Work in Progress: Prediction of Solar Energy for Infrastructure based Wireless Sensor Networks

Vijay S Rao
Faculty of EEMCS
TU Delft, Netherlands
v.rao@tudelft.nl

Shruti Devasenapathy
Faculty of EEMCS
TU Delft, Netherlands
s.devasenapathy@tudelft.nl

R Venkatesha Prasad
Faculty of EEMCS
TU Delft, Netherlands
rvprasad@ieee.org

Prabhakar T V
CEDT, IISc
Bangalore, India
tvprabs@cedt.iisc.ernet.in

Ignas Niemegeers
Faculty of EEMCS
TU Delft, Netherlands
i.g.m.m.niemegeers@tudelft.nl

ABSTRACT

Wireless sensor networks are used in scenarios where many sensors need to collect data and exchange with a central *base station*. These battery powered devices are expected to have a long lifetime as frequent battery replacement is labor intense and in some cases may not be possible due to deployment constraints. Ambient energy harvesting is a promising approach to replenish the energy. However, the current day harvesters typically the size of the sensor node, cannot provide perineal power to sensor nodes and thus energy-neutral operation is non trivial due to the spatio-temporal variations in the source and the low efficiencies of the harvesters. A smart approach is to adapt the system according to the incoming energy.

In this paper, we aim to predict the solar energy with the assistance of a discrete time Markov chain. The base station conveys the diurnal and seasonality cycles of the source to the sensor nodes. The nodes use this data to predict and budget their energy. This approach is a practical one since base stations exchange data periodically with nodes and are capable of heavier computation and storage. The accuracy of our method is evaluated with data from CONFRRM.

Keywords

Markov chains, solar energy prediction, energy harvesting, smart energy budget

1. INTRODUCTION

Wireless sensor networks have been conceived and deployed in wide variety of applications. A major drawback of these WSNs is the energy-constraint, since they rely on portable sources like batteries for power. In many cases replacement of batteries in these networks is restricted by physical or deployment conditions. Hence, just relying on batteries are not sufficient for perennial operation of WSNs.

Recent advances in ambient energy harvesting technology have made it a promising alternative source of energy. Possible sources for energy harvesting are light, vibration, thermal and wind. Each of these sources has a different energy harvesting profile, and rate of energy harvested from a source varies over location, time and size of the harvester. Of all the sources, solar source provides the highest power density [9]. Hence, the solar harvester is the most common harvester used with WSNs.

The goal of the WSN design is to achieve *energy neutral* operation [3]. However, even with a solar harvester it is difficult to achieve perennial operation due to the varied challenges posed by the system: (a) Ambient energy sources do not provide continuous energy; and (b) energy harvested by these sources vary drastically over location and time. For instance, statistics show that the difference can be up to three orders of magnitude among the available solar power in shadowy, cloudy and sunny environments [10]. A better way towards energy neutral operation is to adapt the system's energy consumption according to the incoming energy. A further improvement over this method is to know the incoming energy and then adapt the system's operations accordingly. This method increases the efficiency of the system. Thus, a major challenge is to predict the energy source for better power control and scheduling optimizations.

Solar source has been studied the most with respect to its prediction. However, there is a lack of simple model yet accurate model that can be used in real-world WSN scenarios. In this paper, we aim for solar source prediction using a first order 3-state discrete time Markov chain for an infrastructure WSN.

The paper is organized as follows: Sec. 2 describes the previous work on solar energy predictors. Sec. 3 proposes a simple method to predict based on a 3-state Markov model. Sec. 4 discusses the results of prediction and Sec. 5 concludes the paper.

ExtremeCom '12, March 10-14, 2012, Zürich, Switzerland.

2. LITERATURE REVIEW

Solar energy is the most stabilized one among the set of ambient energy micro-harvesters. However, due to weather changes, the power from the energy source changes from time to time. Many works have looked into predicting the solar source. Few important ones are described in this sec-

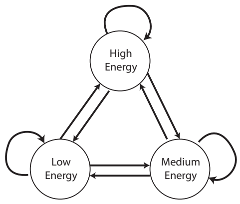

Figure 1: 3-state Markov chain

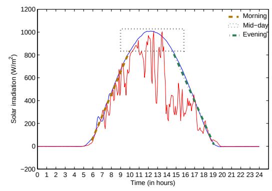

Figure 2: Day divided into 3 periods shown over two different days

tion.

A simple time-series prediction is moving average and exponential smoothing [2] [4]. These methods are not the best predictors given diurnality and seasonality of the solar data, though they are computationally feasible on the sensor nodes. A better predictor is proposed in [7], which uses artificial neural network based prediction.

Markov modelling for solar powered energy harvester has been investigated in [6]. The proposed stochastic model is used to investigate QoS performances for different sleep and wakeup strategies with respect to average queue length, average battery capacity, average delay etc. The Markov chain model considers wind speed, cloud size and probability of having a cloud cover, making it a not-so-simple model for WSN. In [11], a software is used to generate the Markov models. The number of states are not fixed, and may vary depending on the length of statistical data available. The transitions are allowed only between consecutive states ignoring the fact of cloud cover by passing clouds that can have an immediate effect on the amount of energy harvested. Markov models are also proposed in climatology literature. In [8], twenty years of data was analysed and 20 state Markov chain was created - each state with a step of 0.05 of clearness index over the previous state.

As can be seen, a light-weight yet accurate model for prediction is missing. We propose one such model in this paper.

3. PROPOSED MARKOV MODEL

We assume a infrastructure based WSN i.e., a sensor network in which the nodes communicate with a base-station. This communication can be either single-hop or multi-hop. We assume the base-station is capable of heavy computation and has higher memory capacity. We also assume the base-station is always on and powered through mains.

The base-station has all the historical data over different months and years. This data is divided into twelve - one per each month. Further, each day is divided into 3 parts - morning, mid-day and evening (see Fig. 2). This division is necessary due to diurnality i.e., during mornings, the transition probability to state *high energy* is higher. Similary, during evenings, the transition probability to state *low energy* is higher. The base-station creates three transition probability matrices for a day for a 3-state Markov chain as depicted in Fig. 1. We assume no harvesting is done during nights (due to ambient light) and no prediction is done. Each morning the base-station sends a transition probability matrix to the WSN nodes. The nodes use this matrix to predict the energy over the next slot. At the same time, the energy haversted in the next slot is recorded and the transition matrix is updated. At the beginning of mid-day the updated matrices are uploaded to the base-station which updates its own matrices. Then the base-station sends in a new set of transition probability matrix for the next period of the day.

The prediction in the nodes is done by calculating the expected hitting times of the states from the current state. It is done as follows: Let τ_i be the expected time to hit state j starting in state i. Hitting time for i is 0, and for other states:

$$\begin{aligned} \tau_j &= E(time\ to\ hit\ j|start\ in\ i) \\ &= 1 + \textstyle\sum_{k \in S} p_{ik}\tau_k \end{aligned}$$

where p_{ik} is the transition probability from state i to k, and S is the set of states. Obviously, the state j with minimum τ_j is the next possible state. A threshold is used to distinguish whether the transition was to the same state or to a different one.

4. RESULTS

We use CONFRRM data [1] collected by Elizabeth City State University in North Carolina (NC), USA for simulations. The data is collected in real-time and then averaged over five minutes. Several solar data elements are measured and reported by the CONFRRM sites including global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), and global horizontal irradiance measured with a LI-COR pyranometer. Certain other meteorological data are also measured like air temperature, relative humidity, pressure, wind speed, wind direction and peak wind speed. However, for our simulations we consider only the GHI.

We use the data starting from 2006 upto 2010 for the month of July. Sun rises at 06:15 (±10 minutes[1]) and sets at 20:20 (± 5 minutes) on a typical day of July in NC. Accordingly, we divide the day into morning starting from 06:15 to 10:00 hours. From 10:00 to 15:00, we call it mid-day and from 15:00 to 19:30 we call it the evening period. Note, we do not consider the data after 19:30 hours since the harvested energy is negligible. With this data, and the sensor nodes equipped with appropriate transition probability matrices, we try to predict what state will the node be over the next 5 minutes.

With the data of 2006 to 2010, we built up the transition probabilities for the three different periods of the day. We then try to predict for July 2011. For a random day, the results are tabulated in Tab. 1.

A graph for number of errors for the month of July for the evening period is shown in Fig. 4. To demonstrate the implications of a good predictor, we devise a simple scheduling mechanism. The scheduler uses the prediction to determine the incoming energy to decide whether a current task

[1]due to the sun movement

Period	Number of accurate predictions/Max. data points
Morning	45/47
Mid-day	55/60
Evening	50/54

Table 1: Predicted accuracy on a random day

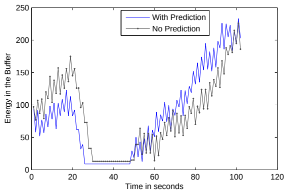

Figure 3: Better energy management with a prediction based scheduler

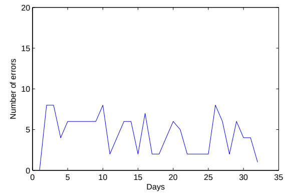

Figure 4: Number of errors in prediction in evening period for the month of July

should be executed or not. We emphasize that there are better schedulers like Lazy Scheduling Algorithm [5] which can better utilize the prediction. As can be seen from Fig. 3, a simple scheduler using the previously descibed prediction mechanism outperforms the same scheduler without any prediction mechanism with respect to energy management. A better energy management leads to longer lifetime of the network, and also higher chances of completion of the tasks. The number of tasks successfully completed is higher with prediction based scheduler, as can be seen in Table 2.

5. CONCLUSIONS

Battery powered WSNs are critically limited by the energy. However, battery replenishment may not be possible due to various constraints. Current advances in technology have made ambient energy harvesting a possibility to replenish the battery in certain cases. With energy harvesting, energy neutral operation is desired. However, due to the spato-temporal variations in the source and the low efficiencies of the harvesters, it is not a possibility. A smart approach is to adapt the system according to the incoming energy.

In this paper, we proposed a simple 3-state discrete time Markov chain to predict the solar energy. The approach is simple enough to be deployed in a infrastructure based WSN. This approach is a practical one since base stations are capable of heavier computation and storage, and the base station and the nodes exchange data periodically. The nodes use this data to predict and budget their energy. The accuracy of our method is evaluated with data from CONFRRM, and it is shown the prediction method produces fewer errors. We built a simple scheduler to demonstrate the performance enhancement that can be derived from the predictor on the energy management of the sensor node. It was also shown more number of tasks can be completed using such a scheduler. As future work, we wish to work on improving the prediction method and test it with near-optimal schedulers like LSA to improve the performance and lifetime of WSN.

With prediction	Number of tasks not completed
Yes	12/51
No	17/51

Table 2: Performance of prediction based scheduler

6. REFERENCES

[1] CONFRRM - Cooperative Networks For Renewable Resource Measurements - solar energy resource data. http://rredc.nrel.gov/solar/new_data/confrrm/.

[2] M. Gorlatova, A. Wallwater, and G. Zussman. Networking low-power energy harvesting devices: Measurements and algorithms. In *2011 Proceedings IEEE INFOCOM*, pages pp. 1602 –1610, april 2011.

[3] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava. Power management in energy harvesting sensor networks. *ACM Trans. Embed. Comput. Syst.*, vol. 6, September 2007.

[4] S. Liu, J. Lu, Q. Wu, and Q. Qiu. Harvesting-Aware Power Management for Real-Time Systems With Renewable Energy. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. PP(99):pp. 1–14.

[5] C. Moser. *Power Management in Energy Harvesting Embedded Systems*. PhD thesis, ETH Zurich, 2009.

[6] D. Niyato, E. Hossain, and A. Fallahi. Sleep and Wakeup Strategies in Solar-Powered Wireless Sensor/Mesh Networks: Performance Analysis and Optimization. *IEEE Transactions on Mobile Computing*, vol. 6(2):pp. 221–236, Feb. 2007.

[7] C. Paoli, C. Voyant, M. Muselli, and M.-L. Nivet. Solar radiation forecasting using ad-hoc time series preprocessing and neural networks. In D.-S. Huang, K.-H. Jo, H.-H. Lee, H.-J. Kang, and V. Bevilacqua, editors, *Emerging Intelligent Computing Technology and Applications*, volume vol. 5754 of *LNCS*, pages pp. 898–907. Springer Berlin / Heidelberg, 2009.

[8] P. Poggi, G. Notton, M. Muselli, and A. Louche. Stochastic study of hourly total solar radiation in corsica using a markov model. *International Journal of Climatology*, vol. 20(14):pp. 1843–1860, 2000.

[9] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, and M. Srivastava. Design considerations for solar energy harvesting wireless embedded systems. In *IPSN 2005.*, pages pp. 457 – 462, april 2005.

[10] M. Rahimi, H. Shah, G. Sukhatme, J. Heideman, and D. Estrin. Studying the feasibility of energy harvesting in a mobile sensor network. In *ICRA '03.*, volume vol. 1, pages 19 – 24 vol.1, sept. 2003.

[11] A. E. Susu, A. Acquaviva, D. Atienza, and G. De Micheli. Stochastic modeling and analysis for environmentally powered wireless sensor nodes. In *WiOPT 2008.*, pages pp. 125–134. IEEE, Apr. 2008.