Adaptive Filter for Energy Predictor in Energy Harvesting Wireless Sensor Networks

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***Abstract*— To design an autonomous Wireless Sensor Network (WSN), the harvested energy from environmental sources has been considered as a potential solution for long-term operations. A power manager embedded in the energy harvesting WSNs adapts the power consumption and computation loads according to the harvested energy to obtain a theoretically infinite lifetime. In order to design an effective power manager, it is of prime interest to benefit from an accurate energy predictor to estimate the energy that can be harvested in the near future. In this paper, a low complexity energy predictor using adaptive filter in proposed. Our predictor has a low memory requirement as it is only based on a previous historical harvested energy to estimate the future energy. Simulation results show that our energy predictor using adaptive filter can be applied for both solar and wind energy with an average error less than 15%.**

I. Introduction

Wireless Sensor Networks (WSNs) are composed of many wireless nodes which are randomly deployed in remote places to collect data from their sensors and transmit to a base station. Many types of sensors provide various monitoring applications based on WSNs such as temparature monitoring in smart buildings, tire pressure monitoring in the automotive industry and vibration monitoring for maintenance of structures [1]. However, these applications require long-term operations as battery replacement is expensive and often impractical. Unfortunately, the available energy in batteries is limited. Therefore, exploiting the environmental energy from ambient sources such as light, wind and vibration can significantly extend the system lifetime. To achieve a theoretically infinite lifetime, a power manager is designed to adapt the harvesting WSN node to Energy Neutral Operation (ENO) [2]. This state ensures that, over the long period, the consumed energy is always less than or equal to the harvested energy. In order to provide a fast convergence to ENO, an energy predictor is designed cooperatively with the power manager to estimate the energy that can be harvested in the near future.

The environmental energy can be found from a wide range of harvesters such as photovoltaic cells (PVs), thermal generators (TEGs) or vibration scavengers. The typical power density of harvesting energy sources commonly used in energy harvesting WSNs can be found in [3]. It is obvious that solar with photovoltaics (PVs) provides the highest power density. Moreover, PVs are small in size, cheap and easy to implement when compared to other strategies. As a consequence, PVs are the most widely used in energy harvesting WSNs.

The energy predictor designed for solar-based WSNs is exploited from the diurnal cycle of solar energy. On the current day, the harvested energy at a given time is expected to be similar to the harvested energy at the same time on the previous day. Therefore, historical values of harvested energy for many days are maintained to predict the future energy profiles. However, a trade-off between the accuracy, the complexity and the memory requirement of the predictor must be considered to cope with the low resources in a WSN node.

In this paper[1], a low complex energy predictor for multiple harvesting sources such as solar, light and wind energy using the adaptive filter is proposed. Our energy predictor has a dynamic configuration in run-time to reduce the prediction error. Based on some previous values of harvested energy, the energy predictor estimates the next value of harvested energy and therefore, has a low memory requirement.

The rest of this paper is organized as follows. In section II, related works are presented. The energy predictor using adaptive filter is proposed in Section III. Simulation results with both solar and wind energy are depicted in section IV. Finally, the paper ends with conclusions.

II. Related works

Prediction algorithms suitable to energy harvesting WSNs can be divided into two categories: prediction based on analysis and prediction based on learning. In the first category, we can find Exponentially Weighted Moving Average (EWMA) [2] and Weather Condition Moving Average (WCMA) [4] for solar energy. The principle of EWMA is to divide the time into several slots with the same duration and to apply a weighting factor to previous predicted values to estimate the energy that will be harvested during the next slot. With an array for previous predicted energy and an array for real harvested energy in a day, a full profile of the predicted energy in the next day can be provided by EWMA. However, EWMA has a low accuracy when a cloudy day is followed by a sunny day or vice versa. The WCMA overcomes this drawback by taking into account some previous harvested energy in a given day to estimate the weather condition. In this way, WCMA provides a better prediction as harvested energy close to the

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present value has a high relevance to the next value. However, both EWMA and WCMA have fixed internal parameters which are optimized for solar energy prediction.

In the second category, QLearning [5] and Neural network algorithms [6] can be used for any harvesting device with learning phase to automatically configure their internal parameters. In QLearning algorithm, a decision maker agent, namely the learner, takes actions to the environment and receives reward. After several tries-and-errors, the agent gradually learns the best policy, which is the sequence of actions that maximizes the total reward. On the other hand, the neural network consists of many neurons whose connections are represented by weighted factors. During the training phase, these weighted factors are updated to respect an error less than a threshold. This phase is the disadvantage of both neural network and QLearning when compared to WCMA or EWMA as it requires an additional energy cost due to their high complexity.

In our approach, an energy predictor based on an adaptive filter is proposed. Our predictor has a low complexity but an acceptable accuracy. The adaptive filter shows the interest of our approach as the internal parameters are updated after each prediction to minimize the error.

III. Energy predictor using adaptive filter

In traditional power manager in [2], the time axis is divided into slots of the same duration and the adaptation calculation is carried out at the end of each slot. Therefore, the energy predictor is also periodically activated together with the power manager to provide the predicted harvested energy profiles. We define the following discrete values for the adaptive filter:

- p, μ : the order and the step size of the adaptive filter.
- $\tilde{e}_H(n)$: the harvested energy during slot n provided by the energy monitor.
- $\tilde{E}_H(n)$: the vector of p historical harvested energy, $\tilde{E}_H(n) = [\tilde{e}_H(n), \tilde{e}_H(n-1), ..., \tilde{e}_H(n-p+1)]$.
- $W(n)$: the vector of p coefficients of the adaptive filter, $W(n) = [w_1(n), w_2(n), ..., w_p(n)]$.
- $\hat{e}_H(n)$: the predicted harvested energy for slot n.
- $err(n)$: the error of the prediction for slot n.
- P_{int} : the predictor interval or the slot duration.

The architecture of the energy predictor using adaptive filter is presented in Fig. 1. Historical harvested energy profile is stored in the vector $\tilde{E}_H(n)$. Based on this profile, predicted harvested energy for the next slot $(\hat{e}_H(n+1))$ is produced by a dot product between $\tilde{E}_H(n)$ and the coefficients of the adaptive filter $(W(n))$ as follows:

$$\hat{e}_H(n+1) = \tilde{E}_H(n)W(n) \tag{1}$$

After a slot duration P_{int}, an energy monitor is activated by a timer to estimate the harvested energy during slot $(n+1)$. The error of the prediction $(err(n+1))$ which is the difference between the predicted energy and the real energy as

$$err(n+1) = \hat{e}_H(n+1) - \tilde{e}_H(n+1) \tag{2}$$

is fed back to adjust $W(n+1)$. Meanwhile, $\tilde{e}_H(n+1)$ is used to update the next historical values $(\tilde{E}_H(n+1))$.

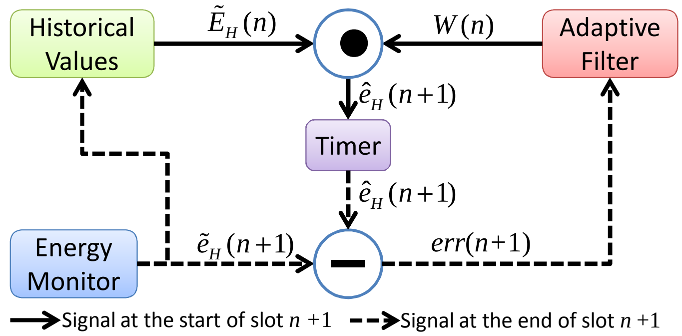

Fig. 1. Energy predictor using adaptive filter architecture. Historical harvested energy profile is kept in a vector $\tilde{E}_H(n)$ to predict $\hat{e}_H(n+1)$ at the beginning of slot $(n+1)$. Until the end of slot $(n+1)$, a Timer is activated to update $\tilde{E}_H(n)$ as well as $W(n)$ based on $err(n+1)$.

Algorithms to adjust the filter coefficients can be divided into two categories : the Least Mean Square (LMS) and the Recursive Least Square (RLS). Compared to the RLS algorithms, the LMS does not involve any matrix operations. Therefore, the LMS requires fewer computation resources and memory requirements than the RLS. The implementation of the LMS is therefore, less complicated than the RLS. The standard LMS updates the coefficients of the adaptive filter as follows:

$$W(n+1) = W(n) + \mu err(n+1)\tilde{E}_H(n) \tag{3}$$

However, the main drawback of the standard LMSs is that it is sensitive to the change of the input vector $(\tilde{E}_H(n))$. Therefore, it is impractical to determine the optimized step size μ. The Normalized Least Mean Squares filter (NLMS) is a modified form of the standard LMS that overcomes this problem by normalizing the input vector. The NLMS algorithm updates the filter coefficients as

$$W(n+1) = W(n) + \frac{\mu err(n+1)\tilde{E}_H(n)}{\left|\tilde{E}_H(n)\right|^2} \tag{4}$$

Unfortunately, the implementation of NLMS faces with divide-by-zero errors when $|\tilde{E}_H(n)| = 0$. This scenario occurs during the night in harvesting WNSs based on solar energy. Therefore, the predictor needs to check $|\tilde{E}_H(n)|$ before updating its coefficients. When $|\tilde{E}_H(n)| = 0$, the next value of harvested energy is simply predicted as zero.

IV. Simulation results

Our simulations are performed on a dataset downloaded from National Energy Renewable Laboratory (NERL) [7]. The visualization of the harvested power, which is another shape of harvested energy is shown in Fig.2. In order to obtain a higher accuracy of the results, only harvested energy profiles during the day are considered. The consecutive zero harvested energy during the night can affect the average error. This set-up simulation is also used in [4].

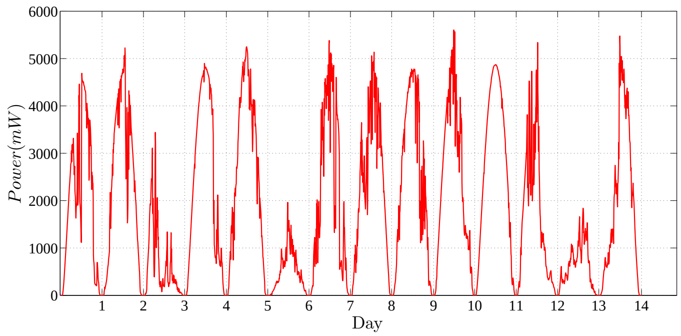

Fig. 2. Harvested power profile over consecutive 14 days.

The energy predictor should have the same activated period as the power manager. Authors in [8] have shown that the optimized adaptation period is a few minutes or even few seconds rather than 30 minutes as in [2]. Therefore, the predictor interval (P_{int}) is set to 5 minutes for simulations carried out in this section. Moreover, the metrics used to compare different energy predictors are defined as follows:

- $E_{avg}(\%)$: the average error of the predictor, defined as

$$E_{avg} = \frac{1}{N} \sum_{n=1}^{N} \frac{|err(n)|}{\tilde{e}_H(n)} \tag{5}$$

  where N is the number of slots over 14 days.
- Mem (16-bit words): the memory space for storing historical energy profiles.
- Mul: the number of multiplications for the predictor algorithm.

The Fig. 3 shows the average error of the predictor with different values of the filter order and also the step size. As it can be observed, the lowest average error (14.7%) is obtained when $p = 1$ and $\mu = 0.3$. This result shows the interest of our approach as the adapter filter only needs one historical value of harvested energy to predict the next one. In this configuration, (4) is simplified as follows:

$$W(n+1) = W(n) + \frac{\mu err(n+1)}{\tilde{e}_H(n)} \tag{6}$$

since $\tilde{E}_H(n)$ only has one element $\tilde{e}_H(n)$. Therefore, the complexity of the NLMS algorithm is significantly reduced.

TABLE I

PERFORMANCE OF DIFFERENT ENERGY PREDICTORS FOR SOLAR ENERGY

	Mem (words)	Mul	E_{avg} (%)
WCMA	1152	20	12.1
NLMS	1	5	14.7
EWMA	288	3	34.4

The Table I shows the comparison of our energy predictor using NLMS with WCMA and EWMA. The WCMA presented in [4] requires five days of harvested energy profiles to estimate the current weather condition and therefore, 1152 words are used to store historical values. The WCMA brings

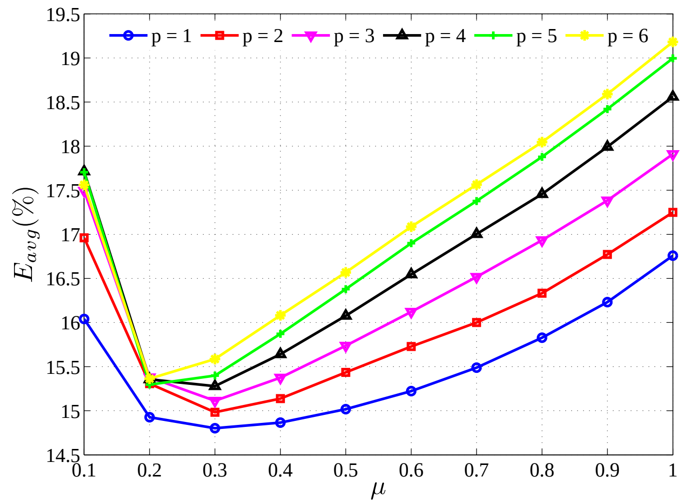

Fig. 3. Average error for solar energy prediction with different combinations of the order (p) and the step size (μ) of the adaptive filter.

the lowest average error but also the highest computations compared to NLMS and WCMA as it needs to compute the GAP factor which represents the difference between the weather on the current day and five previous days at a given time. The predictor based on WCMA takes into account both the previous harvested energy profiles and the current weather condition to improve the accuracy. Meanwhile, the EWMA predictor presented in [2] only needs 288 words for the historical harvested energy profiles in a day. The prediction of harvested energy in a slot is based on the previous predicted energy and weighted with the real energy in the historical profiles at the same slot. In this way, EWMA is able to provide a predicted energy profile for all slots in the next day without waiting for the real energy in some previous slots as NLMS or WCMA. However, this is also the drawback of EWMA when the weather condition changes from a sunny day to a cloudy day or vice versa [4]. Predictor based on EWMA has the lowest computations as the predicted energy is the sum of the previous real energy and the previous predicted energy. In this comparison, the weighting factor for the previous real energy of both WCMA and EWMA is set to 0.5.

In our predictor using NLMS, the next harvested energy is only based on the previous real harvested energy. Therefore, our predictor has the lowest memory space for historical values. However, it is able to provide a low average error (14.7%) with $p = 1$ and $\mu = 0.3$. The improvement of our predictor compared to WCMA and EWMA is the error of each prediction is fed back to adjust the filter coefficients. In this way, the energy predictor is able to follow the tendency of the incoming harvested energy.

The dynamic adaptation of the filter coefficients in our predictor provides a capability to apply with different environmental energy sources. In order to demonstrate this dynamic adaptation, we have performed simulation with a wind power profile extracted from an actual output data recorded by NERL from large wind power plants in the Midwest [9]. The average

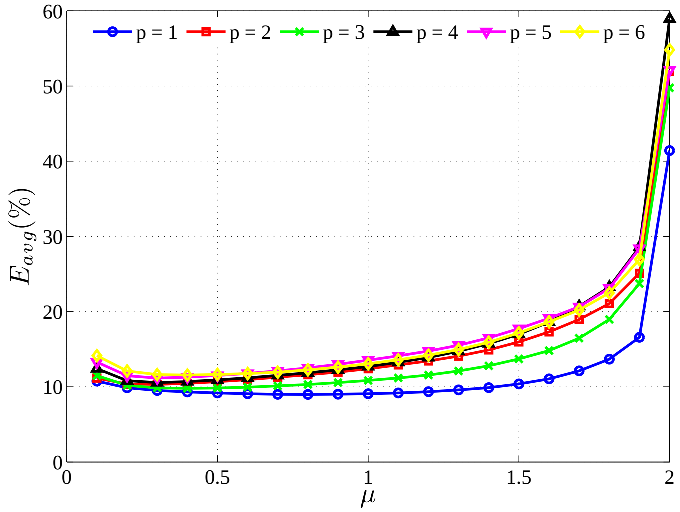

Fig. 4. Average error of the energy predictor when applied to wind energy in consecutive 7 days. With the same order and step size as solar prediction ($p = 1$ and $\mu = 0.3$), the average error is 9.1%.

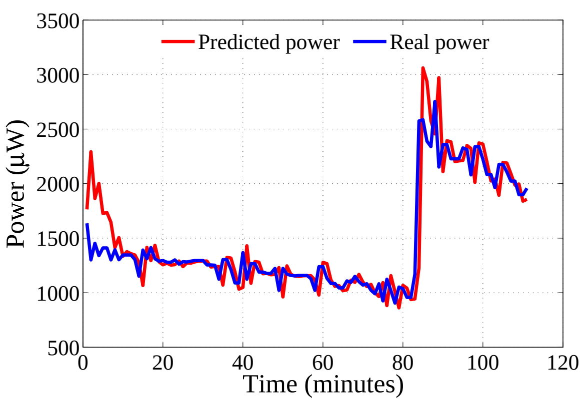

Fig. 5. Energy prediction of harvested energy recorded by a PowWow node near a window in an office with $p = 1$ and $\mu = 0.3$. At around 80 minutes, the curtain is opened and the harvested power suddenly increases.

error with different values of the filter order (p) and step size (μ) is shown in Fig. 4. When $p = 1$ and $0.2 < \mu < 1.5$, the predictor achieves a high accuracy with an average error less than 10%.

Another simulation has been performed with a solar harvested power profile extracted from a PowWow [10] wireless sensor node set up near a window in an office. The Fig. 5 shows that our energy predictor has precise decisions even if there is a sudden change of the harvested power at around 80 minutes, when the curtain of the window is opened. At the beginning, the predicted energy is far from the real energy. However, the error is fed back each prediction to adjust the filter coefficients. From around 10 minutes, the predicted energy follows closely to the real energy. The average error of the predictor in this case is very low, at 2.5%.

The adaptive filter is analyzed with different predictor interval (P_{int}) for $p = 1$ and $\mu = 0.3$. The dataset for solar energy in Fig. 2 and wind energy in [9] are used for this simulation. Simulation results are summarized in Table II.

TABLE II
AVERAGE ERROR (%) OF DIFFERENT PREDICTOR INTERVAL

P_{int} (minutes)	Solar	Wind
5	14.8	9.5
10	27.8	16.0
15	43.7	23.9
20	54.5	27.2

It can be observed that the average error is proportionally increased with the prediction interval as the previous real value has a lower relevance with the next value when P_{int} is increased.

V. CONCLUSION

The energy monitor plays an important role in order to provide the effective power manager strategies in energy harvesting WSNs. Based on an accurate energy monitor, the power manager is able to rapidly converge the WSN node to ENO. In this paper, an energy predictor using adaptive filter has been proposed. Compared to start-of-the-art algorithms, the adaptive filter with NLMS algorithm has a low complexity and small memory space. This algorithm is therefore well adapted for an implementation into a WSN node. The advantage of our predictor is that the filter coefficients are automatically updated by the error of the predictions. By this way, the energy predictor can be used with different energy sources such as solar energy in outdoor environments, wind energy and light energy in offices. The energy predictor performs well when the prediction interval is 5 minutes. In this case, the average error is under 15%.

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