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Original Research Paper

A Performance Evaluation of Solar Energy Prediction Approaches for Energy-Harvesting Wireless Sensor Networks

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Abstract: Energy harvesting from the surrounding environment has been a superior way of eliminating the burden of having to replace depleted batteries in wireless sensor networks (WSNs), thereby achieving a perpetual lifetime. However, the ambient energy is highly time-variable and depends on the environmental conditions, which raises the need to design new approaches for predicting future energy availability. This paper presents a performance evaluation and comparison of three recently-proposed solar energy prediction algorithms for WSNs. In order to provide an accurate performance of the algorithms, real-world measurements obtained from a solar panel were considered. Also, the performance characteristics of the algorithms in four seasons –winter, spring, summer and autumn – were demonstrated. To do this, a month in each season was selected for performance comparison, discussing the performance of the algorithms in each season.

Keywords: *Wireless sensor networks, Energy harvesting, Solar energy.*

1. Introduction

Wireless sensor networks (WSNs) are composed of a collection of sensor nodes designed to perform a common duty and which have the tasks of sensing, processing and communicating data, aiming to deliver it to a remotely-located central point [1]. The sensor nodes are often powered by limited-energy sources, typically small batteries. This makes energy efficiency a vital criterion in the development of WSNs, so the main emphasis has been placed on prolonging the lifetime of WSNs. A sensor node is equipped with four components as depicted in Fig. 1: (1) a sensing unit to detect environmental data such as temperature; (2) a micro-processor to process the data; (3) a radio for communication between the sensor nodes; and (4) an energy unit to supply energy to all the components. It is well-understood that data communication in a sensor node consumes the most energy. Therefore, communication between the sensor nodes has to be managed in an efficient manner. To control the transmission medium in a WSN effectively, medium access control (MAC) protocols are developed to reduce the energy consumption due to inefficient data communication (for example, by collision). There are huge numbers of MAC protocols specifically proposed for WSNs which minimize energy wastage as well as enhancing the channel performance (for example, throughput, delay and fairness) [2, 3]. However, such a WSN system will eventually fail to operate because of the limited energy supply.

In order to handle the inevitable energy depletion in WSNs, energy harvesting (EH) from the environment is an alternative technique to ensure an unlimited energy source. In this technique, each sensor node can harvest energy continuously from its surrounding environment through an EH device. The main purpose is to extract the environmental energy and convert it into electricity to power sensor nodes. The major sources of existing environmental energy for WSNs are solar, wind, vibration and thermal. In order to enable sensor nodes to benefit from EH technology, a new type of sensor node equipped with an EH unit has been developed to perpetuate the lifetime of WSNs [4]. Fig. 2 presents an example architecture of an EH sensor node with the sun as the energy source, a solar panel to produce energy from the sun, and a super-capacitor to store the harvested energy.

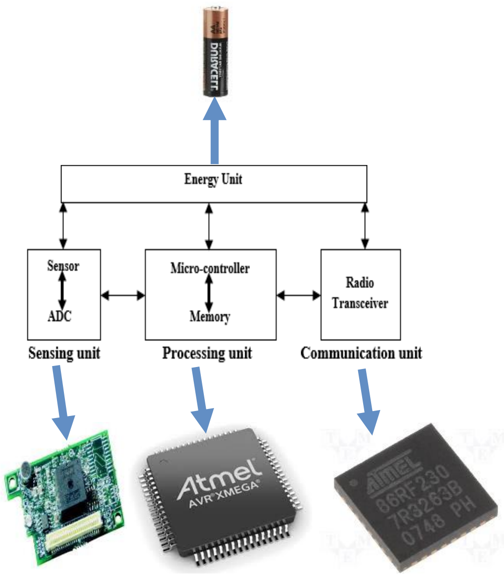

Figure 1. A sensor node architecture with real hardware.

EH sensor nodes potentially provide a perpetual lifetime by exploiting the ambient energy. It should therefore be noted that the fundamentals of MAC protocols that will be developed for energy harvesting WSNs (EH-WSNs) will be re-considered to mitigate the uncertainty of amount of ambient energy over time. This is because ambient energy is highly dependent on environmental conditions and is time-variable. The ambient energy can be harvested using varying ratios at different time slots of a particular day. The main task of new MAC protocols is to maintain the performance of a network at an acceptable ratio with respect to the changing available rate of energy to be harvested. Currently, the design of MAC protocols for EH-WSNs is a fiercely-debated topic and an on-going research area. A number of MAC protocols proposed for EH-WSNs have been surveyed in detail in [5]. This survey explicitly highlights that existing MAC protocols should comfortably meet the energy

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neutral operation (ENO) condition in which the amount of energy generated must always be greater than the energy consumed within a particular time duration. The nodes which satisfy the ENO condition are assumed to operate perennially. In these protocols, a node is allowed to start transmission as long as it stores sufficient power in its battery.

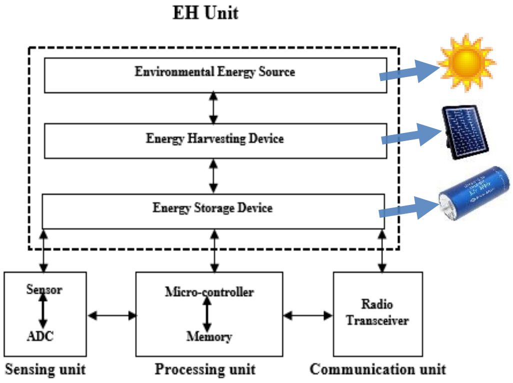


Figure. 2 EH sensor node architecture with real hardware.

Many of the current MAC protocols do not consider future energy availability as they only consider current residual energy level as discussed above. The future energy level, however, may change dramatically resulting in some nodes facing temporary energy shortages. This can cause significant problems, such as some important information might be transmitted very late or get lost. Therefore, future MAC protocols should arrange the transmission policies based on the energy generation ratio [6]. Careful prediction of future energy levels opens a new perspective [7].
The aim of this paper is to study the solar energy prediction algorithms proposed for EH-WSNs, focusing particularly on the performance of the algorithms using real measurements. Solar energy was chosen for this study as it is the most appropriate energy source for EH-WSNs due to its high energy density. We selected three recent prediction algorithms: the exponentially-weighted moving average (EWMA) [8], the accurate solar energy allocation (ASEA) [9] and the weather-conditioned moving average (WCMA) [10]. These approaches had been previously tested in short-term scenarios (a few days) in which the actual performance of the approaches may not have been reflected. To avoid this, we obtained real measurements from [11] for the second month of each season in 2015. Also, the basic operations of the approaches will be described in detail in the following section. It is believed that this study will provide an insight into future research directions in the relevant area.

2. Solar Energy Prediction Approaches

2.1. Exponentially-Weighted Moving Average

The exponentially-weighted moving average (EWMA) is the main approach which has inspired the design of many prediction algorithms in the literature. The fundamental aim of EWMA is to benefit from the daily cycle in solar energy by adapting to seasonal variations. The 24-hour day is divided into slots of equal length, such as 24 one-hour slots. The energy in each slot is predicted based on an exponentially increasing/decreasing rule given by Eq. (1). EWMA uses historical information of the energy generation pattern. For this purpose, the last amount of harvested energy (R) and estimated energy (E) by EWMA are summed with a weighting factor, $0<\alpha<1$, arranging the importance of the R and E. A high value of α corresponds to less importance of the last-harvested energy and *vice versa*.

$$\mathrm{E}(d, n) = \alpha\, \mathrm{E}(d\text{-}1, n) + (1 - \alpha)\, \mathrm{R}(d\text{-}1, n) \tag{1}$$

Where d represents the present day and n is the slot identifier. One of the most important features of EWMA is its high adaptability for seasonal weather variations. The efficiency of EWMA in terms of time taken to adapt to such seasonal change depends on the duration of weather variation and an accurate choice of α. Fig. 3 presents an illustrative example for predicting energy using two different α values. In this example, the energy estimation in slot 2 is performed in a case when the weather condition changes abruptly. The amount of harvested energy continues to be four times greater than the estimated energy. An α value of 0.5 exhibits slower adaptability than an α value of 0.3. This is because, as discussed above, smaller α values take the latest real energy measurement into consideration more aggressively. After a specific time period, both α values start to provide accurate overall predictions.
The major disadvantage of EWMA is its vulnerability to temporary changes. For example, the example presented below shows that the energy expectation on the day after (T+6) day will certainly be a value close to 40. If, however, contrary to expectation, the harvested energy on this day is significantly higher/lower than the expected energy, EWMA produces highly inaccurate results. It is therefore crucial to consider the solar energy conditions on the current day.

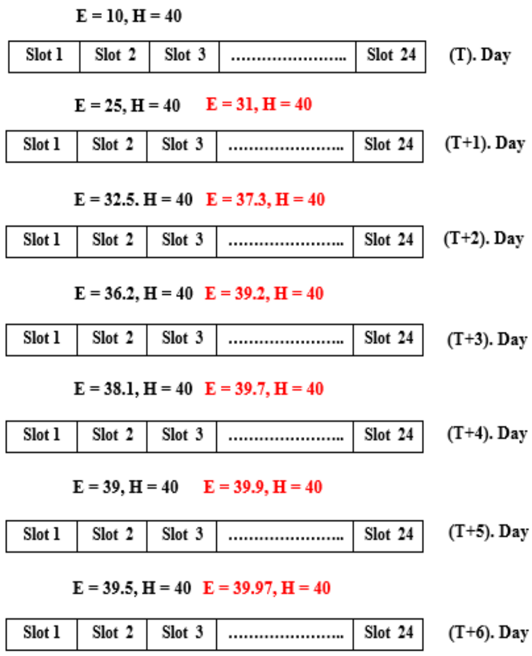


Figure. 3 An example process of EWMA, α = 0.5 and α = 0.3.

2.2. Accurate Solar Energy Allocation

Accurate solar energy allocation (ASEA) attempts to allocate the harvested energy equally to each slot in a particular day for EH-WSNs regardless of the amount of generated energy in any slot. To do this, it modifies the EWMA to cope with the drawback of EWMA. The basic idea of ASEA is to look at the present conditions by adding a new parameter, ψ, to Eq. (1). This parameter represents the ratio between the actual amount of energy harvested and the energy estimated by EWMA in the previous slot. The modified equation is therefore given as:

$$\bar{\mathrm{E}}(d, n) = \mathrm{E}(d, n)\,.\,\psi \quad \text{where} \quad \psi = \frac{\mathrm{R}(d, n\text{-}1)}{\mathrm{E}(d, n\text{-}1)} \tag{2}$$

2.3. Weather-Conditioned Moving Average

The weather-conditioned moving average (WCMA) is another algorithm which takes the current weather conditions into consideration. WCMA collects past energy values which are stored in a matrix, *E(i, j)*, where *j* is a sample on the i^{th} day. One of the main distinctive features of WCMA is that it incorporates previous samples into the prediction equation. Also, the mean value of the corresponding samples from previous days is calculated.

Therefore, the prediction equation related to the previous sample and the mean value of the sample given by Eq. (3) is:

$$\mathrm{E}(d, n+1) = \alpha\,\mathrm{E}(d, n) + (1-\alpha)\,\mathrm{M}(d, n+1)\mathrm{GAP} \tag{3}$$

Where *E(i,j)* is the energy values taken from the E matrix and *M(i,j)* is the mean value of the sample. *GAP* is a new weighting factor introduced in order to reflect current weather conditions. The mean value of the sample is calculated as follows:

$$\mathrm{M}(d, n+1) = \frac{\sum_{i=1}^{\mathrm{D}} \mathrm{E}(i, n+1)}{\mathrm{D}} \tag{4}$$

To compute the GAP value, a vector, $V = [V_1, V_2, \ldots, V_K]$, is first defined. The elements of the V vector are the previous samples in the same day, each of which represents the ratio of the the harvested energy to the mean value. Hence, a value less than 1 means that the harvested energy is less than the mean:

$$V_k = \frac{\mathrm{E}(d, n\text{-}K+k)}{\mathrm{M}(d, n\text{-}K+k)} \tag{5}$$

Once the elements of the V vector are calculated, these values are weighted according to their distance from the actual sample. This is to give more importance to closer samples and less importance to far samples. To do this, a vector, $P = [p_1, p_2, \ldots, p_K]$, is defined as follows:

$$p_k = \frac{k}{K} \tag{6}$$

The weighting factor, GAP, is finally computed as:

$$\mathrm{GAP} = \frac{V.P}{\sum P} \tag{7}$$

The size of the E matrix is an important parameter to establish. Considering the limited memory in sensor nodes, the size should be carefully selected whilst meeting the memory constraint. Also, the value of K which is the number of past samples to weight should be carefully adjusted. It must be large enough to observe the current weather condition but also small enough not to consider some samples that do not have any impact on present conditions, such as night values. In the original paper on WCMA, from an analysis of the choice of dimensions of the E vector, the value of K was calculated. The best values found to minimize the prediction error were D = four days and K = three samples. These values were used in all the experiments in this current study. Also, an α value of 0.7 was the optimum value that gave the minimal error.

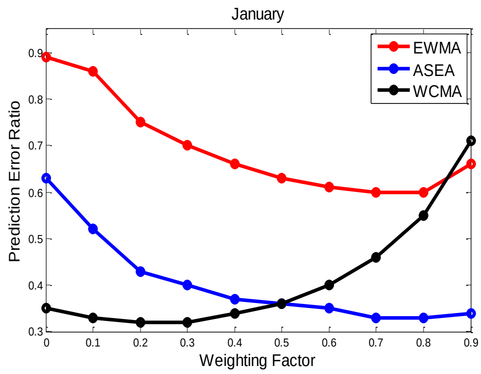
3. Performance Evaluation

The performances of the EWMA, ASEA and WCMA schemes were compared using real solar panel outputs in the second month of each season of 2015. The purpose of this was to demonstrate the behavior of the performance throughout the year. Fig. 4 presents the performance of the schemes in terms of prediction error ratio (PER). Each point in the curves represents the average of 30 days. Additionally, Fig. 4e depicts the prediction accuracy in January.

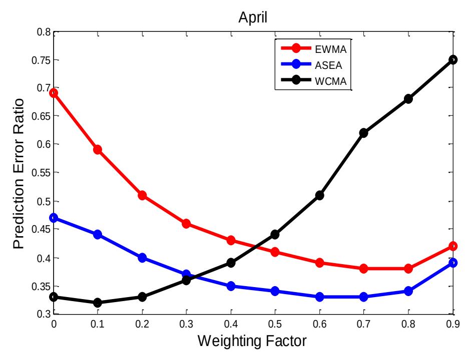
Three popular solar energy prediction schemes have been studied in this paper. The performance of the schemes in terms of the prediction error using real solar panel outputs has been presented and compared. It has been shown that the level of ambient energy to be harvested is highly time-variable, so it is crucial to consider current weather conditions when predicting energy, particularly in changing diurnal weather conditions. Also, the weighting factor, α, in all three schemes plays an important role in enabling accurate prediction. The main conclusion of this study for high accurate energy prediction is to reconcile the past energy generation profile with the current energy pattern.

It is obvious that the weighting factor, α, had a significant effect on the prediction accuracy for all three schemes. EWMA and ASEA exhibited a similar performance as ASEA is an extension of EWMA. ASEA achieved a better performance than EWMA because ASEA reflects the latest current energy condition. The results tell us that high and low values of α in EWMA and ASEA provide highly inaccurate predictions, whereas medium values of α, $0.4 < \alpha < 0.9$, ensure more accurate predictions. In EWMA and ASEA, therefore, the estimated average energy (E) and real measured energy (R) (*see* Eq. (1)) should contribute closely to achieving accurate predictions. However, WCMA provided significantly high accurate predictions at low values of α. Eq. (3) clearly shows that low values of α mean a low contribution of energy in the previous slot. In other words, the mean of the energy in association with the current energy condition has more influence on the prediction. Hence, WCMA with small values of α, $\alpha < 0.6$, predicts energy more accurately than EWMA and ASEA, but the high values of α make WCMA the worst scheme. As discussed above, EWMA would not be a good choice in frequently changing weather conditions. In January, the weather changes almost daily, as shown in Fig. 4e. The PER of EWMA is close to 0.6 (60%) at an α value of 0.7. When the weather does not change frequently, as in July, the PER reduces to 0.18. In all cases, ASEA has a similar curve to that of EWMA improving the PER. In WCMA, on the other hand, the contribution of energy in the previous slot of the same day does not actually seem to be relevant as the PER rises with the increasing influence of the previous slot's energy value.

We conclude that WCMA is the best prediction algorithm as it benefits from the long-term current solar energy condition, provided that α has a small magnitude. EWMA can be considered as a baseline scheme which takes seasonal solar energy into consideration, resulting in high incorrect predictions with frequently changing solar conditions. ASEA considers only the latest solar energy condition which causes high inaccurate predictions in particular in times of temporary weather changes.



(a)



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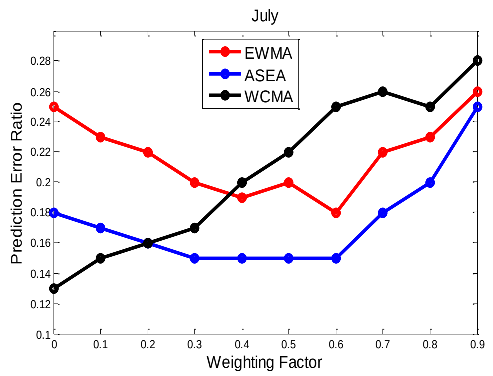

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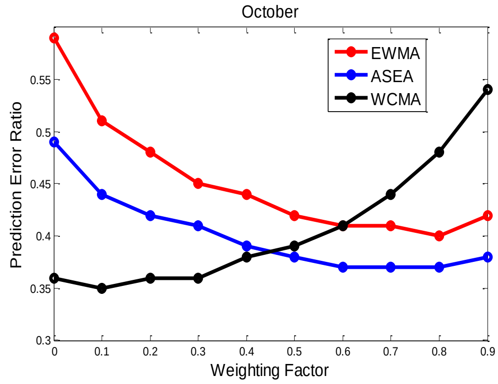

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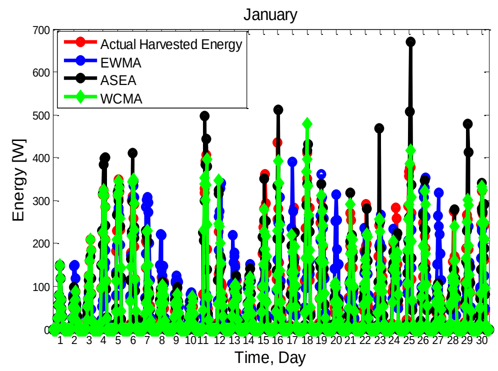

(e)

Figure. 4 Prediction error ratios for three schemes for four months: (a) January, (b) April, (c) July and (d) October, as well as (e) prediction accuracy in January.

4. Conclusions

Three popular solar energy prediction schemes have been studied in this paper. The performance of the schemes in terms of the prediction error using real solar panel outputs has been presented and compared. It has been shown that the level of ambient energy to be harvested is highly time-variable, so it is crucial to consider current weather conditions when predicting energy, particularly in changing diurnal weather conditions. Also, the weighting factor, α, in all three schemes plays an important role in enabling accurate prediction. The main conclusion of this study for high accurate energy prediction is to reconcile the past energy generation profile with the current energy pattern.

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