Poster Abstract: Improving Energy Predictions in EH-WSNs with Pro-Energy-VLT

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ABSTRACT

The increasing popularity of micro-scale energy-scavenging techniques for wireless sensor networks (WSNs) is opening new opportunities for the development of energy-autonomous systems. To sustain perpetual operations, however, environmentally-powered motes must adapt their workload to the stochastic nature of ambient power sources. Energy prediction algorithms, which forecast the source availability and estimate the expected energy intake in the near future, are precious tools to support the development of proactive power management strategies. In this work, we propose Pro-Energy-VLT, an enhancement of the Pro-Energy prediction algorithm that improves the accuracy of energy predictions, while reducing its memory and energy overhead.

Categories and Subject Descriptors

C.3 [**Special-purpose and application-based systems**]: Real-time and embedded systems

General Terms

Experimentation

Keywords

Energy harvesting, solar-powered, energy prediction, prediction algorithm, Pro-Energy, wireless sensor networks

1. INTRODUCTION

Environmentally-powered systems have to deal with the dramatic variations of ambient power sources over time, which results in an alternation between periods in which energy must be sparely used, and situations in which there may even be an excess of energy available. In the case of predictable energy sources, such as solar light, energy prediction models can alleviate the problem of uncertain power availability, allowing the system to make critical decisions about the utilization of the energy available in the near future. Acknowledging the potential of this approach, many works have proposed energy predictions methods for energy-harvesting WSNs (EH-WSNs) [1, 4, 5, 3]. In this work, we propose a simple yet effective enhancement of the Pro-Energy prediction algorithm [1] to improve the accuracy of solar energy predictions, while, at the same time, reducing its memory and energy overhead.

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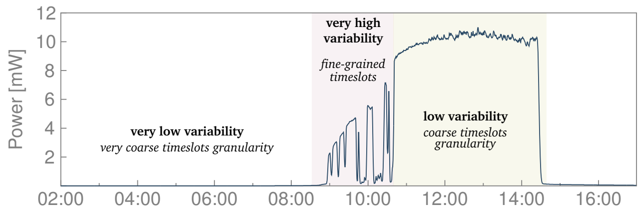
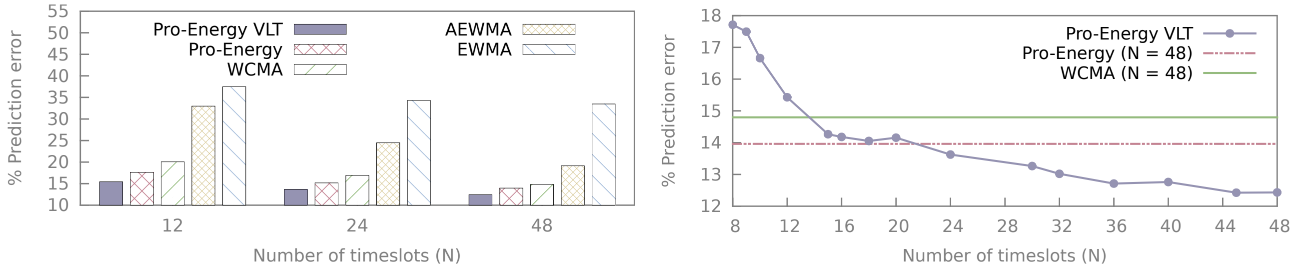


Figure 1: The granularity of the prediction timeslots should depend on the dynamics of the power source.

2. OUR APPROACH: PRO-ENERGY-VLT

Pro-Energy is an energy prediction model for EH-WSNs that leverages past energy observations to provide estimations of future energy availability. To this end, Pro-Energy maintains a pool of D profiles of harvested energy that represent the energy intake recorded during different types of "typical days" (e.g., sunny, cloudy or rainy). Similarly to others state-of-the-art predictors, Pro-Energy divides each day into N fixed-length timeslots, each indicating the amount of energy harvested within it. We argue, however, that the choice of using equal-length timeslots, although very common, may not lead to the best results. In fact, the harvesting process often exhibits patterns that may be better captured by adapting the granularity of the timeslots to the dynamics of the power source. An example is illustrated in Figure 1, which shows a real-life solar energy harvesting trace collected by interfacing a Telos B mote with a XOB17-04x3 solar cell: during a typical day there may be periods in which the harvesting rate varies frequently, and others in which the average amount of power harvested is much more stable. Based on this observation, we propose Pro-Energy-VLT (PROfile Energy prediction model with Variable-Length Timeslots), an energy prediction model that combines Pro-Energy with timeslots of variable lengths, whose granularity is set coarser or finer based on the dynamics of the power source. In Pro-Energy-VLT, the timeslot granularity is estimated based on the average daily harvesting profile, which can be computed off-line by using historical weather data. To determine the size of each of the N times-



(a) (b)

Figure 2: (a) Comparison of the energy prediction error of Pro-Energy-VLT, Pro-Energy, WCMA, AEWMA, and EWMA for varying numbers of timeslots; and (b) Pro-Energy-VLT prediction error for different values of N.

lot, we run an iterative algorithm based on the so-called Perceptually Important Point (PIP) method [2], which identifies the $N+1$ points with the greatest impact on the shape of the daily harvesting profile.

3. PERFORMANCE EVALUATION

We compare the performance of Pro-Energy-VLT with that of Pro-Energy and of three other popular predictors previously proposed in the literature: WCMA [5], the energy prediction model proposed by Noh and Kang in [4] (which we denote for brevity AEWMA), and EWMA [3]. WCMA, AEWMA and EWMA assume the energy harvesting in the near future to be related to the energy intake at the same time on the previous days. While EWMA and AEWMA maintain historical data as a single vector of size N, WCMA stores a matrix of size $D \times N$, where D is the number of previous days used for energy predictions.

We evaluate the accuracy of each predictor over a set of 90 consecutive days of solar traces collected in 2009, obtained from the National Renewable Energy Laboratory at Oak Ridge, Tennessee. From the same source we also retrieved a training dataset of 90 days collected in 2008, which we used to dimension the timeslots used by Pro-Energy-VLT, as explained in Section 2. The error of each energy predictor over the whole dataset is computed as:

$$\%Error = 100 \cdot \frac{\sum |\overline{e}_t - \widehat{e}_t|}{\sum \overline{e}_t},$$

where $\widehat{e}_t$ is the energy predicted for timeslot t, and $\overline{e}_t$ is the actual energy harvested during timeslot t. To perform a fair comparison, the coefficients of each prediction model have been set to the values that minimize the overall error of the predictions.

Figure 2(a) shows the result of such evaluation for $N = 12, 24$ and 48. As shown by the figure, Pro-Energy-VLT consistently outperforms the other algorithms, obtaining a total prediction error that is 10.14% to 12.33% lower than that of Pro-Energy, 15.97% to 23.05% lower than that of WCMA, 35.03% to 53.23% lower than that of AEWMA, and 58.84% to 62.86% lower than that of EWMA. As expected, the prediction error decreases for increasing values of N, as using a higher number of timeslots allows to better capture the source dynamics when the harvesting variability is high.

Figure 2(b) reports a comparison between the error obtained by Pro-Energy-VLT for different values of N and the minimum prediction error of the other predictors, achieved when $N = 48$. The errors of AEWMA and EWMA are not reported, as they are both greater than 19%. Pro-Energy-VLT outperforms the other models in terms of prediction error, using a number of timeslots that is approximately one third and one half of that used by WCMA and Pro-Energy, respectively. This results in significant energy saving, as the overhead of an energy prediction model is directly proportional to N. The number of timeslots also affects the memory overhead of a predictor. For example, assuming $N = 48$ and $D = 20$, WCMA requires approximately 4 KB of RAM to store the matrix of the D previous days needed for energy predictions, which represents 40% of the total memory available on a Telos B mote. Using just 15 timeslots, Pro-Energy-VLT can obtain a prediction error lower of that of WCMA, while reducing at the same time the memory overhead of about 70%. With respect to Pro-Energy, a 50% reduction of the memory overhead is achieved.

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