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Energy profiling in practical sensor networks: Identifying hidden consumers

James Brusey John Kemp Elena Gaura Ross Wilkins Mike Allen

***Abstract*—Reducing energy consumption of wireless sensor nodes extends battery life and / or enables the use of energy harvesting and thus makes feasible many applications that might otherwise be impossible, too costly or require constant maintenance. However, theoretical approaches proposed to date that minimise WSN energy needs generally lead to less than expected savings in practice. We examine experiences of tuning the energy profile for two near-production wireless sensor systems and demonstrate the need for (a) microbenchmark-based energy consumption profiling, (b) examining start-up costs, and (c) monitoring the nodes during long-term deployments. The tuning exercise resulted in reductions in energy consumption of a) 93% for a multihop Telos-based system (average power 0.029 mW) b) 94.7% for a single hop Ti-8051-based system during startup, and c) 39% for a Ti-8051 system post start-up. The work reported shows that reducing the energy consumption of a node requires a whole system view, not just measurement of a "typical" sensing cycle. We give both generic lessons and specific application examples that provide guidance for practical WSN design and deployment.**

I. Introduction

Practical wireless sensor nodes must use minimal power since:

- batteries, when provided, impose a restricted energy budget
- energy harvesting, when provided, imposes a restricted power budget.

A variety of low-power approaches exist (see Anastasi et al. [1], for a summary), addressing different aspects of WSN energy efficiency. Commonly, such approaches have only been validated in terms of simulation or a mathematical model. In practice, energy efficiency approaches can be thwarted by real-world implementation factors not considered in their design:

- an algorithm or approach that reduces cost in one area might increase it in another [2],
- the true energy cost of a component might be a small proportion of the total and thus a large percentage improvement in that component's cost will have a much lower percentage impact on the overall energy consumption [3],
- a behaviour that occurs rarely may, despite its rarity, consume much of the available energy, thus significantly increasing the average consumption.

Table I
RESEARCH-BASED WSN DEPLOYMENTS ORDERED BY PUBLICATION YEAR (UPDATED TABLE BASED ON KUORILEHTO ET AL., [4]). N/S = NOT STATED.

System/Location		Year	Nodes	Duration
ZebraNet	[5]	2004	4	10 days
PicoRadio	[6]	2004	25	1–2 months
GDI	[7]	2004	150	4 months
Vineyard	[8]	2004	65	6 months
Oil tanker (starboard)	[9]	2005	16	19 weeks
ExScal	[10]	2005	1000+	2 weeks
Macroscope	[11]	2005	33	44 days
Oil tanker (centre)	[9]	2005	10	6 weeks
Heathland	[12]	2006	24	16 days
Volcano	[13]	2006	16	3 weeks
Golden Gate Bridge	[14]	2008	64	2 months
Torre Aquila	[15]	2009	16	4 months
GlacsWeb	[16]	2009	8	2 years
Jindo Bridge	[17]	2010	70	4 months
SensorScope	[18]	2010	97	180 days
Flying foxes	[19]	2015	N/S	12 months

Based on two case study applications, which are presented in Section II, this paper demonstrates the need for:

1) measurement-based energy profiling (described in Section III) to identify and reduce both the normal operating cycle costs (Section IV) and the start-up cost (Section V), and,
2) examining long-term system behaviour (Section VI) through longer term measurement of energy use while in-situ.

Section VII concludes the paper.

II. Case study applications

Although energy efficiency is core to WSNs, low-energy techniques are rarely tested in practice. Even those few research systems that have been deployed, as Table I shows (also see Gaura et al. [20]), are typically only tested for a relatively short period of time and their energy performance is rarely analysed in detail in the literature. Large deployments exist but are rare and usually short-lived.

For the above reasons, we believe that it is timely to examine the energy use results for a home monitoring application (based on our Cogent-House PassivHaus (CH-PH) deployment [21], which involved more than

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176 nodes deployed over more than 3 years). To ensure generality, we also investigate energy use for another application, Gas Turbine Engine Monitoring (GTEM), that we developed and deployed a system for and which has different parameters and requirements compared to CH-PH. These two case study applications are representative of two common WSN application classes (one being a long-term in-situ low data rate application, the other being a shorter term, deploy-on-demand, high data rate application). The case studies provided insight into issues that can occur during the operation of many types of WSN and that might not be discovered without the three types of analysis (measurement-based profiling, examining start-up costs, and long-term energy monitoring) and accurate energy exploration that forms the focus of this paper. All three analyses are equally important and demonstrate the need to take a whole system view when characterising the performance of an in-situ WSN.

Observing systems over a longer-term, in particular, has benefits beyond identifying hidden energy consumers. In our long-term deployments, we uncovered issues, such as:

- an increased rate of corrupt packets that pass CRC-16 checks in large, active networks,
- network energy holes that isolate parts of the network due to early/sudden battery depletion,
- disruption in USB communication between root node and gateway due to gateway kernel software problems,
- the need to address potential, temporary server outages (e.g., using on-node buffering) at design stage.

For the two case study applications, we examine the energy consumption profile for each along with the effect of actions taken to reduce energy use.

A. Cogent-House PassivHaus Deployment (CH-PH)

The first case study discussed here is based on Cogent-House[1], a wireless home environment and energy monitoring system. Cogent-House gathers sensor data (such as temperature, humidity, electricity usage, gas usage, heat metering, CO2, and VOCs) from inhabited residential buildings at 5 minute intervals and transmits that data to a remote database where the energy and environmental performance of the building can be evaluated. The system is built on the TelosB platform (with an MSP430 F1611 CPU, a 2.4 GHz CC2420 802.15.4 radio, and integrated Sensirion SHT11 temperature and humidity sensor). A packaged sensor node is shown in Figure 2. The example deployment, referred to here as CH-PH, involved a mix of 23 flats and houses built to PassivHaus standard (see

[1]Cogent House is an open-source project available for download from https://github.com/jbrusey/cogent-house

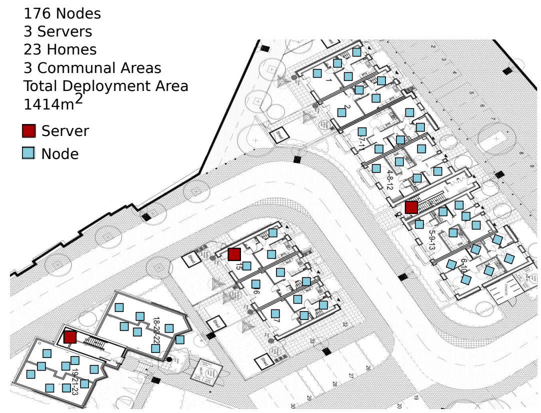

Figure 1. Site overview for CH-PH deployment

Figure 1). For this deployment, the system's base configuration is multi-hop, sense-and-send. Part way through the CH-PH deployment, we reprogrammed nodes in 3 houses to use a transmission reduction algorithm (L-SIP [22], [23]) and this helped us understand the long-term performance characteristics of this approach.

Versions of our Cogent-House system have been deployed in over a dozen independent housing stock monitoring projects over hundreds of homes. Although we mainly refer to CH-PH, we draw from our wider experience from the multitude of Cogent-House deployments.

The sensor node software is based on TinyOS, which provides a network stack with a low power MAC (BoX-MAC-2, also referred to as Low Power Listening (LPL)) [24] and multi-hop tree formation/data collection protocol (CTP) [25].

B. Gas Turbine Engine Monitoring (GTEM)

The second case study, referred to here as GTEM, is a prototype wireless sensing system for gas turbine engine monitoring (see Figure 3). In this application, power harvesting is preferred (to avoid the use of batteries) and is feasible due to the large amount of vibration and high temperature gradients caused by an operating engine. Our system is aimed at monitoring gas path temperatures inside the engine (peak values of 1000 °C) and is based on the CC2530 hardware platform with the Z-Stack network stack [26], a certified ZigBee compliant stack. The nodes are built from CC2530 evaluation modules combined with our own carrier boards for sensor interfacing and power. The base station uses the same CC2530 evaluation module combined with a SmartRF05EB board. The nodes form a single-hop ZigBee-compatible 802.15.4 network, i.e., one coordinator (or sink) and several end devices but no routers. A single-hop network was desir-

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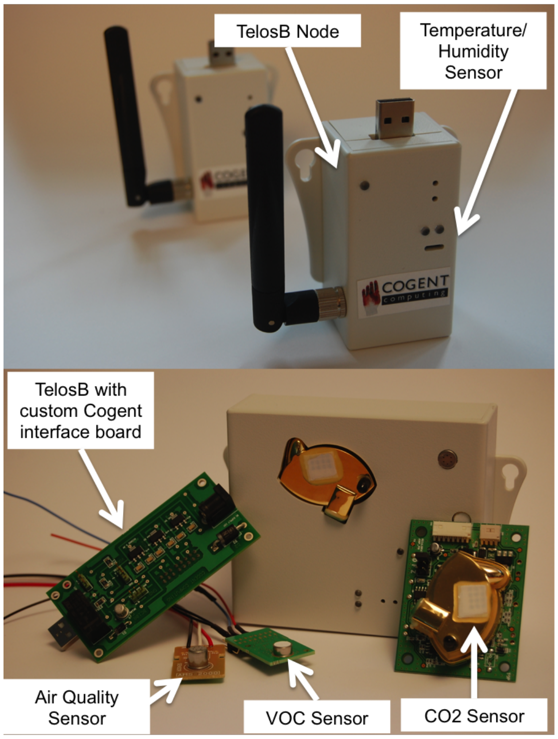

Figure 2. Packaged TelosB sensor node for CH-PH in a basic configuration above and with additional air quality sensors below.

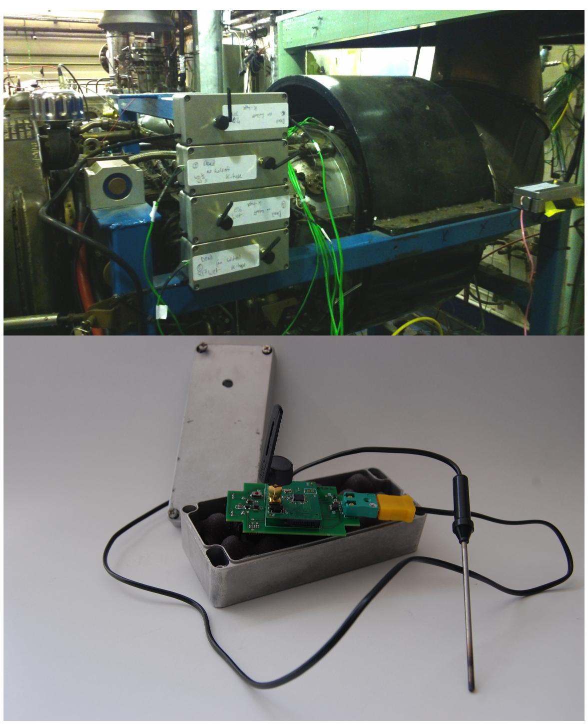

Figure 3. Gas Turbine Engine Monitoring (GTEM) wireless nodes installed on test engine (above) and internals (below).

able since: a) the network structure is simplified, b) end-to-end packet delivery time is small with low variance, and c) packet forwarding is not needed, thus reducing the node energy requirement. Sampling rate for this system was 1 Hz. We performed multiple deployments with durations of 20–50 minutes.

III. Node energy profiling

We propose that profiling the energy use of nodes is an important step in reducing their energy requirements as it allows one to determine the main consumers and therefore make informed choices about what action to take to reduce the overall, system-level energy consumption. Furthermore, such profiling needs to be performed before and after individual interventions to ensure they have had the desired effect.

Energy profiling is based on identifying the node's overall and component power consumption. *Correctly* and *accurately* identifying average power consumption is difficult due to two factors:

1) load to be measured is a mix of small ($\approx 1\ \mu$A) and large (≈ 100 mA) currents,
2) under normal operation, power use varies rapidly over time.

Klues et al., [27] proposed a *microbenchmarking* approach that establishes operation time and current use for individual *components* by repeatedly iterating that component to establish the *time per operation*, while simultaneously using a precision ammeter (possibly with an analog low-pass filter) to measure *average current*. A less accurate, oscilloscope-based approach can also be used. In this case, the oscilloscope measures the voltage drop over a precision shunt resistor that is in series with the load. In either approach, the voltage V is fixed and the resulting measurement, per component i, is the average current I_i and per operation time τ_i.

For CH-PH, we used microbenchmarking and an ammeter, whereas for GTEM, we used oscilloscope-based measurements, mainly due to the difficulty of iterating over components within the Z-Stack software.

These measurements are then aggregated to identify the average power consumption as follows. Considering a node's total energy use to be composed of a set of components C (e.g., CPU operations, radio transmission, sensor reading, sleeping), energy *per use* of component $i \in C$ is given by average power by elapsed time.

$$E_i = V I_i \tau_i$$

where it is assumed that the voltage V is constant allowing one to measure just the average current I_i and time per iteration τ_i. For a chosen fixed period T, each component executes, on average, $w_i \in \Re^+$ times. We

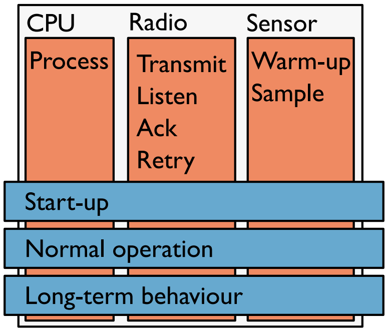

Figure 4. Hardware related components that contribute to energy use within a wireless node (e.g., energy used for sensing) and the cross-cutting temporal aspect of when that energy is used (e.g., during start-up).

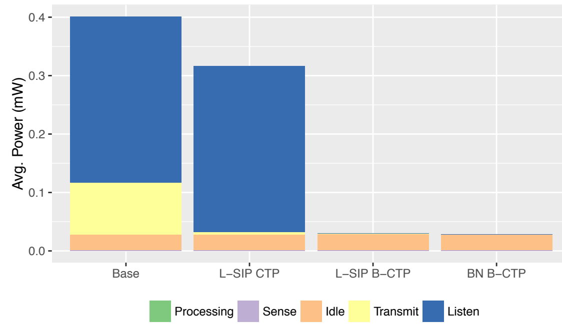

Figure 5. Average power consumption per node for CH-PH with the original profile (Base) and with various other configurations. Note that processing and sensing form only a small fraction of the total energy costs for all configurations here.

assume that the zeroth component is sleeping (or idling) and is executed once. The idle time is thus

$$\tau_0 = T - \sum_{i \neq 0} w_i \tau_i \text{ where } T \geq \sum_{i \neq 0} w_i \tau_i \quad (1)$$

One can consider just the non-idle portion of each energy component, thus removing the need to explicitly calculate the idle time,

$$E_i' = E_i - V I_0 \tau_i = V \left(I_i - I_0\right) \tau_i \quad (2)$$

for $i \neq 0$. The average power consumption is then

$$\begin{aligned} P &= V/T \sum_i I_i w_i \tau_i \\ &= V \left(I_0 + \frac{1}{T} \sum_{i \neq 0} w_i \left(I_i - I_0\right) \tau_i \right) \\ &= V I_0 + \frac{1}{T} \sum_{i \neq 0} w_i E_i' \end{aligned} \quad (3)$$

This formulation makes it easy to see the effect of changing the weights w_i (or duty cycling) some component i. It also allows for other options to reduce power to be explored and evaluated, including: reducing idle current I_0, extending the period T, and lowering the energy per operation E_i' of component i. Performing this analysis provides a solid basis to identify hidden consumers and tune your system for minimal power consumption. We note the recent work by Martinez et al., [28] that also provides a power model for IoT devices in the context of energy harvesters.

Overall, the above analysis provides a framework for dividing the energy use of an individual wireless node within a WSN into components but leaves open the question of how components should be identified. Generally components can be classified according to *where* (which hardware component is involved) and *when* the energy use occurs, as shown in Figure 4. Broadly speaking, the three main hardware-related categories are:

- *CPU* (including run-time processing cost of algorithms such as L-SIP);
- *radio* (including listening, retrying); and
- *sensors*, including any warm-up needed and the associated signal processing (such as the built-in temperature humidity sensor on the TelosB or external cold-junction compensation for a thermocouple).

Cutting across these hardware categories are temporal categories—energy might be used at start-up (when the node initially receives power), during normal operation, or only appear during a longer trial. We begin by examining the normal operation of CH-PH and GTEM.

Remark 1. Although profile components will tend to be named according to the most significant operation occurring (such as radio transmission), other parts of the electronic circuitry may be active concurrently and thus contribute to the current measured. Given the aim of profiling, which is to guide the process of reducing power consumption, it is not necessary to separate such concurrent usage and all such concurrent consumption is lumped together under the nominal component.

IV. Normal operation

Normal operation involves the normal operating cycle (usually sense-process-send-sleep) of a wireless node after the node has been started for a while and not withstanding exceptional behaviour (such as responding to low battery conditions). Three power reduction measures were applied with CH-PH (all of which are to do with radio aspects):

1) use of L-SIP to compress data into 95% fewer transmissions (Section IV-C),
2) use of B-CTP [21] to turn off the radio for leaf nodes unless actively transmitting (Section IV-B),

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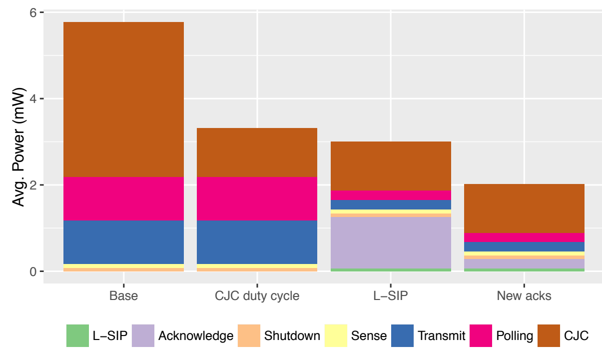

Figure 6. Average power consumption per node for GTEM. Note that L-SIP introduced a need for acknowledgement, which then became a major energy user. This was subsequently reduced by using a more efficient acknowledgement method.

3) implementation of an Edge Mining approach (BN [29], [23]) to further reduce required transmissions (Section IV-C).

The results are summarised in Figure 5. Applying L-SIP instead of *sense and send* (SS) reduced the energy for transmissions dramatically but the overall impact was slight. B-CTP was designed to address this by eliminating multi-hop forwarding for some nodes. It can be seen from the graph that the added benefit of further transmission reduction (BN B-CTP) was slight in comparison to L-SIP B-CTP.

With GTEM, three measures were also applied (but a slightly different set than for CH-PH):

1) (*sensor*) duty cycling the MAX31855 thermocouple Cold Junction Compensation (CJC) interface (Section IV-A),
2) (*radio*) using L-SIP to reduce transmissions (Section IV-C),
3) (*radio*) changing the acknowledgement scheme to use polling (Section IV-D).

The results are summarised in Figure 6. The main improvement is made in this case by duty cycling the thermocouple interface. Introduction of L-SIP reduced power in some areas but initially introduced a large cost due to acknowledgements. This was subsequently reduced by changing the way acknowledgement messages were transmitted.

Note that in comparison to CH-PH, GTEM uses much more power. This is largely due to smaller period T for sampling and transmission (1 second rather than 5 minutes). Also note that the idle power is not shown in the graph for GTEM (Figure 6) as it is much smaller than the other energy consumers.

A. Duty cycling sensor interfaces

Duty cycling of hardware devices that form part of wireless sensor nodes is common practice in reducing their energy consumption. In particular, sensor interfaces are common targets for this. When sensor sampling is infrequent, it makes sense to turn off sensors and their associated signal conditioning circuitry between samples and only turn them on during sensing.

In terms of our model, duty cycling changes the idle current $I_0 \to \bar{I}_0$ since the sensor interface is not active for the whole cycle. (In this analysis, values after duty cycling are denoted with a bar.) When duty cycling, a warm-up period $\bar{\tau_u}$ with current $\bar{I}_u$ is often required to allow the sensor reading to stabilise. The warm-up current may not be equal to the change in idle current $(I_0 - \bar{I}_0)$. For example, sensors that have a heating element tend to require more current to heat-up than to maintain a target temperature. The sampling current $I_s \to \bar{I}_s$ may also change since it incorporates concurrent activity (as per remark 1) and part of this activity is continuing to warm-up the sensor. It is assumed that the sampling time is unchanged.

The per sample contribution of the sensor after duty cycling is $\left(\bar{\tau_u}\bar{I}_u + \tau_s\bar{I}_s - (\bar{\tau_u} + \tau_s)\,\bar{I}_0\right)/T$. Before duty cycling it was, per sample, $\tau_s\,(I_s - I_0)\,/T$ plus the effect on the idle current $I_0 - \bar{I}_0$. Assuming a single sample per cycle, the reduction is therefore,

$$\begin{aligned} P - \bar{P} = V(I_0 - \bar{I}_0 & \\ & + \frac{1}{T}(\tau_s\,(I_s - I_0) \\ & - \bar{\tau_u}\bar{I}_u - \tau_s\bar{I}_s + (\bar{\tau_u} + \tau_s)\,\bar{I}_0)) \end{aligned} \quad (4)$$

In the case of GTEM, prior to duty cycling, the MAX31855 Cold Junction Compensation (CJC) is a major contributor to the total idle current of $I_0 = 1.2$ mA. During each $T = 1$ s period, sampling draws $I_s = 15.5$ mA for $\tau_s = 2.2$ ms. With duty cycling implemented, the idle current drops to $\bar{I}_0 = 2$ µA but there is the addition of a warm-up $\bar{I}_u = 1.86$ mA for $\bar{\tau_u} = 0.2$ s and the sample current also increases slightly to $\bar{I}_s = 16.16$ mA. Thus, duty cycling the CJC reduces the power consumption by $P - \bar{P} = 2.44$ mW (42% of Base).

$$\tau_u\,(I_u - I_0) + \tau_s\,(I_s + I_u - I_0)$$

$$T\,(I_{u0} - I_0) + \tau_s\,(I_s - I_0)$$

$$V\,(I_{u0}T - I_u\,(\tau_u + \tau_s) - I_0\,(T - \tau_u))\,.$$

Remark 2. Power savings are expressed throughout in terms of the difference between power with all previous adjustments applied and power with all previous plus the currently discussed adjustment. Percentage of the Base power consumption represented by this difference is also given. A summary of power savings is given in Table III.

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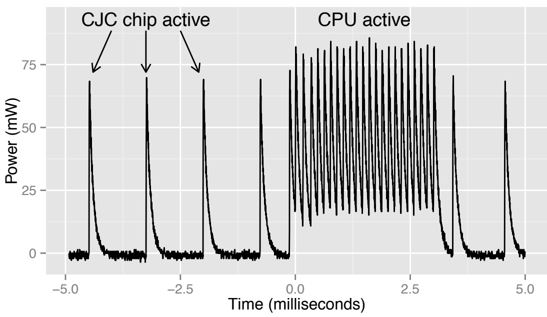

Figure 7. GTEM example of power consumption spikes due to the cold-junction compensation (CJC) chip (based on oscilloscope current measurements). The CPU activity causes higher power use but is only for 3 ms per 1 s cycle whereas the CJC (in this configuration) is constantly active and thus uses more power on average.

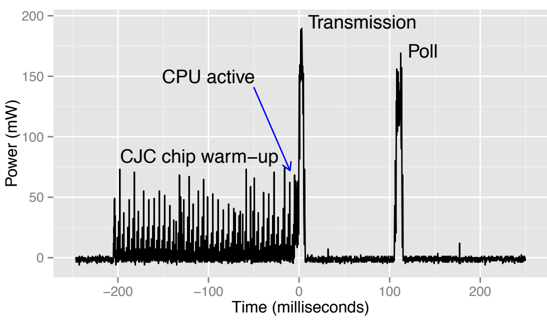

Figure 8. Oscilloscope-based power measured for a sense-transmit-poll cycle after duty cycling the GTEM CJC chip. Note that the CJC needs to be started 200 ms prior to sampling to ensure a reliable measurement is made.

The sensor idle activity is shown in Figure 7 and consists of frequent (≈1 kHz) spikes in power consumption (*CJC chip active*) that are independent of requests for a sample (*CPU active* in the figure). After duty cycling, the CJC consumption is much reduced and is only active 200 ms prior to sampling (see Figure 8).

B. Reducing listening

Radio listening is a key energy user in multi-hop wireless sensor networks and several approaches exist (termed generically, *interval listening*) that can reduce this energy cost. Two common approaches are: low-power listening (LPL), where the transmitter repeatedly transmits over a longer period so that the listener, who only listens occasionally can hear; and time-division multi-access (TDMA), where the listener knows the time slot when the transmitter might transmit and only listens then. LPL is simpler to implement since it does not require synchronised clocks. More efficient variants stop the transmission when the receiver indicates they have heard.

We developed an alternative approach to LPL to attempt to further reduce the listening cost, called Backbone CTP (B-CTP) [21]. B-CTP is an variant of the Collection Tree Protocol (CTP) [25] that can be used when a backbone of mains powered nodes exists and all other nodes can turn off listening. B-CTP operates without LPL—backbone nodes listen constantly while all other nodes only listen when expecting acknowledgement. In comparison with the base CH-PH system (which used LPL with a 1 s interval), B-CTP reduced the average power consumption of the CH-PH nodes by 0.28 mW or 71% of the Base consumption of 0.40 mW.

However, B-CTP causes inflexibility in the network since beacon messages used to configure the routing tables are also not listened to. Other approaches, such as TSMP [30], might be used to maintain network flexibility and are more efficient than LPL.

C. Reducing transmissions

Transmission reduction algorithms, such as L-SIP [22], make use of application-level redundancy in the data being sensed to reduce the number of packets being transmitted. We refer to such on-node processing as *edge mining* [23], in the sense that data mining is being performed on the edge of the network. L-SIP uses a simple linear model to predict the signal (e.g., temperature being measured) and only transmits when the signal varies from prediction. A typical packet reduction ratio is 20:1 for residential temperature data (and assuming a threshold of 0.5 °C). For this packet reduction ratio, the power consumption for CH-PH is reduced by 0.084 mW (21% of the Base).

BN [29] is an alternative edge mining approach that further reduces transmissions by summarising the data according to some scheme (e.g., percentage time for each of n non-overlapping temperature ranges). BN typically produces a packet reduction ratio of 7000:1 compared with sense-and-send for residential temperature data. Based on the CH-PH nodes, BN produces a reduction of 0.089 mW (22% of Base). For this application and given the minimal improvement in comparison to L-SIP and loss of the ability to reconstruct the original signal, BN seems like a step too far.

When applying L-SIP to GTEM, we found a smaller typical packet reduction ratio of around 5:1 due to the large temperature range and rapid variations in temperature that occur for a gas turbine engine. To support L-SIP, application-level (APS) acknowledgements were used however under the Z-Stack system and these cause additional power consumption. Thus the improvement for GTEM is only 0.32 mW (5.5% of Base).

The next section will discuss a further improvement to tune the energy use associated with acknowledgement.

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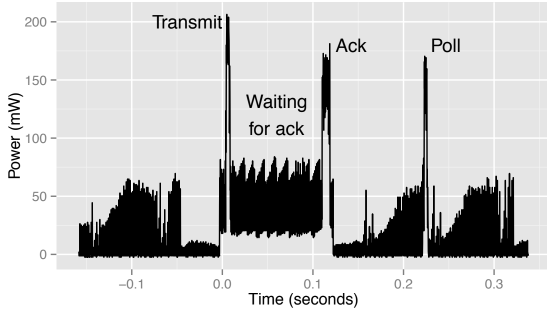

Figure 9. GTEM node with APS acknowledgement showing the elevated power use while waiting for acknowledgement.

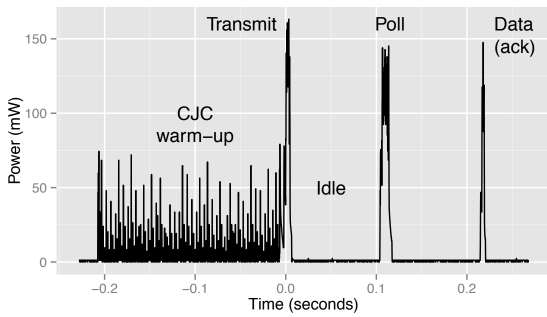

Figure 10. Oscilloscope-based power measurement of GTEM node using data polling to provide acknowledgement showing reduced power use while waiting for the acknowledgement.

D. Alternative acknowledgement schemes

For the GTEM system, acknowledgements are costly but needed for L-SIP to be used [23]. To obtain the best benefit from L-SIP, we needed to tune the acknowledgement approach. Instead of using the standard ZStack APS acknowledgement mechanism, we instead use ZigBee *polling* after each transmit.

In ZigBee polling, an end device polls or requests a message from the coordinator. As shown in Figure 9, ordinary APS acknowledgements cause the processor stay active while waiting. In comparison, with polling, as shown in Figure 10, the node sleeps (and thus is idle) while waiting for the receipt of the acknowledgement.

The resulting reduction in energy is 0.98 mW (17% of Base), which is significant.

V. START-UP ENERGY

The energy required to start-up each wireless node is an important consideration for:

- episodic systems (ones which are turned on for a period and then turned off again), since start-up is a regular occurrence, and,
- power harvesting systems (where the main source of energy is acquired gradually) since the system may not be able to start at all until sufficient power has been harvested.

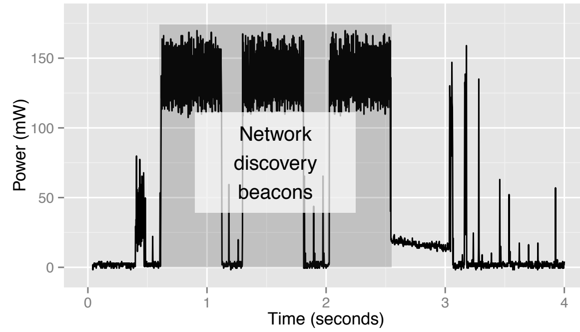

Figure 11. Power consumption for GTEM node during node startup with network discovery beacons shaded.

Table II
GTEM NODE STARTUP WITH AND WITHOUT NETWORK INITIALISATION. WHEN NOT INITIALISING, ROUTING TABLES ARE RESTORED FROM NON-VOLATILE MEMORY.

	Start-up time (s)	Avg. power (mW)	Energy (mJ)
With network creation	3.00	54.6	164
Without network creation	0.85	10.2	8.7

GTEM is both episodic and ultimately aimed to be used with power harvesters rather than batteries.

Experience with early trials of GTEM showed that start-up energy costs were too high for the vibration-based power harvester being developed for the gas turbine engine. Observation of start-up revealed that most of the start-up energy was being used by network creation beaconing, as shown in Figure 11.

ZStack provides the option to restore the previous network configuration, rather than initialise it from scratch, by using the NV_RESTORE flag at compile time. The resulting improvement provided by making this change is summarised in Table II. Note that while the power consumption has only improved by a factor of 5, the energy consumption during start-up has reduced by a factor of 19. This latter figure is more important because energy rather than power is the limiting factor in these types of systems, particularly during start-up.

Although this facility is specific to ZStack, it is likely that other networking stacks will have an equivalent mechanism. The negative aspect of using such a facility is that it means that no network configuration occurs at start-up and that if a network change occurs, the nodes might stop communicating. This might be resolved by detecting communication failure and triggering network reconfiguration to occur.

VI. Long-term measurement

Long-term deployments can help identify problems that were not discovered by analysing energy consumption in normal operation regime for individual nodes or the node / network start-up phase.

While energy profiling of normal operation provides an *estimate* of battery life, the true lifetime may be considerably different and this might only be discovered through long-term trials. Unfortunately, long-term results may take years to emerge and thus it is commonplace to also capture a log of battery voltage, as a proxy for residual charge, during deployment. Battery voltage provides a predictor of residual charge, although the relationship between the two is non-linear and some hysteresis effects may occur [31], [32]. A detailed battery voltage log will also allow for causes of unexpected voltage drops to be identified early. Moreover, continuous logging of voltage allows for maintenance and battery changes to be scheduled in a timely manner to avoid network down time and data loss.

Note that different batteries may have dramatically different lifetimes depending on the load that is applied and the chemistry of the battery. Using a consistent battery type from the same manufacturer across a deployment thus simplifies any comparison of the lifetime results. However it should be noted that even using the same battery brand and type will not necessarily guarantee consistent lifetime results.

We logged voltage in CH-PH and GTEM and this allowed us to observe some long-term effects that might otherwise have remained unexplained. Figure 12 shows battery voltage for a number of nodes during one of our long term Cogent-House deployments that employs L-SIP. Normally, the gradient of this curve is a gentle negative trend with the expected battery life being around 4 years for 2 ordinary AA batteries. However, if the server is turned off (or fails in some other way), battery depletion becomes much more rapid (the lifetime for a fully charged set of batteries reduces to 140 days). In the figure, the longest outage (of 39 days) caused a drop of 0.21 V corresponding to roughly 1/3 of the total battery charge.

The reasons for the increased power consumption during server (or sink) failure include:

- increased transmission retries (up to 20 for CTP),
- longer time spent listening for acknowledgement,
- no transmission reduction with L-SIP (due to the lack of acknowledgement).

We believe that an efficient solution to server / sink failure has not yet been found and the fact that the impact of sink failure is identified by long-term monitoring emphasises the importance of this analysis.

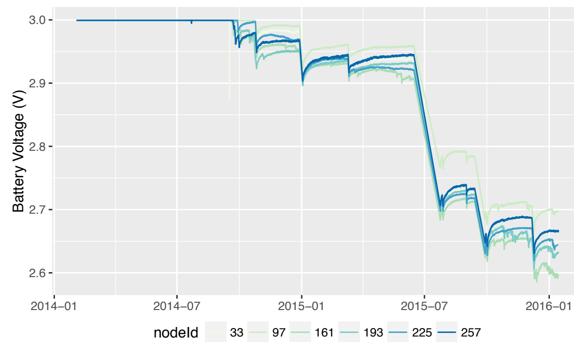

Figure 12. Typical battery voltage for a set of Cogent-House sensor nodes. The large drops in voltage that occur for many nodes simultaneously are due to server outage, which causes each node to try to transmit more often and perform the maximum retries for each transmit, thus expending more power than usual. This effect occurs several times in this graph. Note that this graph is from a more recent deployment of Cogent-House than CH-PH.

	CH-PH		GTEM	
	Energy reduction	% of base	Energy reduction	% of base
Reduce Listening	0.28 mW	71%	—	—
Duty cycle sensors	—	—	2.44 mW	42%
Reduce Transmissions	0.084 mW	21%	0.32 mW	5.50%
Alternative Acknowledgements	—	—	0.98 mW	17%

Table III
Summary of achieved power savings for the CH-PH and GTEM systems.

VII. Conclusions

While energy conservation is a common theme for wireless sensor research, energy saving schemes are rarely evaluated through measurement in a practical setting. This paper addresses that gap.

When profiling a WSN node, per cycle energy is generally the primary consideration, however start-up energy may also be critical in an energy harvesting system and long-term practical issues may also be important. Naturally, it is impossible to fully tune all aspects of a system in a research setting and results may compare poorly with off-the-shelf systems. However, we have shown that the energy consumption of wireless sensing nodes can be significantly reduced by analysing the node behaviour through a combination of short-term measurements and long-term instrumented deployments. We have described the measurement and analysis techniques we used and the results obtained when targeting specific aspects of node operation. Our aim is to guide Wireless Sensor Network (WSN) researchers towards the typical problem areas found and the types of approach that can be used to reduce node energy consumption in these areas. The areas of a) startup, b) sensing, c) processing, d) trans-

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mitting data, and e) routing are generally applicable to all wireless node designs and it is likely that, generally, savings can be made in at least one area, particularly in transmitting and routing. It is important that the node energy consumption be profiled before, during, and after modifications are made in order to correctly identify problem areas, confirm that the modifications have been effective, and find side-effects that may result in lower-than-expected savings.

In the case of the two systems we discussed in this paper, we have reduced the power consumption of the nodes in a home environment monitoring system (CH-PH) by 93% and the power consumption of a gas turbine engine monitoring system (GTEM) by 65%. We have also reduced the startup costs of the latter nodes by 95%, an important achievement when targeting the use of power harvesters, and identified long-term issues that may not be apparent from short-term analysis.

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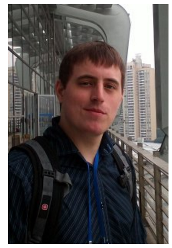

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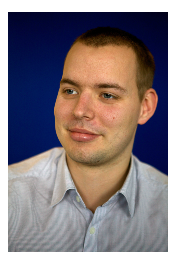

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