Investigating a Design Framework for Energy Harvesting Wireless Sensors

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Abstract

The installation and wiring of instrumentation currently presents a significant cost to the Water Corporation. The use of wireless alternatives could potentially mitigate this cost; however, this introduces the maintenance requirement of battery replacement every 1-10 years. As the Internet of Things is a growing technology space, it is logical to focus on small, low power solutions. Energy harvesting for low power wireless sensors has the potential to supplemental or perhaps completely negate the requirement for batteries. This project seeks to provide a framework for determining the available operating time of an energy harvesting wireless sensor, using input parameters common to any predictable or controlled energy source, sensor types or wireless technology. The work is presented in the context of a Water Corporation case study, considering solar energy and using test hardware for the verification of results.

1. Introduction

Installation and the wiring of instrumentation is currently a significant cost to the Water Corporation. Wireless sensor networks can be used to provide data monitoring for sites and locations that are generally not easily accessible, or for which wiring of traditional instrumentation would be costly or impossible. There is however a problem introduced by such sensors; the need for power. Traditional wireless sensors typically run from batteries that require replacement after 1 – 10 years, depending on conditions (Vullers et al. 2009). The replacement of just a few batteries may not prove a large expense, however if a significant number of these sensors are in the field then battery replacement will become a regular occurrence.

A solution to the battery problem for wireless sensors is to employ energy harvesting techniques, to either supplement or completely replace the need for onboard energy storage. Energy harvesting uses ambient available energy such as radio frequency, solar, piezoelectric and thermoelectric (Vullers et al. 2009) (Shaikh & Zeadally 2016). The amount of power available from these sources is typically rather small, so systems designed to work with such harvesters must be constructed with low power applications in mind, overengineering the solution is undesirable. With the increasing interest in energy harvesting and the potential to investigate many different harvesting technologies, it is important to develop a methodology for determining potential performance of any harvesting technologies. The contribution of this project is to propose a general framework that can take input parameters of different energy sources, sensors, or wireless transceivers and provide constraints on the available operational time, given a secondary energy storage element.

Various potential site applications have been identified from within the Water Corporation, and the key parameters from these have been synthesised into a case study. The application under consideration is asymmetrical point-to-point transmission over approximately 500 m, sensing pressure and converting this to a ground based water tank level measurement using solar as the energy source. Several sites have been identified for obtaining typical solar irradiance levels during the design stage. At this stage it is unknown what kind of transmission schedule a low power sensor in such a setup would be able to maintain.

The current state of the art in capacity planning for energy harvesting wireless sensors involves the prediction of the available harvestable energy given inputs (power, duration) and outputs (V,I, duration). The most prominent form being solar exposure prediction models (Diagne et al. 2013). The requirement for having energy availability data is that the energy source must be either controlled and predictable or uncontrolled and predictable (Buchli et al. 2014). Beyond the power consideration, the rest of the system design is often conducted in an ad-hoc method and heavily coupled with the specific design requirements of the project being undertaken.

2. Methodology

The proposed energy harvesting wireless system under consideration in the case study is shown in Figure 1. Given the already large design scope associated with this project, the energy source chosen to harvest was solar. This was done both based on the ease of obtaining small solar panels as well as the availability of solar data which could be used to evaluate the model. The choice of microcontroller and sensor were made to reflect typical low power hardware found in the literature (Wu, Rudiger & Yuce 2017) and the LoRa wireless transmitter was chosen for its low power and long-range capabilities (Augustin et al. 2016). The whole system is designed to run on 3.3 V to further lower power consumption compared with traditional 5 V systems. State of the art energy harvesting is strongly dependent on the type of integrated circuit (IC) chosen to manage the power. The energy harvesting IC selected was the Linear Technology LTC3106, a DC-DC low start-up voltage Buck-Boost converter. This IC was selected as it was suitable for photovoltaic (PV) inputs was able to supply a regulated output voltage of 3.3 V, and charge a secondary storage element when excess energy is available.

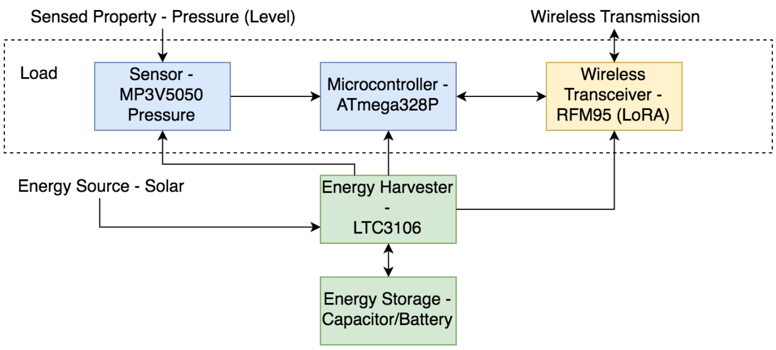

Figure 1 Schematic of energy harvesting wireless sensor

To model the predicted behaviour of the energy harvesting wireless sensor a modular system was developed in Python, consisting of four separate modules as shown in Figure 2. With each module representing a different logical component of the system, the load, the energy availability, the storage element and the energy harvester. The motivation behind structuring the model as such is to allow for the future reusability of the system, potentially using alternative harvesting, wireless, or energy storage technologies.

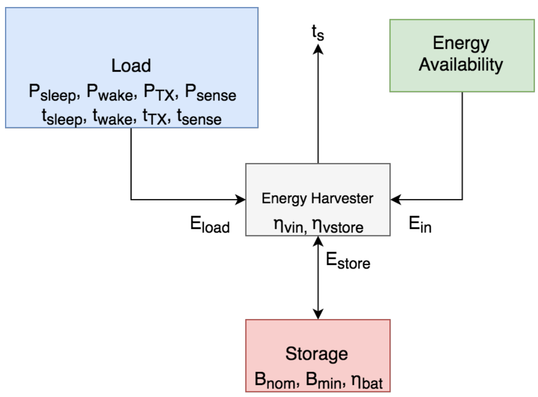

Figure 2 Wireless sensor block diagram of modules

2.1 System Load Model

The sensor, wireless transceiver and microcontroller can be grouped together as the components providing the load in the circuit. For wireless sensing applications, it is useful to divide the load profile up into four general states. Sleeping, waking, sensing/processing and transmitting/receiving. Figure 3 shows the power draw of the system as measured during a measurement, processing and transmission cycle as measured for the system in Figure 2.

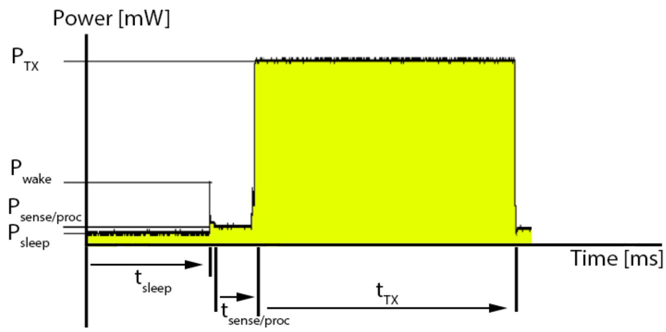

Figure 3 Power consumption in a single measurement and transmission cycle showing sleep, waking, sensing and transmission

The load module provides the output parameters, P_{sleep}, P_{wake}, P_{TX}, $P_{sense/proc}$ subsequently used in the model developed, where each parameter represents the power at their respective state as shown in Figure 3. In addition the parameters t_{sleep}, t_{wake}, t_{TX}, $t_{sense/proc}$, representing the total amount of time spent in each state during a cycle are also used as parameters within the model.

2.2 Energy Availability

As the case study considers the use of solar energy, a model must be used for predicting the available solar energy at select locations; two methods are considered here. The first is to consider the global solar exposure at select locations from historical data available from the Bureau of Meteorology as an indicator of future solar energy availability. The available solar energy may also be modelled using slightly more sophisticated techniques, such as the modified astronomical model which, despite still being relatively simple, has been found to accurately predict harvestable solar energy, allowing for up to 53% smaller batteries than the previous state-of the art (Dave, Halpern & Myers 1975; Buchli et al. 2014). In this model the total energy is a function of:

$$E_{astro}(\cdot) = E_{sun}(d, t, L, \phi_p, \theta_p, \tau) + E_{sky}(d, t, L, k, \theta_p, \tau) + E_{gnd}(d, t, L, k, R, \theta_p, \tau)$$

Where d is the day of the year, t is the hour of the day, ϕ_p is the azimuth angle, θ_p is the other inclination angle and τ, k, and R are dimensionless characteristics of the absorbent gases in the atmosphere. The contribution of diffuse sky radiation is given by k, the atmosphere's optical thickness by, τ, and the reflective properties of the ground by R. Using either the Astronomical model, or historical data, the final parameter passed from the energy availability is:

$$E_{in} = E \times \mu_{eff} \times A$$

Where $E(W/m^2)$ is the predicted solar energy, μ_{eff} is the photovoltaic panel efficiency, and A (m^2) is the area of the panel.

2.3 Energy Storage

The transfer of energy from harvester to battery storage has been shown to be quite complicated, with several models in the literature able to predict charge and discharge behaviours (Ferry et al. 2011) . In this work a simple battery charging method has been used to identify the key issues (Castagnetti et al. 2012). The energy storage element is modelled simply, using the parameters B_{min} (mAh) for the minimum capacity the storage element must maintain and B_{nom} (mAh) for the nominal battery capacity. To attempt to account for inefficiencies when charging and discharging the battery some previous works have used efficiency factors for scaling, $\eta_{bat_{in}}$ and $\eta_{bat_{out}}$, with loses from internal resistance and electrochemical processes being represented by $\eta_{bat_{in}}$ (Buchli et al. 2014).

2.4 Energy Harvesting Model

The harvesting model takes the load inputs to account for the energy required for a single measurement, process and transmit cycle:

$$E_{load}(t) = P_{sleep}t_{sleep} + P_{wake}t_{wake} + P_{sense/proc}t_{sense/proc} + P_{TX}t_{TX}$$

Inefficiences in transfering to the input energy to the load and to the storage are considered by V_{IN} efficiency, η_{vin}, and V_{STORE} efficiency, η_{vstore} as given on the datasheet for the LTC3106. Using a similar approach to (Buchli et al. 2014), at a given time the available energy stored energy is:

$$E_{store}(t_n) = E_{store}(t_{n-1}) + \eta_{vstore}\eta_{bat_{in}}E_{in} - (\frac{1}{\eta_{vin}\eta_{bat_{out}}})E_{load}$$

If we define t_s as the sleep time between transmissions, then it is possible to move through as many days of predicted energy availability as desired, testing smaller values of t_s until a point is reached where $E_{store}(t) < B_{min}$.

2.5 Case Study

The case study parameters are derived from representative situations that the Water Corporation would find a use for asymmetrical point-to-point transmission from a wireless sensor. Table 1 shows examples from within the Water Corporation.

Case	**2016 Solar Exposure MJm^{-2}**		**Transmission Distance**	**Measured Property**
	Winter	Summer		
Canning Dam - Site Tank	9	30	~ 450 m	Tank water level (0 – 100%)
Wungong Dam - Site Tank	8.9	29.4	~ 520 m	Tank water level (0 – 100%)
Yanchep Smart Metering	7.7	24.3	~ 500 m	Flow

Table 1 Summary of case study parameters

The first two case studies are applicable to the hardware selected, and the third representing another that this framework may be applied to in the future. To meet the case study requirements LoRa transmission parameters that could realistically meet the 500 m transmission requirements are to be used. LoRa has a number of different parameters that can effect the power consumption of a transmission, the largest of which are the Existing work shows the range of parameters that should easily provide this distance(Augustin et al. 2016).

For verification, the Linear Technology LTC3106 energy harvesting integrated circuit is used on a demonstration board, coupled with a LoRa RFM95 radio module ATMega328p microcontroller and MP3V505V pressure sensor. The harvester is able to employ Maximum Power Point Control, allowing for maximum power transfer between the selected Photovoltaic (PV) Panel and the load or secondary storage element. The chosen PV panel for this work was selected to be sufficient but is likely still overprovisioned, at 99mm x 69mm.

3. Preliminary Results

Figure 4 shows the output with a battery where B_{min} = 25 mAh, B_{nom} = 50 mAh, using the astronomical prediction model with data between days 280 and 285 of the year, at a latitude of $L = 31.9812\,°$, using typical atmospheric parameter values of $k = 0$, $\tau = 0.1$ and $R = 0$ (Dave, Halpern & Myers 1975; Buchli et al. 2014). The astronomical model values are within the recommended range in the literature (Dave, Halpern & Myers 1975; Buchli et al. 2014). Figure 4 shows the predicted battery charge output for the minimum determined value of t_s, obtained by stepping down from , $t_s = 7200\ seconds$. For this case $t_s = 120\ seconds$. So the minimum sleep time between transmissions over this period is predicted as 120 seconds.

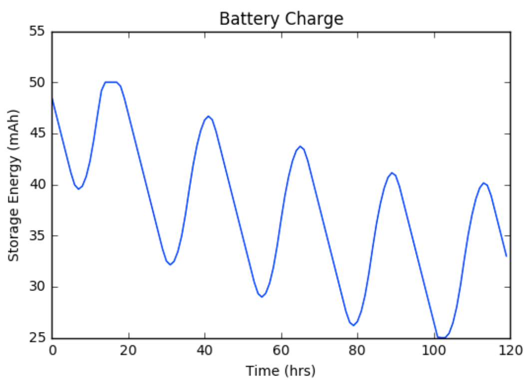

Figure 4 Modelled battery charge at the minimum predicted sleep time between transmission cycles

4. Conclusions and Future Work

The validity of the model presented here is yet to be properly tested. However, if the predicted operational schedules prove to be valid, then future work could involve investigating alternative predictable energy sources using the same framework, such as vibrational energy harvesting, replacing the solar energy availability with vibrational. This work only considers a simple transmitter, however the load could be generalised to encompass a receive element as well.

5. Acknowledgements

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