Solar Energy Harvesting Optimization for Wireless Sensor Networks

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***Abstract*—The energy optimization of resource constrained energy harvesting Wireless Sensor Networks (WSN) have constituted a major research topic in recent years in areas such as environmental monitoring, hazard detection and industrial applications. Current approaches leverage techniques such as adaptive duty cycling, transmission power adaptation and data reduction methods to minimize energy consumption. However, the majority of the state of the art approaches with WSN research assume that energy generation, although variable, is not controllable in-situ to optimize energy generation.**

In this paper, we design a low power, low cost, open source solar tracking mechanism for energy harvesting wireless sensors. Furthermore, we formulate the dynamic energy generation system as an optimization problem and from this design an adaptive, lightweight, distributed, prediction free algorithm to maximize the energy generation of the system. Moreover, we evaluate the proposed method using a combination of real trace-driven real solar data based simulation, comparison to a centralized globally optimum solution and real world experimentation. From our evaluation, an improvement of up to 165% in energy generation has been seen when compared to traditional tracking methodologies and that the lightweight distributed implementation is, on average, 99.1% as efficient as the globally optimum solution across 28 distinct testing scenarios.

I. Introduction

Recently, WSN technologies research has matured to become a viable solution for real world applications. Practical obstacles to the adoption of WSN have been the narrow use cases if powered by mains electricity and limited lifetime if operated on primary batteries [1]. Energy Harvesting WSN (EH-WSN) technologies have been introduced from sources such as solar, wind, thermoelectric and vibration as a potential solution to this problem [2]. with solar energy generation being most advanced among these solutions [3].

Current research in EH-WSN seeks to effectively utilize energy using methods such as duty cycle adaptation [4], [5], and Energy Neural Operation (ENO) [6], [7]. However, this work considers reducing energy consumption or scheduling operations at times when energy is available rather than optimizing the production of energy from energy harvesters.

In parallel, improving solar energy generation efficiency has been a major topic in research for decades with work on areas such as new materials [8], [9], more efficient power management techniques [10] and solar tracking techniques [11]. However, these do not intelligently adapt to maximize energy generation in a WSN system.

The novelty of this paper lies in the creation of an adaptive, lightweight, distributed algorithm to maximize energy generation in a solar tracking EH-WSN. Traditionally solar tracking has not been implemented in WSN due to the small size of the energy harvesting element, where the energy cost of actuation can be higher than the energy gained by tracking the sun, resulting in a net loss in the system. In order to maximize energy generated in an EH-WSN system and ensure no energy is lost; a novel efficient low cost, low power, solar tracker is designed. Furthermore, the decision making around solar tracking is formulated as an optimization problem and a lightweight distributed prediction free algorithm developed to maximize energy generated.

To the best of our knowledge, this paper is the first to create such a system. Within solar tracking research, work has been undertaken to improve energy generation; however, this work does not consider the perspective shown here. For instance, the work of [12] considers the use of a ZigBee based wireless sensor network to efficiently track the motion of the sun. However, this work utilizes WSN to facilitate optimization of energy generation for large scale grid tied solar systems, rather than having solar tracking technologies facilitate EH-WSN. Work, such as [13], designs a solar tracker for WSN systems utilizing a purely mechanical approach. Utilizing a mechanical clock mechanism the system will continually follow the sun. However, this work would not be adaptive to inclement weather and crucially the system is purely explored through abstract simulation and not tested in real world conditions. Finally, the work of [14] considers a high accuracy solar tracker for WSN applications, this work has several intelligent design choices in terms of device initialization. However, the impact of this paper lays in the hardware design to ensure the most accurate tracking possible for the paper's light focusing optics, rather than the lowest energy consumed to track as in our testing apparatus.

The contributions of this paper can be summarized as follows:

- We formulate the optimization problem to maximize solar generation for a WSN application
- A lightweight, prediction free, distributed algorithm is designed to solve the optimization problem presented in this paper and is compared to a brute force based optimal approach
- The proposed algorithm is verified by simulation using

real trace driven energy generation data

- We design a low cost, low power, open source solar tracking apparatus and perform real world testing to prove the efficacy of the work

The results show that an increase in energy generation of 165% can be achieved. Furthermore, the lightweight algorithm is shown to be, on average, 99.1% as efficient as the globally optimum solution.

II. System Model

In this paper, we consider an energy harvesting wireless sensor which operates in discrete timeslots. Within these timeslots, a sensor node can undertake tasks such as sensing, wireless transmission, and actuation.

$$E_{sen} = (E_{tr} + E_{se} + E_{co}) \tag{1}$$

where E^{tr}, E^{se} and E^{co} are the energy consumption per transmission, sensing and energy consumption of the active sensor node respectively.

In a timeslot, t, the battery state B_t of a node can then be expressed as

$$B_t = B_{t-1} + H_g - (E_{sen})D_t - E_{ce} \tag{2}$$

where B_{t-1} is that battery state at the previous time slot, $t-1$, H_g is total energy generated from the energy harvesting source within the timeslot, t, D_t is the duty cycle of the node at t, and E_{ce} is the energy consumption when the node reverts to a sleep state.

Within WSN system, the aforementioned duty cycle adaptation research focuses on varying D_t in order to vary the energy consumption of a wireless sensor system. However, (2) assumes that the variable H_g cannot be varied by the WSN and is dependent entirely on the source of the energy harvester e.g. the sun intensity and direction for a solar energy harvester. This paper seeks to introduce solar tracking to improve energy generation in WSN systems.

With the introduction of solar tracking, H_g is no longer static. The goal of a solar tracking system is to minimize the angle of incidence between the incoming solar energy and the solar cell by undertaking an actuation action to rotate the solar cell in order to maximize the energy generated.

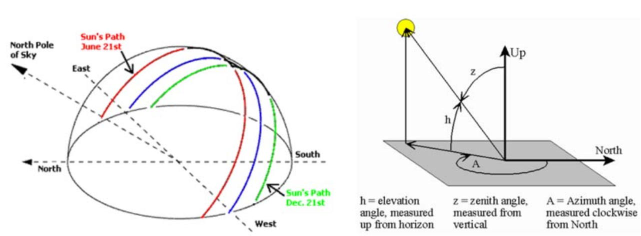


Figure 1: Graph of solar movement and graphical representation of variables involved [15]

To calculate the new H_g, taking into account the actuation of the solar tracker, consider the following

$$H_g = E_{pv} - E_{au} \tag{3}$$

Where E_{pv} is the energy generated by the solar cell and the energy cost of actuation, and E_{au}, the cost per actuation of the solar tracker, can be expressed as

$$E_{au} = E_{ac} + (E_{mo})m_t \tag{4}$$

where E^{ac} is the activation energy required for the motor to begin moving, E^{mo} is the energy required to move the motor by one degree and m_t is the number of degrees moved in time t. Consider, E_{pv}, the energy generated by the solar cell

$$E_{pv} = \eta_{pv} A_{pvg} G_{bn} \cos\theta \tag{5}$$

where η_{pv} is the solar conversion efficiency, A_{pvg} is the solar panel area and $G_b n$ is the solar irradiation hitting a tilted solar plane, and θ is the angle of incidence of the suns rays on the tilted plane,

Equations (4) and (5) take into account movement in the azimuth orientation, as in Figure 1, for 1 Degree of Freedom (1DOF) only. It would be trivial to expand this expression to include both elevation and azimuth for 2 Degree of Freedom (2DOF). However, this is deemed to be outside the scope of work as 2DOF produces a much smaller improvement in energy generation over 1DOF systems [11].

A. Problem Formulation

By considering the goal of maximizing energy generation, an optimization formulation seeks to achieve a solution to the following problem:

$$(\textbf{P1}) \quad \max \sum_{t=1}^{Nw} H_g. \tag{6}$$

Subject to:

$$constraints\ (2),\ (3),\ (4),\ (5)$$

The objective function (6) seeks to maximize energy generation over time window N_w. The constraints specified ensure that the characteristics of the solar tracker are correctly represented. From (3) the goal of an optimization would be to maximize energy generated by minimizing the angle θ between the solar cell and the current position the sun while minimizing the energy consumed by updating the position of the solar tracker, E_{au}.

In order to solve the formulated problem, we propose two solutions. Firstly a centralized exhaustive search method which is referred to as the Bruteforce method. Secondly, novel Lightweight method suitable for in-node implementation.

B. Brute Force Solver

One, centralized, approach is to use an exhaustive search approach to solve for every movement permutation of over N_w.

By calculating every permutation of solar tracking movement over N_w, the resulting energy harvested from this

Algorithm 1: Proposed Bruteforce Algorithm

Input : E_{ac},E_{mo},η_{pv},A_{pvg},G_{bn},θ,azi,H_g
Output: H_{gmax}, movement$_{Nw}$
Set ← (1 **for** I in E_{bn} if I $\neq 0$);
// Reduces Set Size
Permut ← `FindPermutations` (Set,[0,1])
// Creates nested array of all possible permutations of bool decision to actuate for each t over N_w
for *i in permut[]* **do**
  for *j in i* **do**
    if *j = True* **then**
      ; $E\_au \leftarrow E\_ac + E\_mo * azi[j] - \theta$ from eqn. 4
      $\theta \leftarrow$ azi[j] ▷ // Update solar cell position
      $E_{pv} = \eta_{pv} A_{pvg} G_{bn} \cos\theta$ from eqn. 5
      $H_g[j] = E_{pv} - E_{au}$ from eqn. 3
    else
      ; $H_g[j] = \eta_{pv} A_{pvg} G_{bn} \cos\theta$ ▷ // As no actuation
  if $sum(H_g) > H_{gmax}$ **then**
  $H_{gmax} = sum(H_g)$
  movement$_{Nw} = i$;

method will be the optimal strategy for solar tracking. However, this is computationally heavy solution, which is quantified in the evaluation section of this paper. As this algorithm operates over N_w, it naturally follows that prediction of G_{bn} [6] is needed, introducing errors into the Bruteforce method. For the evaluation of this paper, the Bruteforce method is used to benchmark the efficacy of the proposed Lightweight method using real solar trace data. The errors introduced by solar prediction are considered outside the scope of this paper and will be explored in future work

C. Lightweight Solver

In order to overcome the limitations of the Bruteforce method, a Lightweight method is proposed here to solve the formulated problem. It is designed to be calculated, in node, at every time t without the need for prediction of future solar energy harvesting performance.

The Algorithm 9 returns a decision to move in the current time slot, t, and by how much the solar tracker should move. In order to further understand the dynamics of this system, evaluations are performed.

III. Evaluation

In order to test the efficacy of our proposed models, simulations are undertaken. Furthermore, the novel Lightweight method is simulated over a year period to understand the performance over a long term period. In order to test the true efficacy of the proposed solution real world testing is undertaken utilizing a micro solar tracking harvesting test rig.

In order to test over long term periods three elements are needed; long term environmental data [16], an accurate

Algorithm 2: Proposed Lightweight Algorithm

Input : E_{ac},E_{mo},η_{pv},A_{pvg},G_{bn},θ,azi
Output: movement$_t$
E $_{pv}$ ← `measureEnergy` ()
// Measure the energy production of the energy harvester
$G_{bn} \leftarrow \frac{E_{pv}}{\eta_{pv} A_{pvg} \cos\theta}$
$E\_au \leftarrow E\_ac + E\_mo * (azi - \theta)$
$E\_pv2 \leftarrow E_{pv} = \eta_{pv} A_{pvg} G_{bn} - E\_au$
if $E_{pv2} > E_{pv}$ **then**
; return $azi - \theta$
else
; $return$ 0 ▷ // As no actuation

solar model to generate realistic energy data from said environmental data [17], [18] and an accurate knowledge of the cost of actuation of the tracker which is measured from the experimental rig designed, described in Table I. The time window N_w is chosen to consist of 48 timeslots, each lasting 30 minutes, to reflect the cyclical natural of solar energy.

Table I: Variables utilized in evaluation

Variable	Value
Solar Cell Size	58mm*48mm
η	15%
$E_m a$	400 mA
$E_m m$	140 mA
N_w	48
t	30 minutes
elevation	50.5° (Brasilia)
elevation	19.8° (Seattle)

Broadly this section compares and contrasts the performance of 4 different methods:

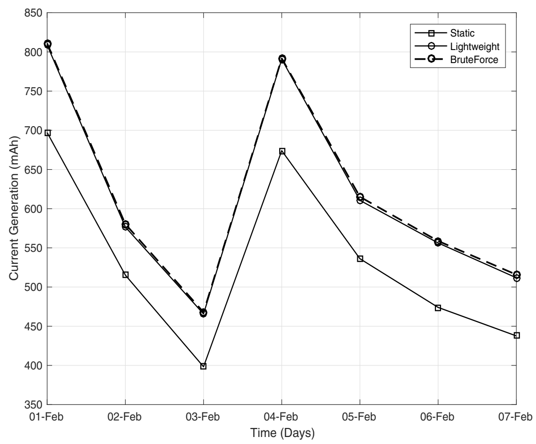
1) Static: a non moving solar cell, facing due south
2) Traditional: The established method of solar tracking through consistent actuation at discrete time slots
3) Bruteforce: The centralized brute force algorithm proposed in this paper
4) Lightweight: The novel lightweight, prediction free, distributed algorithm proposed here

To begin this evaluation we perform a comparative analysis of the lightweight and brute force method.

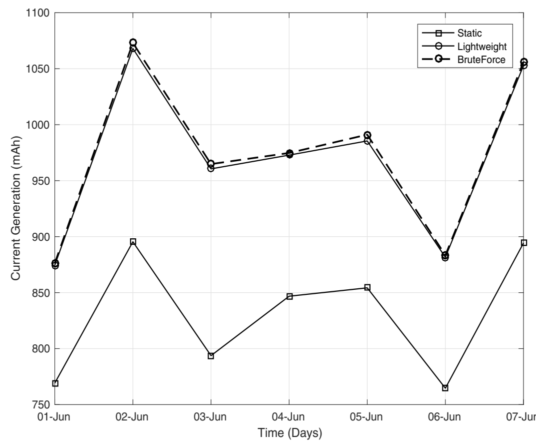
A. Algorithm Evaluation

To understand the efficacy of the Bruteforce and Lightweight methods 28 day long simulations are undertaken. Due to the aforementioned complexity of the centralized solution, these were performed across 7 separate cloud based servers to expedite the process. The Static method is included to provide a baseline and the Traditional method is excluded from this section for clarity and is explored at a later stage.

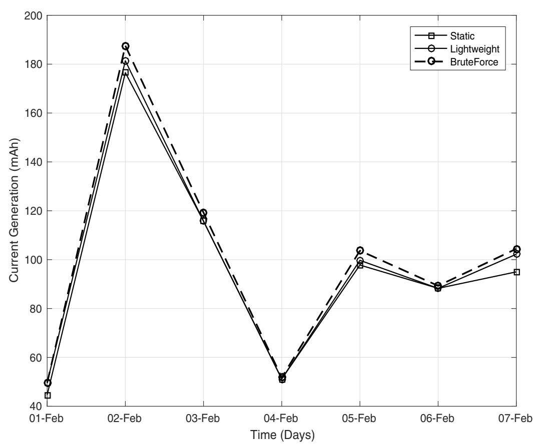
Figure 2 performs 7 day long tests across four unique solar exposure types, which were chosen to give a broad range of solar energy harvesting to test the resilience of the two methods. Broadly these exposure types are:



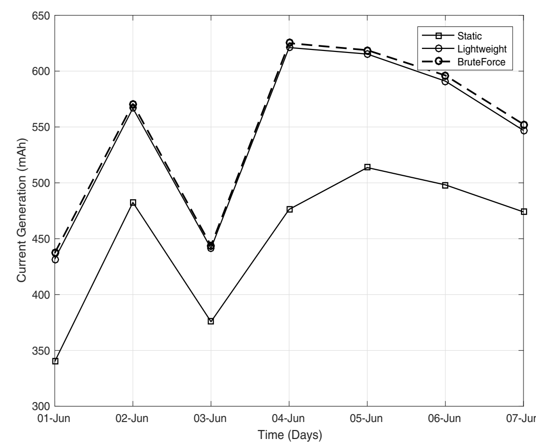
(a) HO_Solar: A week of energy generation simulations using real data from February in Brasilia, Brazil



(b) HC_Solar: A week of energy generation simulations using real data from June in Brasilia, Brazil



(c) LO_Solar: A week of energy generation simulations using real data from February in Seattle, USA



(d) LC_Solar: A week of energy generation simulations using real data from June in Seattle, USA

Figure 2: 28 Day long (in 4 week long groups) simulations showing the total energy produced per day for the Static, Brute force and Lightweight methods

1) HO_Solar: High incident solar energy and cloudy or overcast sky
2) HC_Solar: High incident solar energy and clear sky
3) LO_Solar: Low incident solar energy and cloudy or overcast sky
4) LC_Solar: Low incident solar energy and clear sky

The simulations in Figure 2 highlight the similarities between the Bruteforce and Lightweight methods proposed in this paper. Throughout the simulations the Lightweight method averaged 99.1% the energy generation per day when compared to the Bruteforce approach, with a minimum of 96.1% energy produced and a maximum of 100% of energy produced. Figure 2c highlights the performance of the adaptive solar tracking methods on a day with low energy production.

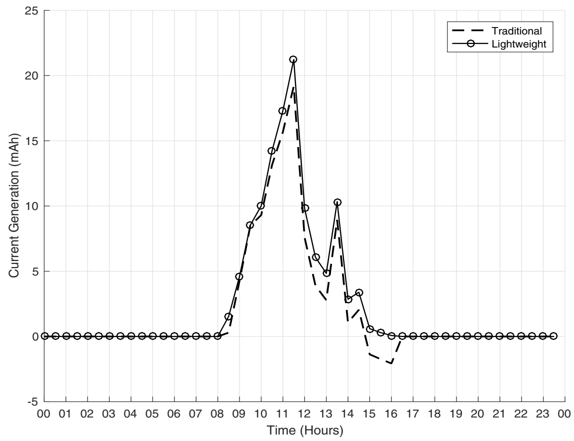
The time complexity of each approach is worth highlighting, with the Bruteforce approach taking an average of 11.8 hours to calculate a days operation, N_w, whereas the Lightweight method could be calculated, on average, in 1.2 seconds over N_w.

Considering the overhead of complexity of the Bruteforce method in comparison to the Lightweight method, the 99% average performance of the globally optimal solution and the potential errors that could be introduced in the Bruteforce method; the Lightweight method is considered by the authors to be the superior solution for further exploration in this paper.

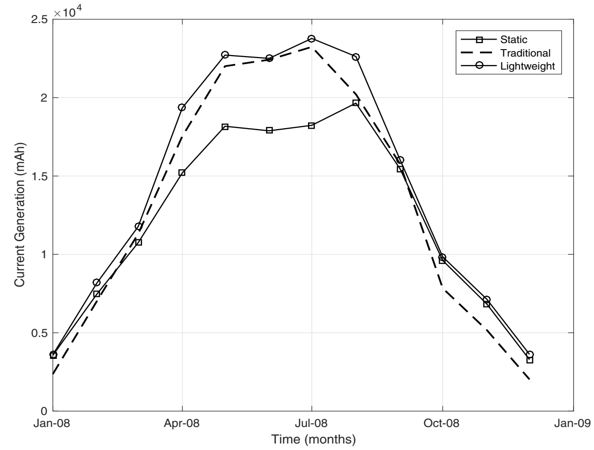
B. Lightweight Adaptive Solar Tracking

The following simulations are undertaken to quantify the benefits of the Lightweight solar tracking method, Figure 3a explores a sample day with both the Traditional, Static and Lightweight methods and Figure 3b reveals the performance over a full year.

Figure 3a highlights the benefits of the Lightweight method, over a LO_Solar day with dynamic periods of low



(a) Simulation of example LO_Solar day



(b) 1 Year of solar data used to compare methods over the long term utilizing real data from Seattle, USA

Figure 3: Graph of simulation of Lightweight method compared to Traditional and Static methods

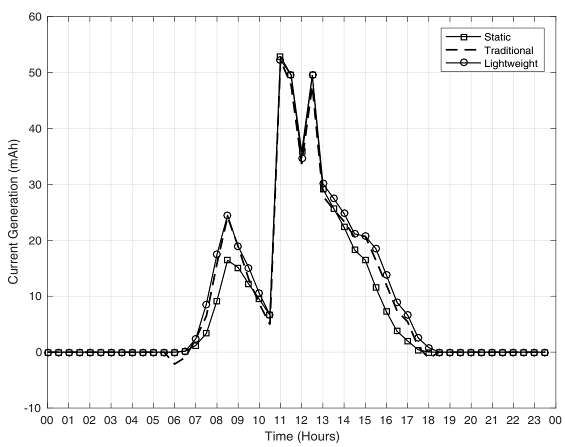


Figure 4: Results of real world testing, undertaken 26/03/2017

energy production it can be seen that the Traditional method can consume more energy than it produces in a timeslot. The Lightweight method conserves energy when it is most needed, during periods of low energy production to allow greater energy production when the system is operating in challenging solar harvesting conditions, which can help to promote sustainability in an EH-WSN and reduce the chance of failures. Results show a 26.4% increase in solar energy harvested over the course of the day for the Lightweight method over the Traditional method with a 165% increase in H_g in one timeslot, t.

Figure 3b explores the energy generation over a full year. It can be seen that the Lightweight method consistently outperforms both the Traditional and Static methods. Comparing both methods to the Static approach, the Traditional generates 9.8% greater energy over a year period whereas the Lightweight approach generates 17.3% greater energy.

C. Real World Experimentation

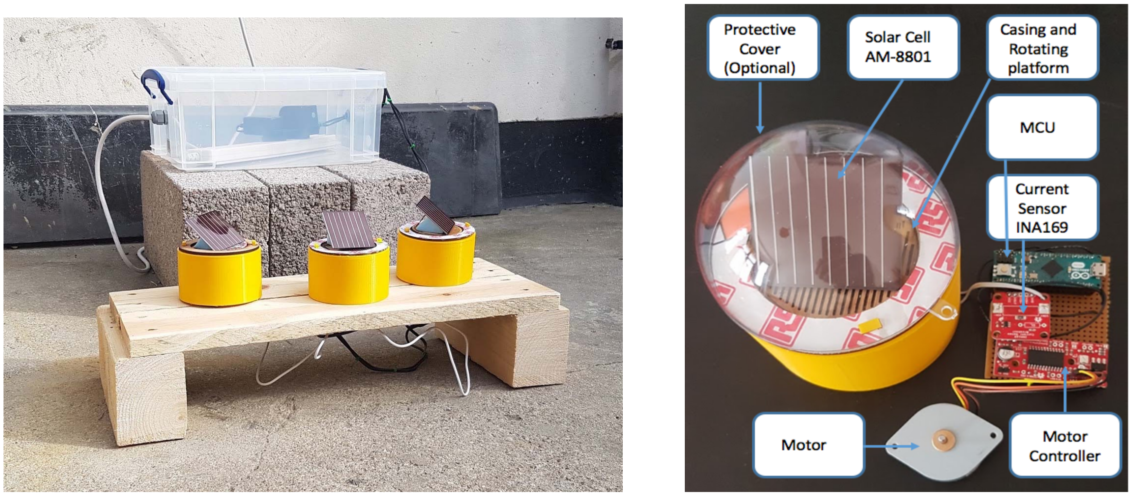
In order to understand the performance of the Lightweight method, real world experimentation is undertaken, as can be seen in Figure 5a, utilizing an open source testing apparatus designed for this paper, as can be seen in Figure 5b. The experimental setup operates the Static, Traditional and Lightweight methods described in this paper to evaluate their performance in a real world scenario.

Figure 5b highlights the individual components of each solar tester, which contain a motor and motor controller for actuation, solar cell for energy generation, current sensors to understand the performance of the solar cells and an MCU to run the algorithms necessary to perform the testing. Testing data is passed via serial to an Intel Edison Linux based microcontroller which parses and stores the evaluation data from each solar tester. The physical enclosure and movement mechanism is manufactured utilizing 3d printing and laser-cutting digital manufacturing techniques. Further information, including source files for the physical enclosure design, circuit design, firmware for both the algorithms and Edison aggregator and a time-lapse video of the deployment is available at https://goo.gl/AYs7GB.

Figure 4, shows the results from the first outdoor real world testing of the testing apparatus, conducted on a HC_Solar day. Results show a 7.8% increase in solar energy harvested over the course of the day for the Lightweight method over the Traditional method. This is to be expected from simulations on the day of the testing, next steps will include extended testing in the real world to incorporate the other testing environments classified in this paper.

IV. Conclusion

Insufficient energy generation can be a major issue during the operation of WSN systems. To achieve the goal of perpetually powered EH-WSN, maximizing energy produced by solar energy harvesters is essential. In this paper, we



(a) Deployment of real world test

(b) Exploded view of hardware with labels

Figure 5: Graph of testbed designed for real world testing of the algorithms designed

have shown that, by using our novel Lightweight tracking algorithm, it is possible for WSN applications to increase their energy generation by up to 165%. The ability to maximize energy generation of a WSN improves the ability for it to undertake sensing, transmission, and data processing tasks. For access to open source hardware, firmware, casing design and software analysis tools developed for this paper as well as a video of the deployment testing, please visit https://goo.gl/AYs7GB.

Next steps will include extended deployment of the testing apparatus to gather long term data to validate the methods proposed here as well as examining trade-offs associated with different actuator technologies and their associated energy consumption, solar cell technologies, and size.

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