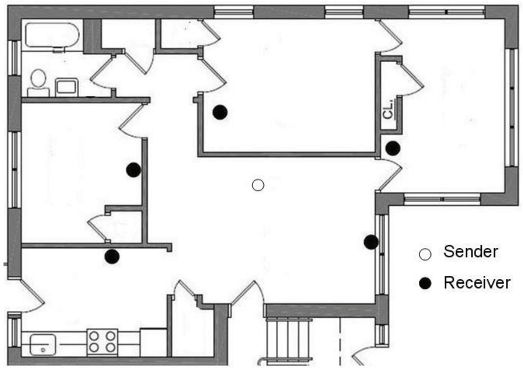


Fig. 6. Floor plan of an apartment used in the study.

TABLE II
THE SETTINGS AND DATES WHERE THE LINK DATA WAS COLLECTED

	Begin Date	End Date
Apt. 1	Sept. 30, 2009	Oct. 1, 2009
Apt. 2	Sept. 30, 2009	Oct. 1, 2009
Apt. 3	Oct. 3, 2009	Oct. 4, 2009
Apt. 4	Oct. 3, 2009	Oct. 4, 2009
Apt. 5	Sept. 30, 2009	Oct. 1, 2009
Apt. 6	Sept. 12, 2009	Sept. 13, 2009
Apt. 7	Oct. 3, 2009	Oct. 4, 2009
Apt. 8	Sept. 18, 2009	Sept. 19, 2009
Apt. 9	Oct. 6, 2009	Oct. 7, 2009
Apt. 10	Oct. 6, 2009	Oct. 7, 2009

only four of the apartments in this study are the same as those instrumented in the spectrum study.) Figure 6 shows an example floor plan of one of the apartments used in the study; a similar topology was deployed in the other apartments. Each experiment was carried out continuously for 24 hours with the residents' normal daily activities.

Our experiments were carried out using networks of Tmote Sky and TelosB [20] motes. Each mote is equipped with an IEEE 802.15.4 compliant Chipcon CC2420 radio [21]. IEEE 802.15.4 radios like the CC2420 can be programmed to operate on 16 channels (numbered 11 to 26) in 5 MHz steps. We leverage the CC2420's Received Signal Strength (RSS) indicator in our experiments to measure the signal power of environmental noise. Our experiments are written on top of the TinyOS 2.1 operating system [22] using the CC2420 driver's default CSMA/CA MAC layer.

We measure the packet reception ratio (PRR), defined as the fraction of transmitted packets successfully received by the receiver. PRR is not only a direct indicator of link reliability, but also closely related to other important QoS metrics such as latency and energy consumption. To measure the PRR of all channels at a fine granularity, we deployed a single transmitter node in each apartment which broadcast packets over each of the 16 channels. Specifically, the transmitter sent a batch of 100 consecutive packets to the broadcast address using a single wireless channel, then proceeded to the next channel in a round robin fashion. The process of sending 16 batches of 100 packets repeated every 5 minutes. The recipient nodes record the PRR over each batch of packets into their onboard flash memory. The use of a single sender and multiple recipients allowed us to test multiple links simultaneously while avoiding interference between senders. (Inter-link interference is not a major concern in many HANs due to the low data rates that are typically employed; for example, 1 temperature reading every 5 minutes is sufficient for an HVAC system to control ambient temperature.)

It is worth noting that HAN applications such as smart energy require persistent, long-term reliability. Transient link failures are non-negligible — these failures represent periods where parts of a household may experience sporadic service or no service at all (e.g., changing the thermostat may have no effect until a wireless link is restored minutes or hours later). Hence, our study looks not just at the average PRR of each link but at its entire range of performance, including those outliers that indicate temporary failures.

In [12], links with a PRR below 10% were found to be poor-quality, and links with a PRR between 10% and 90% to be bursty. Accordingly, we use a PRR of 90% throughout this section as a threshold to designate links as "good" or "reliable".

B. Is There a Persistently Good Channel?

We first analyzed our data from the perspective of finding a single, persistently good channel across all of the tested apartments. Again, if a common good channel exists across all apartments, then it could be used as a preset default channel for HANs. For this analysis, we grouped the data from all links in all apartments together and then subdivided it by channel. Figure 7 presents a box plot of the PRR in 4 channels in all the apartments, where the PRR has been calculated over 5-minute windows. (The remaining 12 channels exhibit similar behavior and are omitted for reasons of clarity.) From this figure, we see significant variations in PRR on the same channel when moving from apartment to apartment. For example, channel 11 achieves a median PRR $> 90\%$ in apartments 1, 3, and 9, albeit with many outliers; however, the same channel has a near-zero median PRR in apartment 2. Only channel 26 has a median PRR above the 90% threshold in all apartments.

We also see significant variations in PRR from channel to channel, even in the same apartment. Strikingly, these variations even affect channel 26, which is often considered an open channel since it is nominally outside the 802.11 spectrum in North America. Although channel 26 achieves uniformly high *median* PRR in all apartments, there are numerous points during the experiment where the PRR falls much lower. For example, apartment 9 has a 25th percentile PRR of 0.0%, indicating a substantial portion of the experiment where the channel experienced total link failure.

Further analysis showed that there is not likely to be a single good channel across multiple links in the *same* apartment. We regrouped the PRR data, this time looking at the performance of each link/channel pair individually. Figure 8 presents a box-plot of the PRR for all five links within one apartment; again, for reasons of clarity, we present the data from only 4 of the 16 channels. We observe that the median PRR on a given channel varies greatly across links, particularly for outlier points. Again, this variation even affects channel 26: all five links have at least one outlier below the 90% threshold, and four links have numerous outliers below the threshold. Link 1 shows particularly high variance on channel 26, with a

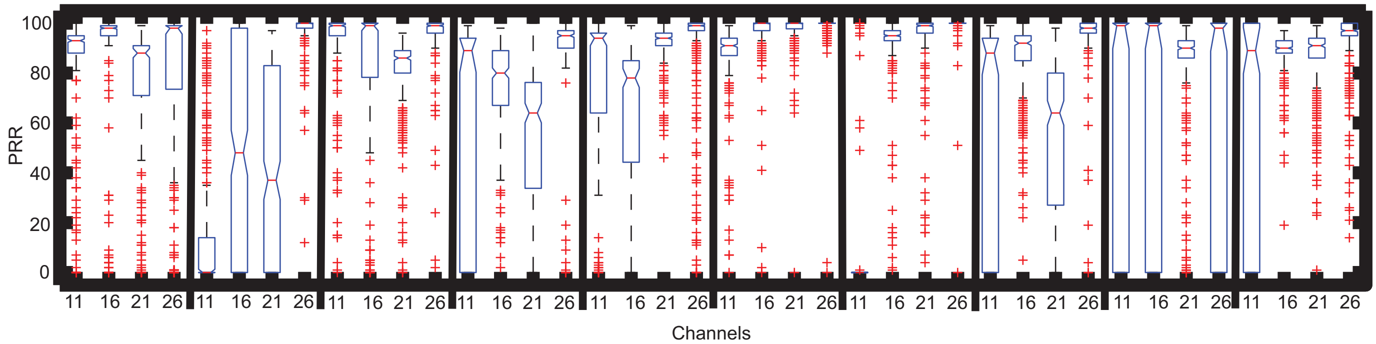


Fig. 7. Box plot of the PRR for four channels in all ten apartments, calculated over 5-minute windows. Central mark in box indicates median; bottom and top of box represent the 25th percentile (q_1) and 75th percentile (q_2); crosses indicate outliers ($x > q_2 + 1.5 \cdot (q_2 - q_1)$ or $x < q_1 - 1.5 \cdot (q_2 - q_1)$); whiskers indicate range excluding outliers. Vertical lines delineate apartments.

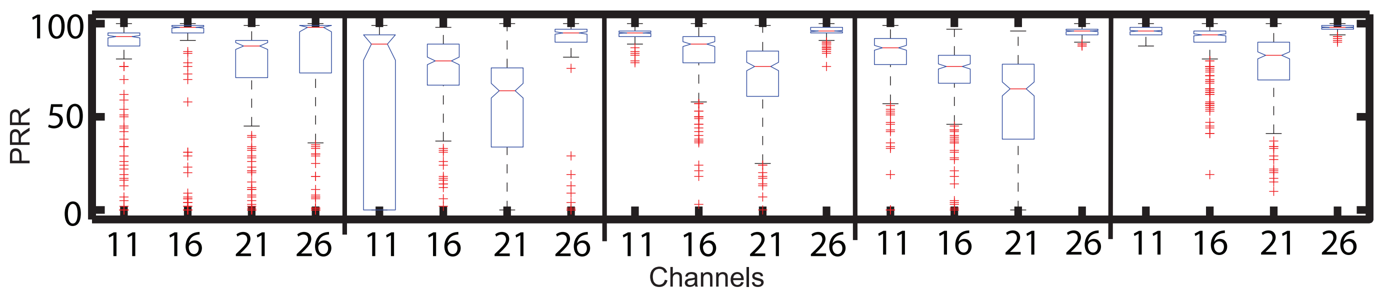


Fig. 8. Box plot of the PRR of five different links in the same apartment on four channels, calculated over 5-minute windows. Vertical lines delineate links.

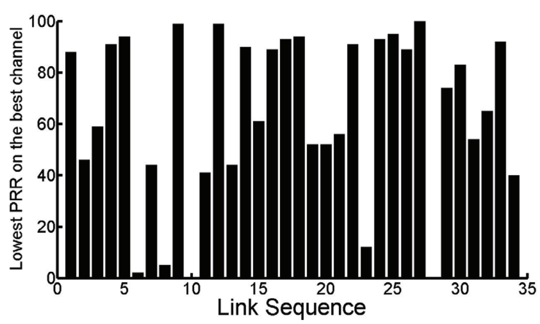


Fig. 9. The lowest PRR observed on each link's most reliable channel.

25th-percentile PRR of only 73.5% in spite of a 98.0% median PRR. We also note that *all four* channels had numerous outliers below a PRR of 10%; that is, any single channel selection would have led to at least one link experiencing near-total disconnection at some point during the day.

Notably, each link had at least one channel with a high median PRR and low variance. For instance, as shown in Figure 8, link 1 shows a particularly high quality on channel 16 with a 99.3% median PRR and a variance less than 10%, while this link presents a high variance on channel 26, with a 25th-percentile PRR of only 73.5% in spite of a 98.0% median PRR. This indicates that all the links in our study are relevant to HAN applications given proper selection of channels.

Observation L1*: Link reliability varies greatly from channel to channel.*

Looking at the entire dataset across all apartments, we found that few links were able to achieve a consistently high PRR, even on their most reliable channels. Figure 9 plots the lowest PRR observed on each link's most reliable channel: i.e., for the channel which achieves the highest average PRR over 24 hours, we plot the worst PRR out of all the 100-packet batches. Notably, only 12 of the 34 links in our dataset are able to persistently reach the 90% PRR threshold on even their best channel. Indeed, even lowering the threshold to 70%, more than half the links in our dataset would still have no persistently good channel.

Observation L2*: Link reliability varies greatly over time, even within the same channel. Hence, even when selecting channels on a per-link basis, there is not always a single persistently reliable channel.*

C. Is Retransmission Sufficient?

Because retransmissions are effective in alleviating transient link failures, we next analyze whether it would be effective in alleviating the link failures observed in our experimental traces. However, we found that retransmissions alone are insufficient in residential environments, due to the bursty nature of the packet losses.

Figure 10 illustrates this problem with the cumulative probability density (CDF) of consecutive packet drops for all links on four channels. Specifically, we measured consecutive packet losses *within each batch* of 100 packets; we did not include inter-batch losses due to the 5-minute gap between batches. Even on the best channel (channel 26), up to 85 consecutive packet drops were observed, and 10% of link failures lasted for more than 60 consecutive packets. On the remaining three channels, bursts of more than 95 consecutive packet drops were observed.

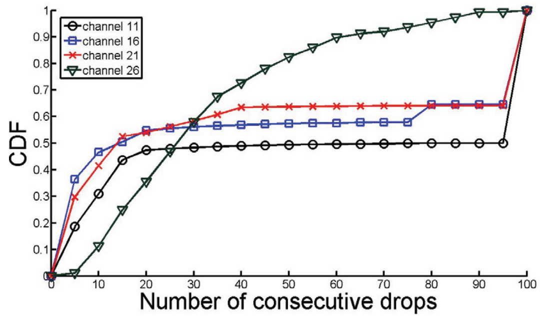
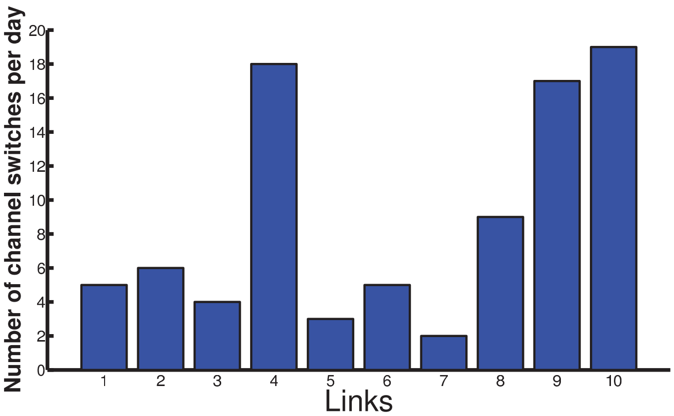
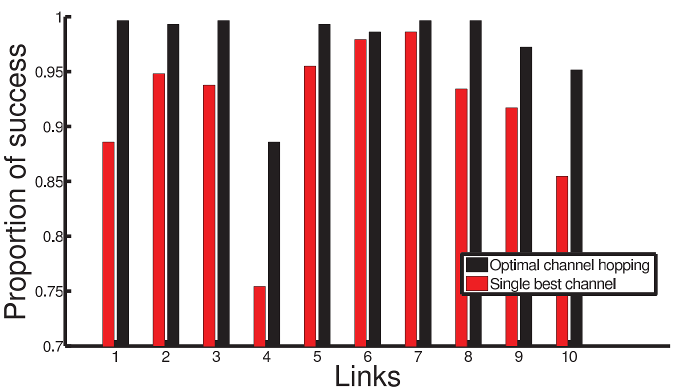


Fig. 10. CDF of number of consecutive drops.



(a) Minimum number of channel hops required; one link randomly selected per apartment.



(b) The proportion of windows where the PRR threshold was met.

Fig. 11. Retrospective channel-hopping analysis in different apartments.

Observation L3*: Retransmissions alone are insufficient for HANs due to the burstiness of packet losses.*

D. Is Channel Diversity Effective?

Our analysis above indicates that using a single channel is often not acceptable when long-term reliability must be maintained. Thus, a natural question to ask is whether it is feasible to exploit channel diversity to achieve reliability in situations where single channel assignments are not practical.

To understand the potential for channel hopping, we retrospectively processed our dataset to find the minimum number of channel hops needed to maintain a 90% PRR threshold using a greedy algorithm. We prove the optimality of the algorithm in Appendix A. Figure 11(a) plots the number of channel hops required for 10 links in the dataset, one randomly selected from each apartment. We find that relatively few channel hops are needed to maintain link reliability; in no case is more than 20 hops required per day.

We note that there are periods where none of the 16 channels meet the PRR threshold, and hence no channel hopping occurs during these times. Nevertheless, channel-hopping can significantly reduce the number of link failures compared to picking the single "best" channel (i.e., that with the highest average PRR). Figure 11(b) compares the proportion of windows which meet the 90% threshold under two retrospective strategies: an ideal channel-hopping strategy that maintains the PRR threshold with the minimum number of channel hops, and a strategy that fixes each link to its single "best" channel with the highest average PRR. (Note that both strategies make decisions based on the entire data trace retrospectively, and hence cannot be employed at run time; they are chosen here to analyze the *potential* benefit of channel hopping.) In some cases, the improvements achieved by channel hopping are modest. For example, links 6 and 7 only achieve a 0.7% and 1.0% higher success rate under channel hopping, largely because their success rates were already high without channel hopping. However, in most cases, we find notable improvements in link success. For example, 6 out of the 10 links experience at least 5% fewer failures with channel hopping than with their single best channel; and links 1 (11.0%) and 4 (13.1%) have substantially higher success rates with channel hopping.

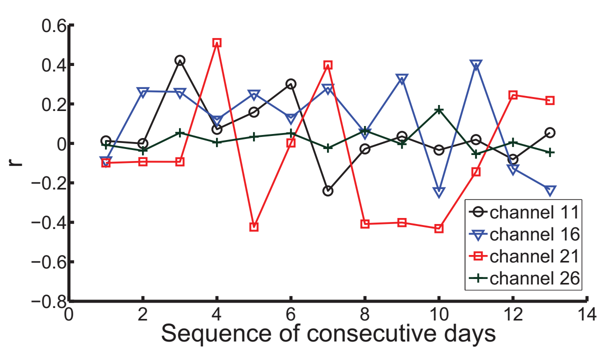
Channel hopping has been proposed in industry standards as a means for improving wireless link reliability, including established standards like Bluetooth's AFH [23] and newer standards such as WirelessHART's TSMP [24] and the forthcoming IEEE 802.15.4e [25]. The results of our analysis confirm that this feature is indeed beneficial for maintaining link reliability in challenging residential environments.

Observation L4*: Channel hopping is effective in alleviating packet loss due to channel degradation. Infrequent channel hopping can effectively maintain reliable communication.*

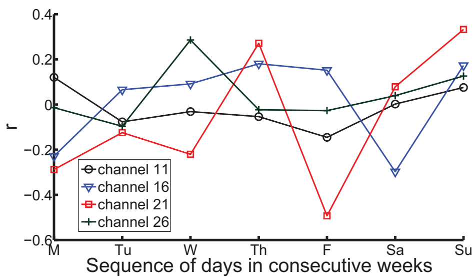
E. Can Hopping be Scheduled Statically?

Because channel quality varies over time, we next explored whether it exhibits cyclic properties (e.g., due to recurrent human activities and schedules). If so, then channel-hopping could be implemented in a lightweight fashion by generating a static channel schedule for each environment. To perform this comparison, we carried out an extended experiment using same setup in one apartment over a period of 14 days. We then calculated the Pearson product-moment correlation coefficient (PMCC) [26], a common measure of dependence between two quantities, as r. Intuitively, r values near -1 or 1 indicate strong correlation, while values near 0 indicate independence.

Figure 12(a) plots r for PRRs calculated at the same times on subsequent days (e.g., 4 PM on Monday vs. 4 PM on Tuesday). Figure 12(b) compares the PRR during the same time in consecutive weeks (e.g., 4 PM on Monday vs. 4 PM on the next Monday). $|r|$ is almost always smaller than 0.4, regardless of the channel used; this indicates that there is no obvious correlation between consecutive days or consecutive weeks. Therefore, channel-hopping decisions must be made *dynamically* based on channel conditions observed at runtime.



(a) PMCC of PRRs during the same time on consecutive days.



(b) PMCC of PRRs during the same time in consecutive weeks.

Fig. 12. The Pearson's product correlation coefficient (PMCC) comparing the PRR at the same time on consecutive days or weeks.

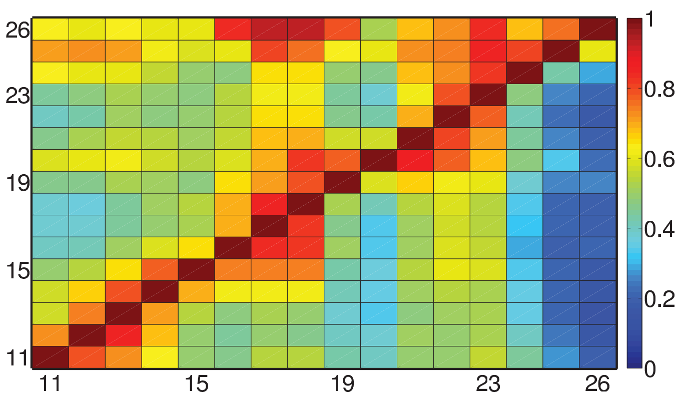


Fig. 13. Correlation of channel reliability. The X and Y axes indicate channels; the color indicates the probability that channel x's PRR $< 90\%$ when channel y's PRR $< 90\%$.

***Observation L5**: Channel conditions are not cyclic, so channel-hopping decisions must be made dynamically.*

F. How Should New Channels be Selected?

Since channel-hopping must be performed dynamically, it is important to pick a good strategy for selecting new channels when the current channel has degraded beyond use. For the purposes of this analysis, we studied the effect of *channel distance* (the absolute difference between channel indices) on the *conditional probability* of channel failure (the probability that channel x is below the PRR threshold when channel y is also below the threshold).

We observe that not all channels are equally good candidates for channel hopping: from Figure 13, we can see that performance is strongly correlated across adjacent channels.

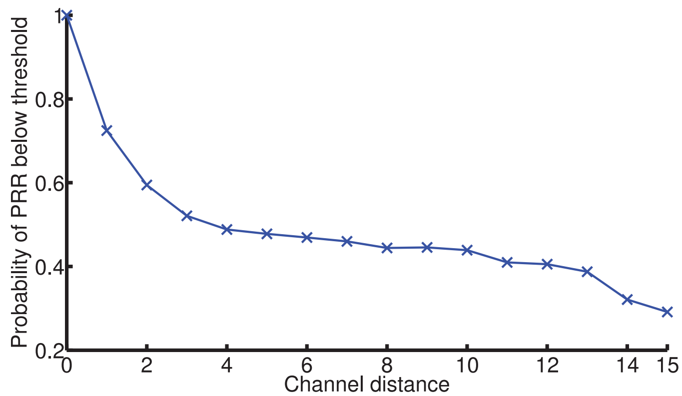


Fig. 14. Correlation of channel reliability as a function of channel distance.

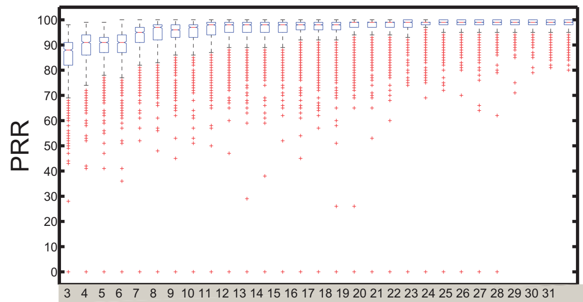
For instance, when channel 20 has poor PRR ($< 90\%$), there is a probability greater than 76.8% that channels 18, 19, 21, and 22 also suffer from poor PRR. In Figure 14, we plot the conditional probability of link failure as a function of channel distance. We observe that this probability can be as high as 70% between neighboring channels and 60% between every other channel, but drops off as channel distance increases. When facing a failing channel, a probabilistic approach on new channel selection should be used to avoid jamming the new channel. Designing a channel selection algorithm is out of the scope of this paper. The focus of this paper is on the empirical studies that provide ground truth and insights for designing and managing HANs. We have since developed a practical channel selection scheme [27] based on the findings presented in this paper.

***Observation L6**: Reliability is strongly correlated among adjacent channels; a device should probabilistically select a new channel that is at least three channels away from the failing channel.*

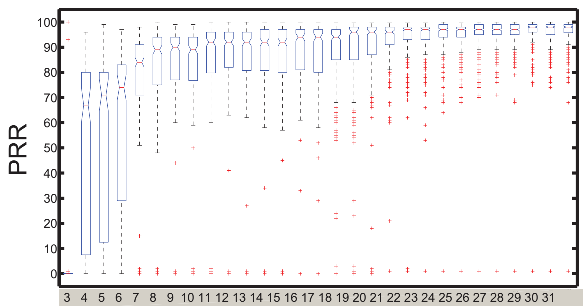
G. How effective is increasing transmission power for improving link reliability?

As an orthogonal approach to channel hopping, transmission power control [28] [29] aims to maintain link quality by dynamically adjusting transmission power. We evaluate transmission power control's potential for maintaining channel reliability through a microbenchmark experiment. For this evaluation, we repeat the same experimental setup used in the previous experiments, except using multiple transmission powers. Specifically, the transmitting node was configured to send 100 consecutive packets at a given transmission power; this was repeated over 29 of the CC2420's 31 distinct power settings in a round-robin fashion. (The two lowest power settings were excluded from this experiment, as the manufacturer has indicated that the CC2420's output power is unstable at these settings [30].)

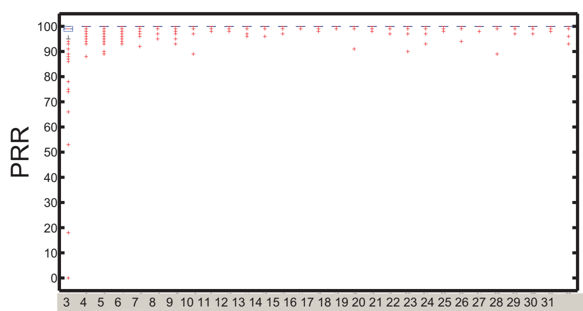
Figure 15 plots the PRR on three different channels in one apartment; results for other apartments and other channels are similar but omitted for space. We observe that adjusting transmission power can indeed be effective at improving link quality. Figure 15(b) presents the PRR from the worst channel (18): on this channel, the median PRR increases from 68% to 91% when the transmission power level increases from



(a) Channel 11



(b) Channel 18



(c) Channel 26

Fig. 15. Box plot of the PRR of a link over 29 different transmission power levels.

4 to 11, and further increases to 95% at the maximum transmission power (level 31). Nevertheless, the impact of switching channels may be even more pronounced, as seen by comparing Figure 15(a) through 15(c). By changing to channel 26, a link on channel 11 or 18 could have achieved a comparable increase in PRR while remaining at power level 3. Moreover, switching channels can be significantly less expensive than increasing transmission power: for example, on the CC2420, increasing the transmission power can increase the radio's current consumption from as low as 8.5 mA to as high as 17.4 mA [30]. Hence, leveraging channel diversity *in conjunction* with transmission power control can potentially result in significant energy savings.

Observation L7*: Increasing transmission power may be effective for maintaining channel reliability, but is potentially expensive. Combining channel diversity with transmission power control is a promising strategy for controlling energy consumption while maintaining network reliability.*

V. Conclusion

HANs based on wireless sensor network technology represent a promising communication platform for emerging home automation applications such as smart energy. These emerging applications often impose stringent network management requirements in terms of network reliability, which are made challenging by the complex and highly variable wireless environments in typical residential environments. This paper presents an empirical study on the performance of HANs in real-life apartments, looking both at passive spectrum analysis traces and an active probing link study. The observations made in our study highlight the significant challenges that face HAN applications for achieving acceptable network management in residential settings. Nevertheless, our observations also suggest that these challenges may be tamed through the judicious use of channel diversity. Specifically, we may distill our findings into set of key design guidelines for developing reliable HANs:

1) Channel selection can have a profound impact on HAN reliability. Channel selection cannot be simply relegated a static channel assignment, whether made at the factory or at deployment time. (S1, L1, L2)
2) Retransmissions alone cannot always compensate for a poor-quality channel. (L3)
3) Short time channel assessment is effective in estimating channel condition, since larger time window of measurement cannot bring more benefit. (S3)
4) Although Wi-Fi is a major source of channel usage, other wireless technologies may also contribute significantly to channel usage. Solutions which target a single interfering technology are not always sufficient in residential environments. (S4)
5) Reliable communication can be maintained through infrequent channel hopping. (L4)
6) Channel hopping cannot be performed based on a static, cyclic schedule. (L5) Instead, channel-hopping decisions should be made dynamically based on conditions observed at runtime. (S2, L2)
7) A device should probabilistically select a new channel that is at least three channels away from the failing channel. (L6)
8) Increasing transmission power may be effective for maintaining channel reliability, but is potentially expensive. Combining channel diversity with transmission power control is a promising strategy for controlling energy consumption while maintaining network reliability. (L7)

We believe that our findings and insights will provide general design guidelines and impact the development of HANs that are gaining increasing importance with the emergence of smart energy as the "killer app" for wireless sensor networks.

Acknowledgment

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APPENDIX A
OPTIMAL CHANNEL-HOPPING SCHEDULE

In our multi-channel link study, the transmitter sent a batch of 100 consecutive packets to the broadcast address using a single wireless channel, then proceeded to the next channel in a round robin fashion (16 channels in total). The process of sending 16 batches of 100 packets repeated every 5 minutes. The recipient nodes recorded the PRR over each batch of packets, calculated a binary value for whether the PRR meets or misses the 90% threshold, and then saved the value into their onboard flash memory. For each recipient, our dataset includes 16 binary sequences of channel quality. To understand the potential for channel hopping, we design a greedy data analysis algorithm to retrospectively process our dataset to find an optimal channel-hopping schedule that meets the PRR threshold (whenever possible) with a minimum number of channel hops. We describe the algorithm and prove the optimality of the resulting channel-hopping schedule in this Appendix.

We initially pre-process these channel quality sequences to identify any infeasible time windows. An infeasible time window is a time window in which none of the channels can meet the PRR threshold. We remove the binary values in these infeasible time windows from the channel quality sequences since there is no need to switch channels. The pre-processing makes sure that there must exist at least a *1* among the channel quality sequences in any time window.

Algorithm 1 Channel-Hopping Schedule Analysis Algorithm

Input: $S = \{s_{m1}s_{m2}...s_{mn} | m \in [1, 16]\}$ //binary sequences of 16 channels with length of n.
Output: ϕ //set of sequences of consecutive *1*s.

```
1: Initialize φ = ∅, t = 1;
2: repeat
3:    Find the longest sequence of consecutive 1's in S,
      which begins at s_yp and ends at s_yq where p = t and
      y ∈ [1, 16];
4:    Set t = q + 1, φ = φ ∪ {s_yp...s_yq}
5: until t>n
```

The pre-processed channel sequences ($\{s_{m1}s_{m2}...s_{mn} | m \in [1, 16]\}$ where n is the length of sequences) are then input into the data analysis algorithm shown in Algorithm 1. The algorithm continuously searches for the longest sequence of consecutive *1*s (i.e., windows of uninterrupted reliability) among all the channels until reaching the end of the dataset. The output of the algorithm is a set of sequences of consecutive *1*s ($\{s_{yi}s_{yi+1}...s_{yj} | y \in [1, 16], i \in [1, n], s_{yi} = s_{yi+1} = ... = s_{yj} = 1\}$). These output sequences can be used to create a channel hopping schedule by hopping to channel y at time window i and hop away at time window $j + 1$.

To clarify the proof, we define a problem P as a set of pre-processed sequences of channel qualities as input and a solution ϕ as a set of output sequences of consecutive *1*s. An optimal solution is defined to be a solution with minimum number of channel hops ($min(|\phi|)$) with a condition of the number of nonoverlapping *1*s is equal to n. We prove the algorithm's optimality by proving the three properties of greedy algorithm and then performing induction as below:

Greedy Choice Property: Let $s_{a1}...s_{ai}$ ($a \in [1, 16]$) be the first sequence of consecutive *1*s chosen by the greedy data analysis algorithm. There exists an optimal solution containing $s_{a1}...s_{ai}$.

Proof: Let ϕ^* be any optimal solution with x channel hops and n nonoverlapping *1*s.

If $s_{a1}...s_{ai} \in \phi^*$, the property is proven.

Otherwise, let $s_{b1}...s_{bj}$ ($b \in [1, 16]$) be the first sequence of consecutive *1*s in ϕ^*. Construct a new solution ϕ from ϕ^* by discarding $s_{b1}...s_{bj}$ and adding $s_{a1}...s_{ai}$. The rest of the solution did not change. $s_{b1}...s_{bj}$ and $s_{a1}...s_{ai}$ begin at the same place (time window 1) but $s_{a1}...s_{ai}$ has the longer consecutive sequence of *1*s; hence all bits equal to *1* in ϕ^* will be the same in the new solution ϕ. Thus the number of nonoverlapping *1*s in ϕ is not smaller than the number in ϕ^*. Since the number cannot exceed n, the number of nonoverlapping *1*s in ϕ is n. Moreover, the number of channel hops in ϕ is not more than x in ϕ^*, so ϕ is still optimal.

Inductive Structure Property: After making the greedy choice $s_{a1}...s_{ai}$, we are left with a subproblem with a smaller length of sequences, and with no external constraints.

Proof: We assume the sequences selection problem is P and get the subproblem $P^{'}$ by removing the first greedy choice $s_{a1}...s_{ai}$. Now any feasible solution to subproblem $P^{'}$ can be combined with $s_{a1}...s_{ai}$, since $s_{a1}...s_{ai}$ has longest consecutive *1*s beginning at time window 1. Any optimal solution for subproblem $P^{'}$ combing with this sequence $s_{a1}...s_{ai}$ is a feasible solution for the whole problem P.

Optimal Substructure Property: If $\phi^{'}$ is an optimal solution to subproblem $P^{'}$, then $\phi^{'} \cup \{s_{a1}...s_{ai}\}$ is an optimal solution to P.

Proof: Let $\phi^{'}$ be an optimal solution to subproblem $P^{'}$. Then $\phi = \phi^{'} \cup \{s_{a1}...s_{ai}\}$ is a feasible solution to P because of Inductive Structure Property. Now suppose ϕ is not optimal. Let ϕ^* be an optimal solution also picking $s_{a1}...s_{ai}$ because of Greedy Choice Property. Then $\phi^* - \{s_{a1}...s_{ai}\}$ is a feasible solution for $P^{'}$ with $|\phi^*| - 1 > |\phi| - 1 = |\phi^{'}|$, contradicting optimality of $\phi^{'}$. Conclude that ϕ must be optimal.

With the proof of three properties, we now prove the optimality of the algorithm by induction on size of problem P.

Basis Step: if P has size 1, greedy solution is trivially as good as optimal (it picks the only sequence s_{a1}).

Inductive Assumption: Suppose the solution is optimal for problem instances of size $< k$.

Consider an instance P of size k. Let $P^{'}$ be subproblem obtained from P after making first greedy choice, and let $s_{a1}...s_{ai}$ be the greedy choice. Observe that $|P^{'}| < |P|$. By Inductive Assumption, algorithm optimally solves $P^{'}$. Let $\phi^{'}$ be the solution it produces. Inductive Structure Property guarantees that $\phi^{'} \cup \{s_{a1}...s_{ai}\}$ is a feasible solution. Moreover, Optimal Substructure Property guarantees that $\phi^{'} \cup \{s_{a1}...s_{ai}\}$ is an optimal solution for P. Hence, algorithm optimally solves P of size k.

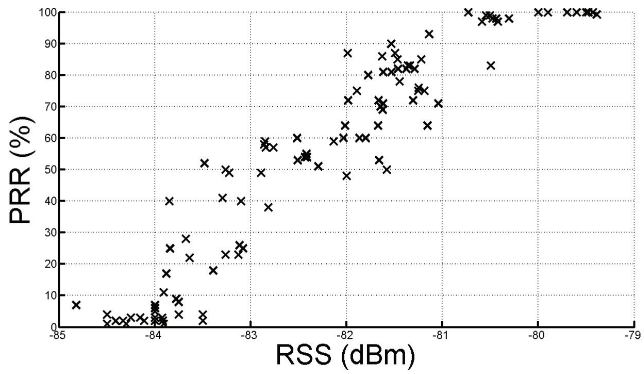

Fig. 16. Relationship between RSS and PRR, as measured experimentally.

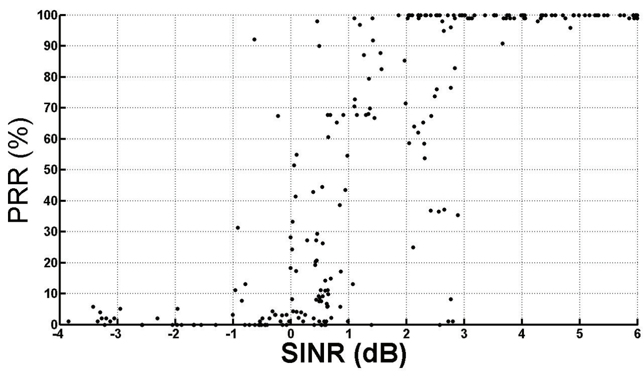

Fig. 17. Relationship between SINR and PRR, as measured experimentally.

Appendix B
Threshold Selection

According to wireless communication theory, a packet can be successfully decoded if the signal-to-interference-plus-noise-ratio is above a certain threshold [31] [32]. To determine the threshold used to decide if a channel is busy or idle in our spectrum study, we study the impact of interference on packet reception empirically as follows. Let N_{dBm} be the total signal strength of the noise and interference measured at the receiver. Let RSS_{dBm} be the total signal strength associated with an incoming packet by the CC2420 radio, including the packet, noise, and interference. We can calculate the signal-to-interference-plus-noise-ratio ($SINR_{dB}$) as:

$$SINR_{dB} = 10log_{10}\frac{10^{RSS_{dBm}/10} - 10^{N_{dBm}/10}}{10^{N_{dBm}/10}} \tag{1}$$

From Eq. (1), we get

$$10^{SINR_{dB}/10} = \frac{10^{RSS_{dBm}/10} - 10^{N_{dBm}/10}}{10^{N_{dBm}/10}} \tag{2}$$

$$10^{N_{dBm}/10} = \frac{10^{RSS_{dBm}/10}}{10^{SINR_{dB}/10} + 1} \tag{3}$$

Figure 16 plots the correlation between receive signal strength and PRR as obtained experimentally between a pair of TelosB motes at varying distances and transmission powers. We see that $RSS_{dBm} = -80$ dBm places the link outside of the transitional "gray" region; similar results were observed in [12], [33]. Following the methodology in [32], we estimated the relationship between SINR and PRR experimentally using a pair of TelosB motes and a third interfering mote operating at varying distances and transmission powers. We plot this relationship in Figure 17. A threshold of $SINR_{dB} = 4$ dB places the link outside of the transitional region; this result matches experiments performed in [32]. Therefore, we get

$$10^{N_{dBm}/10} = \frac{10^{-80dBm/10}}{10^{4dB/10} + 1} \tag{4}$$

$$N_{dBm} = -85 \text{ dBm} \tag{5}$$

Thus we choose -85 dBm as the threshold to distinguish a channel as busy or idle.

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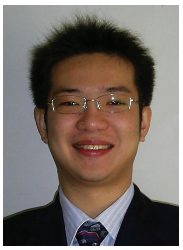

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