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PII: S1084-8045(17)30142-X
DOI: <http://dx.doi.org/10.1016/j.jnca.2017.04.003>
Reference: YJNCA1900

To appear in: *Journal of Network and Computer Applications*

Received date: 25 April 2016
Revised date: 24 January 2017
Accepted date: 4 April 2017

Cite this article as: Ahmad H. Dehwah, Shahrazed Elmetennani and Christian Claudel, UD-WCMA: An Energy Estimation and Forecast Scheme for Solar Powered Wireless Sensor Networks, *Journal of Network and Computer Applications*, <http://dx.doi.org/10.1016/j.jnca.2017.04.003>

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UD-WCMA: An Energy Estimation and Forecast Scheme for Solar Powered Wireless Sensor Networks

Ahmad H. Dehwah^a, Shahrazed Elmetennani^a, Christian Claudel^b

^aComputer, Electrical and Mathematical Sciences and Engineering,
King Abdullah University of Science and Technology,
Thuwal 6900-23955, Saudi Arabia.

^bCivil Architectural and Environmental Engineering,
The University of Texas at Austin,
Austin, TX.

Abstract

Energy estimation and forecast represents an important role for energy management in solar-powered wireless sensor networks (WSNs). In general, the energy in such networks is managed over a finite time horizon in the future based on input solar power forecasts to enable continuous operation of the WSNs and achieve the sensing objectives while ensuring that no node runs out of energy. In this article, we propose a dynamic version of the weather conditioned moving average technique (UD-WCMA) to estimate and predict the variations of the solar power in a wireless sensor network. The presented approach combines the information from the real-time measurement data and a set of stored profiles representing the energy patterns in the WSNs location to update the prediction model. The UD-WCMA scheme is based on adaptive weighting parameters depending on the weather changes which makes it flexible compared to the existing estimation schemes without any precalibration. A performance analysis has been performed considering real irradiance profiles to assess the UD-WCMA prediction accuracy. Comparative numerical tests to standard forecasting schemes (EWMA, WCMA, and Pro-Energy) shows the outperformance of the new algorithm. The experimental validation has proven the interesting features of the UD-WCMA in real time low power sensor nodes.

Keywords: Solar energy forecast, WCMA, Solar powered WSN

1. Introduction

Energy availability is a critical issue in most Wireless Sensor Networks (WSNs) [15, 20, 17]. In most applications of WSNs, energy harvesting can be used to extend the lifetime of the sensor network, particularly when the lifetime energy requirements of the sensor network makes batteries impractical. Solar energy represents an available and inexpensive source of energy, with solar panels commonly installed in WSNs, for example in [9, 1, 2]. Unfortunately, the intermittency due to daily and seasonal variations, dust, hardware aging [7], and shading (both ambient and structural) is a critical issue in WSNs. The unpredictable changes in the irradiance levels are faced using oversized batteries, raising costs significantly.

Controlling the energy consumption of the sensor network can be an alternative to maximize the utility of the system while ensuring that no node runs out of en-

ergy [8]. To optimize the utility of the solar driven sensor network, efficient algorithms are required to forecast the solar power that will be available over some time horizon in the future, to best manage the energy needed for the sensing, computation and communication tasks. Both the accuracy and robustness of the forecast are crucial, since the WSN operations are optimized depending on the power predictions.

Different estimation approaches have been proposed in the literature to forecast solar power availability. Some of these schemes target the neutral-energy usage enhanced with prediction of the available energy [4]. Exponentially weighted moving average (EWMA) [12], proposed by Kansal et al., is among the first prediction methods. It is based on a weighted moving average approach. More recently, energy estimation has been improved by introducing a new factor to handle the weather fluctuations in [16]. In 2012, Cammarano et al. have proposed a different forecasting approach using a

selected profile from a set of stored profiles combined with the observed weather conditions [5] to generate an estimate value of the available energy.

Most of existing estimation techniques in [6], [16] and [5] are based on a prediction model weighted by a fixed factor α . This factor is usually tuned at the beginning of the experiment to ensure an acceptable prediction error for the considered set of data. Having a fixed weighting factor to be tuned is a constraint for the standard prediction schemes and might significantly affect the accuracy of the estimation under uncertain weather fluctuations. Therefore, this requirement is incompatible with solar powered WSNs, for which each solar panel has a different and unknown set of parameters attached to it (orientation, presence of cast shadows or dust [7]).

In the present study our goal is to propose a new forecasting algorithm by introducing a dynamical model with adaptive tuning of the weighting factor depending on the weather changes. The proposed scheme consists of a dynamic version of the WCMA prediction scheme with adaptive weighting factors named Universal Dynamic-WCMA (UD-WCMA). The estimation model is based on the last measured irradiance level combined with the mean value of the stored profiles at the current time, and the value of the closest profile matching the current power fluctuations. Numerical tests involving real solar irradiance profiles show satisfactory performance of the proposed algorithm, while retaining a sufficiently low complexity to be implementable on low-power WSN nodes. Also, the proposed forecast scheme significantly outperforms existing estimation models. To assess the performance of the UD-WCMA in an urban sensor network scenario, we have implemented the algorithm in several custom-designed sensor nodes as part of a WSN-based flash-flood and traffic monitoring system. This experimental validation shows that the UD-WCMA algorithm retains his excellent prediction performance, while running in real-time on low-power sensor nodes.

The contributions of this article can be summarized as follows:

- We propose a new forecasting scheme by introducing a dynamical version of the weather conditioned moving average (WCMA) forecast algorithm.
- We propose a dynamical forecast scheme with adaptive parameters to solve the problem of pre-tuning arising in the standard solar power estimation techniques.
- We propose an adaptive scheme that leverages a

set of historical profiles, and fuses it with real-time data. This increases the prediction accuracy by combining the historical information from past data and from current patterns.

- We validate this algorithm by comparing it to classical estimation techniques, showing that it outperforms such algorithms using both numerical and experimental datasets.

2. Related Work

Several approaches for solar energy forecast in WSNs have been presented in the literature. Most of these prediction methodologies are based on a combination of current data with data generated during a set of previous days, at different time instants. The time is generally divided into equal time slots. The solar energy prediction at a particular time instant is based on the current data and the previous time instants over an analysis window of varying size. One of such algorithms is the scheme developed by Kansal et al. in [12], in which an Exponentially Weighted Moving Average (EWMA) approach is considered for energy prediction. This approach, initially introduced in [6], is based on the assumption that the energy availability at a certain time slot n of the day depends on the last measured amount of energy and is comparable to the available energy at the same time slot of the preceding days. However, this method leads to inaccurate prediction when the weather changes abruptly over short time scales. To overcome this problem, a new approach known as Weather-Conditioned Moving Average (WCMA) has been proposed by Piorno et al. in [16]. For a given time slot, WCMA averages the measurements of the previous days over an analysis window and then scales the resulting mean value. The scaling factor is computed by comparison of the current weather conditions with the weather variations in the previous days. As per Bergonzini et al. [3], WCMA produces an error which is referred to as a shift displacement. To address this error, [3] introduced WCMA-PDR, a newer version of the WCMA algorithm, which uses a feedback mechanism to take into consideration the error in the previous predictions. Subsequently, Cammarano et al. [5] have proposed a new strategy for energy prediction named Pro-Energy. In this approach, the energy profile of the node obtained in the previous days is stored in a matrix. Then, the measured data during the current day is compared to the stored profiles over a comparison window in order to obtain the most similar energy changes. The closest profile to the current energy variations is selected

by minimizing the mean absolute error (MAE). Then, the harvested energy of the selected profile at the current time is combined with the last measurement of the current day to predict the available energy. Pro-Energy has presented interesting features for both short and medium-term energy prediction using a specific choice of the weighting parameter. Another work presented by Renner in [18] has shown the advantage of incorporating online weather nowcasts and forecasts (ex. clouds cover forecast) in solar power estimation and prediction. Hassan et al. presented in [10] another algorithm for solar energy prediction based on additive decomposition (SEPAD) model. In this model, they considered both seasonal and daily trends along with sun's diurnal cycle. Continuous investigations are conducted to improve the prediction performance. Renner in [19] presented a new architecture that automatically obtains global weather forecasts from freely available online resources and disseminates them into the sensor network. Another solar energy prediction scheme is proposed by Kosunalp using Q-learning to improve the estimation [13].

As stated previously, the objective of this study is to improve the performance of the energy forecast by introducing adaptive weighting parameters to scale the information used for the estimation without added computational or hardware complexity. Taking into consideration that our prediction model is developed based on the EWMA, WCMA and Pro-Energy schemes, we briefly present these standard prediction schemes in the following sections. To ensure that all methods use the same amount of information, we consider d stored profiles as reference, combined with real-time data over a window of K time samples.

2.1. Exponentially Weighted Moving Average (EWMA):

EWMA is among the oldest approaches used for energy forecast. In this scheme, the harvested energy measurements of the d previous days are stored along the day with a fixed sampling time. The data is saved in a set of vectors x_i for $i = \{1, \dots, d\}$. For the same time grid, the measured energy along the current day is stored in the observation vector θ . Considering the EWMA approach, the energy value at time step $(n+1)$ can be estimated by $\hat{x}(n+1)$ using the most recent observation $\theta(n)$ and the mean value of the harvested energy at that time $(n+1)$ during the previous days. Therefore, the estimated value $\hat{x}(n+1)$ is given by:

$$\hat{x}(n+1) = \alpha \theta(n) + (1 - \alpha) \mu_d(n+1), \quad (1)$$

where α is the weight of the current observation in the prediction, and $\mu_d(n+1)$ denotes the mean value of

the energy observed at time step $(n+1)$ in the previous days:

$$\mu_d(n+1) = \frac{1}{d} \sum_{i=1}^d x_i(n+1), \quad (2)$$

such that $x_i(n+1)$ represent the values at time $(n+1)$ for the i^{th} energy profile from the d historical energy patterns.

2.2. Weather Conditioned Moving Average (WCMA):

WCMA is an improved version of EWMA, which has been proposed to improve prediction accuracy when weather patterns change over a short time scale. The energy estimated value $\hat{x}(n+1)$ depends on an additional factor named GAP , which has been introduced to scale the current energy pattern variations with respect to their stored counterparts over a time horizon of K time steps. The predicted energy is expressed as:

$$\hat{x}(n+1) = \alpha \theta(n) + GAP (1 - \alpha) \mu_d(n+1). \quad (3)$$

Similarly to EWMA, α is a weighting factor to be tuned, while GAP is computed in order to scale the changes in solar conditions for the present day, relative to the previous days. It is defined by:

$$GAP = \frac{v \cdot p}{\sum_{k=1}^K p_k}, \quad (4)$$

where v represents the ratio of the past K measured energies along the comparison window over the average available solar energy for the stored profiles. The components v_k of v at each instant in the window, for $k = \{1, \dots, K\}$, are expressed by:

$$v_k = \frac{\theta(n-K+k)}{\mu_d(n-K+k)}. \quad (5)$$

p is a weighting vector defining linearly decreasing weights over the time horizon K :

$$p = \left[\frac{1}{K}, \dots, \frac{k}{K}, \dots, 1 \right] \quad (6)$$

2.3. Pro-Energy:

The Pro-Energy scheme considers a set of various energy harvesting patterns characterizing different weather conditions (cloudy, sunny or rainy days). The estimation combines the latest measurements with the harvested energy at the current time in the profile that is closest to the current energy profile. The closest profile is selected such that to minimize the mean absolute error between the current energy measurements and the changes of the stored profiles over the time horizon K .

Consider x_{i^*} to denote the historical energy profile minimizing the difference with the current energy profile over the time horizon K , in the L_1 norm sense:

$$i^* = \arg \min_{i \in d} \mu_{\theta_i} = \arg \min_{i \in d} \frac{1}{K} \sum_{k=1}^K |\theta(k) - x_i(k)|. \quad (7)$$

Therefore, the Pro-Energy scheme yields an energy estimate at time $n+1$ given by:

$$\hat{x}(n+1) = \alpha \theta(n) + (1 - \alpha) x_{i^*}(n+1), \quad (8)$$

3. Universal Dynamic Weather Condition Moving Average Energy Prediction (UD-WCMA)

All the prediction methods outlined earlier involve a fixed weighting parameter α , which is generally tuned for a particular set of data to balance the current measurements with historical data. Tuning this factor a priori will not necessarily ensure that the previously described schemes will adapt well to fast varying weather situations. To overcome this issue, we first propose a dynamic WCMA (D-WCMA) in which the value of (α) is adjusted dynamically to give the best prediction performance with respect to the mean value of the stored data. We then update the prediction to account for the closest energy pattern in terms of variations, resulting in the universal dynamic WCMA (UD-WCMA).

3.1. Dynamic Weather Conditioned Moving Average (D-WCMA):

The proposed dynamic scheme (D-WCMA) is based on a WCMA model using a time varying weighting parameter $G_1(n+1)$. This gain is adapted depending on the variations in the reference profiles stored in memory. Subsequently, the energy prediction is ensured by combining the information acquired from the last observation $\theta(n)$ with the mean value $\mu_d(n+1)$ of the harvested energy from the stored profiles. The mean value $\mu_d(n+1)$ is scaled using the factor GAP defined previously for the WCMA scheme. Consequently, a general representation of the D-WCMA prediction model is given by:

$$\hat{x}(n+1) = G_1(n+1) \theta(n) + [1 - G_1(n+1)] GAP \mu_d(n+1), \quad (9)$$

where:

$$G_1(n+1) = \frac{1}{2} \frac{\sigma(n+1)}{\sigma(n+1) + \sigma_1(n+1)}, \quad (10)$$

In the above equation, σ denotes the standard deviation of the irradiance levels of the stored profiles at time $n+1$ with respect to the mean value. σ_1 is the standard deviation characterizing the energy variations in the stored profiles between the time slots n and $n+1$. They are respectively defined, for $i = \{1, \dots, d\}$, by:

$$\sigma(n+1) = \sqrt{\frac{1}{d} \sum_{i=1}^d (x_i(n+1) - \mu_d(n+1))^2}, \quad (11)$$

and

$$\sigma_1(n+1) = \sqrt{\frac{1}{d} \sum_{i=1}^d (\Delta_{1_i}(n+1) - \mu_1(n+1))^2}, \quad (12)$$

where

$$\Delta_{1_i}(n+1) = x_i(n+1) - x_i(n), \quad (13)$$

and

$$\mu_1(n+1) = \frac{1}{d} \sum_{i=1}^d \Delta_{1_i}(n+1). \quad (14)$$

3.2. Universal Dynamic Weather-Conditioned Moving Average (UD-WCMA):

To improve the accuracy of the D-WCMA based estimation with robustness to weather changes, we propose to modify the prediction model by replacing the last observation $\theta(n)$ with a weighted linear combination of the last observation $\theta(n)$ and the closest energy pattern in memory denoted by $x_{i^*}(n+1)$.

The linear combination is weighted by an adaptive factor $G(n+1)$ depending on the variations of the current day measurements, as follows:

$$\hat{x}(n+1) = G_1(n+1) [G(n+1) \theta(n) + (1 - G(n+1)) x_{i^*}(n+1)] + (1 - G_1(n+1)) GAP \mu_d(n+1), \quad (15)$$

where:

$$G(n+1) = G_1(n+1) + G_2(n+1), \quad (16)$$

and

$$G_2(n+1) = \frac{1}{2} \frac{\sigma(n+1)}{\sigma(n+1) + \sigma_2(n+1)}, \quad (17)$$

In the above equation, $\sigma_2(n+1)$ defines the standard deviation of the variations in the solar irradiance measurement vector θ between consecutive time steps along a window of size K . Precisely, the vector of consecutive variations defined by $\Delta_2(n+1)$ is given by:

$$\Delta_{2_k}(n+1) = \theta(n+1-k) - \theta(n-k), \quad k = 1, \dots, K-1 \quad (18)$$

Therefore, the corresponding mean and standard deviation are defined by:

$$\mu_2(n+1) = \frac{1}{K-1} \sum_{k=1}^{K-1} \Delta_{2_k}(n+1), \quad (19)$$

and

$$\sigma_2(n+1) = \sqrt{\frac{1}{K-1} \sum_{k=1}^{K-1} (\Delta_{2_k}(n+1) - \mu_2(n+1))^2}. \quad (20)$$

4. Data Analysis and Performance Evaluation

In order to evaluate the performance of the UD-WCMA, we have carried several numerical tests considering different working scenarios. The prediction accuracy of the proposed approaches D-WCMA and UD-WCMA has been compared to the standard methods EWMA, WCMA and Pro-Energy. All energy forecast in the upcoming subsections is based on a set of $d = 6$ reference profiles. The stored energy patterns are real irradiance profiles acquired every half an hour from a weather station. These profiles have been chosen to represent different weather conditions, with smooth and abrupt changes at different levels (low, medium and high) as shown in Figure 1.

Besides, we have considered a set of 6 different profiles of the solar irradiance to be predicted (see Figure 2). The algorithm behavior and the forecast efficiency are tested for each profile with a prediction every half an hour. For better analysis, we covered a wide range of weather variations. Indeed, the irradiance profiles chosen to be predicted, have been selected in order to represent different levels of solar radiation. Some profiles vary slowly while others present some drops and abrupt changes in the irradiance level.

4.1. Validation test

We first performed a series of tests to evaluate the D-WCMA and UD-WCMA algorithms performance with respect to the standard estimation algorithms described above. We have carried out prediction tests using the standard approaches for all profiles of Figure 2, considering different values of α and a comparison window of size $K = 4$.

4.1.1. Selection of the optimal parameter α for the standard prediction algorithms

As indicated in Equations (1, 3, 8), EWMA, WCMA, and Pro-Energy prediction methods all depend on a

fixed weighting parameter α . Based on error analysis, the obtained results give the optimal value of the weighting parameter α to be used with each profile for the considered set of data over a comparison window of size $K = 4$. Figure 3 shows the relative prediction error generated for different values of α .

From Figure 3, the performance of standard forecasting techniques is very sensitive to the choice of the weighting parameter α . Moreover, the optimal value of α is a function of the future energy profile to be predicted, which is unknown at the beginning of the experiment. As shown in Figure 3, the optimal value of α in EWMA for profile 1 is $\alpha = 0.45$, while for profile 4 it is $\alpha = 0.65$ and in both cases it is a concave up function. However, for profile 6, it is a decreasing function having an optimal value of $\alpha = 0.8$. Similarly, the optimal value of α in Pro-Energy for profile 1 is $\alpha = 0.2$, while for profile 2 it is $\alpha = 0.5$ and for profile 6 it becomes $\alpha = 0.8$.

From Figure 3, we can observe that the prediction error for EWMA, WCMA and Pro-Energy are very close when α is close to 1. This is due to the fact that when $\alpha = 1$, the forecast energy for the next time step becomes the current observation in all these algorithms.

The proposed techniques, D-WCMA and UD-WCMA, also depend on some design parameters G_1 and G_2 . However, these parameters are updated dynamically as new measurements become available. The advantage of the adaptation of these gains can be clearly noticed from Figure 3, in which the error level of D-WCMA and UD-WCMA is consistently below the error levels of EWMA, WCMA and Pro-Energy.

4.1.2. Prediction performance evaluation

To evaluate the performance of the D-WCMA and UD-WCMA with respect to existing prediction methods (EWMA, WCMA and Pro-Energy), we have chosen the optimal values of α obtained from the numerical results of Figure 3. Note that in practice, this value is tuned without any guaranties on the prediction performance, and may not be optimal, which implies that the prediction accuracy of EWMA, WCMA and Pro-Energy will be in practice worse than the results shown in this subsection. This also ensures that D-WCMA and UD-WCMA are compared with respect to the best possible prediction performance of EWMA, WCMA, and Pro-Energy, with the design parameter α tuned a priori to minimize the relative prediction error. Figure 4 shows the solar irradiance forecast of the different profiles over a day using the existing prediction methods compared to the proposed algorithms D-WCMA and

Figure 1: Set of historical profiles used for energy prediction.

Figure 2: Set of energy profiles to be predicted.

UD-WCMA. The corresponding absolute error for each profile is presented to better visualize the results. As it can be seen, D-WCMA and UD-WCMA significantly outperforms existing prediction methods (in their best-case situation), leading to the lowest prediction error for all profiles.

4.2. Influence of the size of the comparison window

In this subsection, we study the effect of the observation time horizon on the results generated by UD-WCMA. For this purpose, we consider comparison time

windows of different sizes $K \in \{1, \dots, 6\}$, for a sampling period of half an hour. Figure 5 illustrates the effect of the window dimension K on the forecast accuracy for each profile. Note that in this test, the forecast is done over a single time step (*i.e.* a prediction time horizon of 30 minutes). As it can be observed from this Figure, the accuracy of the prediction of EWMA tends to improve with increasing values of K , while the prediction quality of Pro-Energy is more affected by the chosen profile than by the time horizon. In general, the performance of D-WCMA and UD-WCMA improves with increasing values of K , though the error is quite robust

Figure 3: Relative error of the prediction for $K = 4$ and different values of α .

to incorrect choices of K . In the tested scenarios, the improvement becomes insignificant starting from $K = 4$. Therefore, $K = 4$ appears to be the most suitable choice for Wireless Sensor Network applications, best balancing prediction accuracy with computational complexity.

4.3. Medium term prediction

In this subsection, we study the performance of UD-WCMA and D-WCMA with respect to existing prediction methods by comparing the results of the energy forecasts for a medium term horizon, corresponding to multiple time steps in the future. The short term prediction usually ranges from a few minutes to half an hour, while the mid-term horizon starts from half an hour to three hours [5].

Figure 6 shows the forecast results using different estimation methods over varying prediction time horizons. Based on the mean absolute error of the six predicted profiles, we have investigated the overall performance of the proposed UD-WCMA. Considering profiles (1, 2, and 3), which are all smooth, it is clear that UD-WCMA outperforms all other forecasting methods for all time horizons. Similarly, D-WCMA and WCMA both presents a good consistent estimation accuracy as well. This is followed by Pro-Energy and then EWMA, which has the worst performance among all other prediction methods. Also, considering profiles 4 and 5,

it can be observed that UD-WCMA generally presents better accuracy compared to all other prediction methods, having the least absolute error. It is worth noting that these profiles are associated with abrupt drops in the irradiance levels, with peaks of approximately 950 and 1500 W/m^2 respectively. Similarly, D-WCMA and WCMA have shown acceptable performance, followed by Pro-Energy and then by EWMA. The last profile 6 exhibits random variations in irradiance level, with a sharp drop during the day. For this case, UD-WCMA performs the best considering a forecasting window size of 30 minutes. However, its performance degrades for bigger forecasting intervals, in which WCMA and Pro-Energy tends to be more accurate. While UD-WCMA lost some accuracy for the long term forecast horizon with respect to high variations of profile 6, it is important to note that the coefficients α used in other algorithms have been optimally calibrated in advance, which is not available in a real-life situation. Hence, in this specific situation (profile 6), UD-WCMA is less accurate than the best possible estimates of existing algorithms, which may not be achieved in experimental settings (in which α cannot be tuned using apriori). Overall, the performance of UD-WCMA is still excellent, outperforming the best-case estimates of existing algorithms in the vast majority of cases.

Figure 4: Solar irradiance forecast and corresponding prediction error for $K = 4$.

4.4. Performance evaluation over one year of energy data

In this subsection, we evaluate the performance of the UD-WCMA over a larger dataset of one year of irradiance data, acquired by the KAUST meteorological station. This station permanently monitors ambient tem-

perature, solar panel temperature, irradiance, air pressure, air humidity and precipitation, with a time resolution of 1 hour. For robustness, we selected 6 reference profiles, and used a comparison window of 2 hours. We show in Figure 7 the probability density functions of the absolute prediction errors for the forecast schemes out-

Figure 5: Effect of the time horizon K on prediction accuracy.

Figure 6: Prediction methods evaluation (mean absolute error) over different prediction horizons.

lined earlier.

As it can be seen from this Figure, UD-WCMA has the best prediction accuracy over the test period. In-

deed, the absolute error distribution of UD-WCMA is characterized by a distribution centered around a peak in the neighborhood of $24W/m^2$, which is clearly lower

Figure 7: Probabilistic distribution of the absolute error over one year

than the other schemes.

5. Hardware Implementation and Experimental Validation

To evaluate the feasibility of using UD-WCMA on practical WSNs, we developed an experimental sensor network test bed on which we implemented UD-WCMA. In this experimental validation, we have deployed 10 nodes over 6 months period to collect the measured data. For this experiment, we used custom-developed sensor boards (see Figure 10), which have been developed by [11] to construct a solar-powered wireless sensor network that monitors traffic flow and flash floods [14]. These nodes are built around a 32-bit ARM Cortex M4 micro-controller with 192 kB RAM, running at a frequency of 168 MHz (though this frequency can be dynamically adjusted down to 8 MHz for energy management purposes). The platform draws its energy jointly from a $20W_p / 20.8V_{oc}$ solar panel, and a rechargeable single-cell Lithium Iron Phosphate battery of capacity 10Ah. To maximize solar power harvesting, it is equipped with a MPPT (maximum power point tracking) circuitry. It also has a battery monitoring chip DS2745, which provides the current, voltage and battery temperature. This platform is also equipped with a cell switch mode battery charger MP2635 with power path management features.

In this test, the UD-WCMA scheme was applied to forecast the solar irradiance, using the measurement of the current generated by the solar panel. The solar current was measured and recorded every half an hour, generating 48 samples per day. Throughout the experiment period, we have selected six historical data profiles for each node to be used as our reference prediction profiles along with a forecasting time horizon of two hours ($K = 4$). The historical profiles are saved in a micro SD card (the platform used is equipped with a micro

SD card reader) and pulled out by the algorithm during the prediction process. UD-WCMA is executed on each node, since transmitting this information to a central node would require more energy than distributing the computation on the nodes. The predictions are transmitted back to a sink node (connected to a database) for storage purposes. Figure 8, shows the 6 historical reference profiles along with the current day energy profile to be predicted. Figure 9, compares the current energy profile with the energy profile predicted by the node running UD-WCMA. The prediction metric used in this validation is root mean square error (RMSE). The UD-WCMA exhibits a very good performance, reproducing the profile to be predicted with an excellent accuracy generating an RMSE equal to (18.79 mA) and an execution time of 1 ms on this resource-constrained platform.

6. Conclusion

In this article, we presented a new forecast algorithm applicable to solar-powered WSNs: the Universal Dynamic Weather-Conditioned Moving Average (UD-WCMA). The proposed estimation scheme is based on a weighted moving average model with adaptive weighting parameters. The considered approach combines the information acquired from a set of stored data with the real time measurements to predict the future evolution of the available solar energy. Considering a dynamical prediction model gives to the presented algorithm (UD-WCMA) the ability to be efficient under all weather conditions. In addition, the weighting parameters are updated depending on the evolution of the past energy measurement, considering the set of stored energy profiles, which makes the UD-WCMA very robust to weather changes. We extensively validated the performance of UD-WCMA in comparison with existing algorithm, using experimental irradiance data generated. The consistently excellent prediction performance of UD-WCMA and the lack of tuning parameter make the algorithm very suitable for distributed energy harvesting applications such as WSNs, in which the environmental parameters (presence of dust, cast shadows, solar panel orientation, cloud cover) can drastically change between nodes. It is worth mentioning that the number of reference might vary. It has been chosen in this series of tests to be equal to six 6 in order to cover different levels of energy (low, medium, and high) with different variations characteristics (smooth and abrupt). Future work will focus on the integration of the proposed scheme with WSN energy management schemes, such as the scheme developed in [8], which requires ac-

Figure 8: Six experimental profiles of the generated solar current measured by a node of the wireless sensor network.

curate solar irradiance forecasts to optimally plan the operations of the WSN over some finite time horizon.

Figure 9: Comparison between measured and predicted energy profiles.

Figure 10: **Left:** K-mote based on ARM Cortex M4 microprocessor. **Right:** System packaging.

7. Acknowledgment

The research reported in this manuscript is supported by King Abdullah University of Science and Technology (KAUST).

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