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A New Energy Prediction Algorithm for Energy-Harvesting Wireless Sensor Networks With Q-Learning

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ABSTRACT Traditional wireless sensor networks (WSNs) face the problem of a limited-energy source, typically batteries, resulting in the need for careful and effective utilization of the energy source. However, inevitable energy depletion will eventually disturb the operation of a WSN. Energy harvesting (EH) technology is acquiring particular interest, because it has the potential to provide a continuous energy supply in battery-powered WSNs. Solar energy is the most effective environmental energy for EH-WSNs because of its high energy intensity, which comes from a non-controllable source. Therefore, the prediction of future energy availability is a critical issue, as the amount of the harvestable energy may vary over time. In this paper, a novel solar energy prediction algorithm with Q-learning, called Q-learning-based solar energy prediction (QL-SEP), is proposed. Q-learning is an effective way of predicting future actions based on past observations. The distinctive feature of QL-SEP is that not only past days' observations but also the current weather conditions are considered for prediction. The performance of QL-SEP is simulated in this paper using real-world measurements obtained from a solar panel in comparison with the state-of-art approaches.

INDEX TERMS Energy harvesting, prediction algorithms, solar energy, wireless sensor networks.

I. INTRODUCTION

Wireless sensor networks (WSNs) are an emerging and rapidly growing research area with a wide spectrum of potential applications including environmental monitoring, industrial, military and medical systems [1]. The importance of WSNs lies in a practical and economic approach to enabling continuous observation of real-world conditions within harsh and mostly inaccessible locations with no human activity for long periods of time. In order to limit the overall cost of the devices which form a WSN, a large number of resource-constrained sensor nodes which are capable of sensing, processing and communicating collaborate to perform a common task. A distinctive property of WSNs is random deployment without access to external resources. A typical sensor node relies on the finite capacity of an energy supply from an initially full battery. A replacement or recharging of depleted batteries is often impractical, which renders nodes with exhausted energy non-operational. Emphasis has, therefore, been critically placed on energy efficiency, thereby maximizing the lifetime of WSNs. To achieve this, the capacity of the power source must be utilized effectively. Energy efficiency is the priority in the design of WSNs with traditional performance metrics forming the secondary criterion.

It is well-known that the mechanism of wireless communication consumes more energy than computation and sensing. Efficient utilization of radio capability is therefore of paramount significance. The main sources of energy wastage in a sensor network include *overhearing*, *idle listening*, *control packet overhead* and *retransmissions*. Overhearing means that a node receives packets which are not directed to itself. Sensor nodes spend a major amount of energy listening to an ideal channel for possible incoming packets. Before actual packet transmission starts, the sensor nodes exchange control packets to ensure successful transmission. It is commonly assumed in simulation and analytical models that when more than one packet arrives at a receiver simultaneously, these packets collide either fully or partially. The collided packets are believed to be corrupted and lost and they must be re-transmitted. However, a recent practical study proved that the first-arriving packet among the collided packets could be received with success through the capture effect [2]. As a result, these causes of energy wastage could be minimized in an efficient manner.

Medium access control (MAC) protocols determine the rules of channel access in order to avoid the unnecessary energy wastage described above. The prime role of

MAC protocols is to provide successful operation for packet transmission while achieving a good level of energy efficiency. Many MAC protocols specifically designed for resource-constrained WSNs have been proposed in order to enhance the performance of the WSNs in terms of energy efficiency, channel throughput and overall delay [3]–[5]. These protocols have provided significant performance improvements, in particular impacting on overall energy consumption. Unfortunately, the performance of most protocols has only been evaluated using simulation tools which makes the feasibility of the protocols in practical scenarios questionable. Therefore, the complexity and overheads of the protocols must be smoothly arranged in order to meet the resource constraints of the sensor node, such as limited memory and transmission range. Although MAC protocols do extend the lifetime of WSNs by assigning intelligent and efficient transmission policies, inevitable energy depletion will eventually interrupt the operation of the sensor node, gradually degrading the lifetime of the entire WSN. This opens a new research direction for the long-term, maintenance-free operation of WSNs.

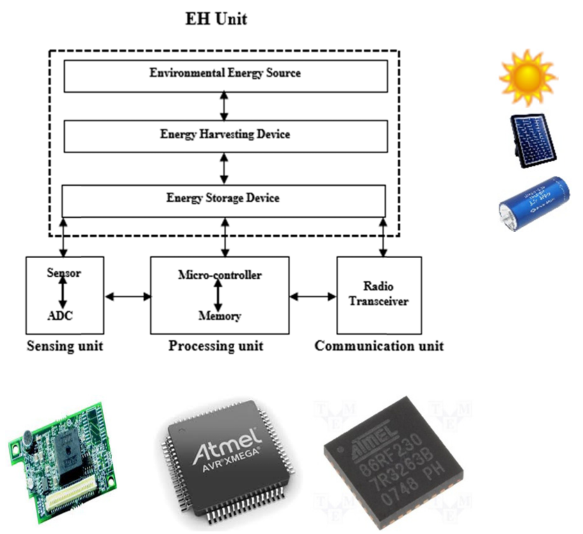

FIGURE 1. Structure of an EH node harvesting solar energy.

Energy harvesting (EH) from the surrounding environment has recently come to be regarded as a superior way of prolonging the lifetime of WSNs, in that an energy harvesting unit is employed to remove the burden of having to replace/recharge exhausted batteries. Recent studies in EH technology have revealed the development of new types of sensor node which have the capability of harvesting ambient energy [6], as illustrated in Fig. 1. The fundamental concept of exploiting environmental energy is the conversion of the harvested energy into electricity in order to ensure the energy burden of the sensor nodes. A storage component, typically a rechargeable battery or super-capacitor, is often used to accumulate the harvested energy.

EH sensor nodes continuously harvest an ambient source of energy in order to avoid the depletion of energy, resulting in a perpetual lifetime for a battery. This has, of course, changed the fundamentals of MAC protocols as energy is now potentially infinite, leading to the development of new MAC protocols for EH-WSNs. The main task of such protocols is to maximize energy utilization efficiently. A number of MAC protocols have been proposed for EH-WSNs with the aim of maintaining the perpetual operation of EH-WSNs [7]. To achieve a perpetual lifetime, the existing protocols follow the condition of energy neutral operation (ENO). The nodes satisfying the ENO condition harvest more energy than they consume within a specified time duration. One of the main challenges is the time-variable and space-dependent environment which limits the amount of available energy to be harvested. The level of ambient energy depends highly on the current environmental conditions which can exhibit significant fluctuations. Therefore, the time-varying nature of environmental energy poses a new challenge because of the uncertainty of the availability of ambient energy. Many of the current MAC protocols check the residual energy level in order to coordinate the communication. However, predicting future energy availability as accurately as possible is an important property for reconciling a varying energy source with a fixed demand. It is believed that an accurate estimation of future energy level should be integrated in the design of MAC protocols. With accurate energy prediction, nodes can save some parts of current energy for future use. This avoids facing temporary energy shortages when the energy falls below a critical level necessary to transmit important information. Therefore, careful prediction of future energy levels at specific time durations opens a new perspective.

The majority of the proposed prediction algorithms have attempted to predict solar energy because of its advantages over other forms of environmental energy [8]. Solar energy is the most effective energy source for EH-WSNs because it has the highest power intensity. Another key distinction of solar energy is that it has a periodic cycle which makes its prediction possible, subject to prediction errors. Fig. 1 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. A popular way of predicting solar energy is to exploit the historical summary of an energy harvesting profile. Energy generation patterns from past days are observed to predict the current energy generation rate. Not only the past days' energy generation pattern but also the current weather condition are vital to minimizing prediction errors in particular in frequently changing weather conditions.

In this paper, a new solar energy prediction algorithm which considers the current weather conditions to accurately predict the available energy is proposed. The Q-learning method is employed to determine the accuracy of current weather conditions [9]. We therefore call the algorithm 'Q-learning based solar energy prediction' (QL-SEP). In order to demonstrate the performance of QL-SEP, we evaluated it using real measurements obtained from a solar panel in 2015 [10]. The performance results show that QL-SEP makes more accurate prediction than other state-of-art approaches. The rest of this paper is organized as follows. Existing work on MAC protocols for EH-WSNs is summarized in section II. Section III presents detailed descriptions of solar energy prediction algorithms. The underlying basics of QL-SEP are presented in section IV. The performance outputs are presented in Section V. Finally, Section VI concludes the paper and possible directions for future work are discussed.

II. MEDIUM ACCESS CONTROL FOR EH-WSN

The majority of the MAC protocols proposed for traditional battery-powered WSNs have focused on the concept of a duty-cycle in order to effectively arrange the sleep and active times of radio with the aim of reducing energy consumption. EH technology has revealed a new perspective in the field of WSNs and has attracted increasing significant attention. Designing new MAC protocols for EH-WSNs appeals to researchers in a few of the proposed schemes. These schemes are summarized next with their operating principles and underlying features.

Sensor MAC (S-MAC), perhaps the most popular and most studied MAC scheme, introduced the concept of a duty cycle which inspired the design of many MAC protocols centering on the theme of S-MAC [11]. It has a fixed duration duty-cycle period. Emphasis has been therefore placed on the design of new schemes which are designed to adaptively adjust the nodes' active and sleep periods. The throughput performance of S-MAC with energy harvesting has been studied in a solar-based, energy-harvesting environment [12]. The achievable throughput is derived from an analytical model of an energy harvester based on the impact of the duty cycle of sensors. A suitable range for choosing the duty cycle was also discussed in order to provide the desired network lifetime depending on application-level requirements. The relationship between the average energy level and the duration of the duty cycle was developed by a queueing model. As a result, it was shown that the average energy level is a function of the duty cycle. In [13], two dynamic duty-cycle scheduling schemes were proposed to shorten nodes' duty cycles and provide a good balance of energy consumption among sensor nodes. The current residual energy level is the only criterion for calculating the duty cycle in the first scheme. Due to the fluctuations in energy-harvesting opportunity, the second scheme improved the first scheme by including the prospective increase in residual energy. With the estimation of such prospective energy increases, the duty cycle can be reduced more quickly. This is achieved by estimating the difference between the energy-harvesting rate and the energy-consumption rate at the beginning of every duty cycle.

ODMAC, an on-demand MAC protocol, was proposed to support individual duty cycles letting nodes operate in the ENO state by exploiting the maximum harvested energy [14]. It exploits the fact that sensor nodes often have low traffic in order to remove the burden of idle listening by Carrier Sensing. Therefore, sensor nodes will turn their radios off most of the time, which reduces the energy wastage particularly at the transmitter end. The receiver sends out a beacon packet periodically to broadcast its availability to accept possible incoming packet transmissions. This is to eliminate idle listening at the receiver end. Nodes which have packets to be transmitted listen to the channel to hear an appropriate beacon to start transmission. Upon reception of the beacon, the associated transmitter attempts to transmit its packets to the source of the beacon. The duration of the carrier sensing and beacon is dynamically decided according to the current energy-harvesting rate. The concept of an opportunistic forwarding technique is incorporated to reduce the long waiting time of the beacon when a receiver has a high duty-cycle period. In this way, packets without a beacon are opportunistically transmitted to the sender of first beacon received which has woken up first. A drawback of ODMAC is the lack of retransmissions, so the successful reception of packets is not acknowledged, which might result in discarding all the packets involved in collisions.

EH-MAC is an ID-polling-based MAC protocol proposed for multi-hop EH-WSNs and it achieves high channel performance in terms of network throughput and fairness [15]. The distinctive feature of EH-MAC is that it uses a probabilistic polling mechanism in which the polling packet contains a contention probability, p_c, in order to alleviate the likelihood of packet collisions. Instead of broadcasting the ID of a sensor, the contention probability is sent in the polling packet. Then, the nodes receiving the polling packet decide whether to transmit or not. These nodes generate a random number in the range from 0 to 1 and compare p_c with the generated number to make the decision. The nodes with a p_c greater than the generated number start transmission. One node out of all the nodes is ideally expected to send its packet successfully. The value of p_c is dynamically adjusted depending on the response of the nodes. In particular, the p_c reduces collisions and it remains at its current value with successful reception. If the sink detects nothing after sending the polling packet on the channel, it increases the p_c. It has been shown that the optimum p_c that maximizes throughput is $1/n_{active}$, where n_{active} represents the total number of estimated active nodes that are able to receive the polling packet.

ERI-MAC is a receiver-initiated MAC protocol for EH-WSNs designed to dynamically adjust the duty cycle of the nodes considering the energy-harvesting condition of the network [16]. It uses a carrier sensing multiple access/collision avoidance (CSMA/CA) scheme to avoid collisions. ERI-MAC has a similar packet transmission schedule to that of ODMAC and EH-MAC. When a transmitting node receives the expected beacon, it immediately transmits a data packet. The tiny beacon packet contains the address of its source node to announce the node's availability. Successful packet transmission is confirmed by a small acknowledgement (ACK) packet which is also used as a new beacon. ERI-MAC employs a packet concatenating scheme to aggregate several small packets into a bigger packet. The purpose of this is to reduce the cost of overheads of exchanging control packets as well as to improve the latency and energy efficiency. It is assumed that the energy-harvesting rate is a constant, so the performance of the protocol with a time-varying energy-harvesting profile is realistically unknown. Also, the latency is only considered for performance metrics which do not reflect the actual performance in terms of network throughput.

III. SOLAR ENERGY PREDICTION APPROACHES

In this section, state-of-the-art solar energy prediction algorithms are reviewed and their operating principles and underlying properties are described. The characteristic of the solar energy model for EH-WSNs is also described in order to enable further understanding of the design trade-offs of the approaches.

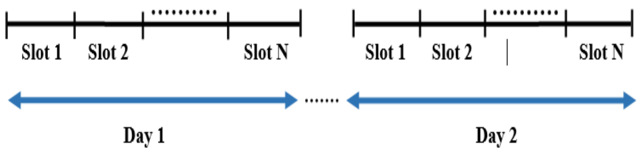

FIGURE 2. Repeating time slots with 24-slots.

A. FUNDAMENTALS OF THE SOLAR ENERGY MODEL FOR EH-WSNs

Studies into renewable energy generation for solar-powered systems often refer to predicting the total amount of energy harvested in a large-scale implementation, typically a year [17]. In a WSN's domain, accurate prediction of short-term energy, from a few minutes to a few hours, is particularly important for avoiding short-term energy shortages as sensor nodes are required to operate whenever an environmental feature is sensed. Therefore, current prediction algorithms for EH-WSNs focus mainly on the estimation of the near future energy availability with as small a prediction error as possible. Solar energy, because of the rotation of the earth, has a diurnal cycle in which consecutive days are likely to exhibit similar weather conditions. Existing approaches exploit the diurnal cycle of solar energy by dividing a complete day into equal-length time slots as depicted in Fig. 2. The prediction of energy for each slot is derived at the onset of the associated slot. The length of a time slot depends on the application requirements and resources. It is typically set to one hour, so that each day is composed of 24 slots of one-hour duration. The purpose of splitting a day into slots is to observe the energy generation profile of past days in each slot and to record it in order to predict the current energy level accurately.

B. EXPONENTIALLY-WEIGHTED MOVING AVERAGE (EWMA)

EWMA is the most popular and used algorithm and has inspired the development of many prediction approaches in the literature benefiting from the diurnal cycle in solar energy [18]. It assumes that the energy generation profile at a particular time slot of the day exhibits similar behavior within the same slot to that of previous days. The fundamental principle of EWMA is to adapt to seasonal variations by maintaining the amount of harvestable energy in each time slot as a weighted average of energy available over a set of previous days. Therefore, EWMA considers the historical information of an energy generation profile combining the energy estimated and the energy harvested as presented in Equation 1.

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

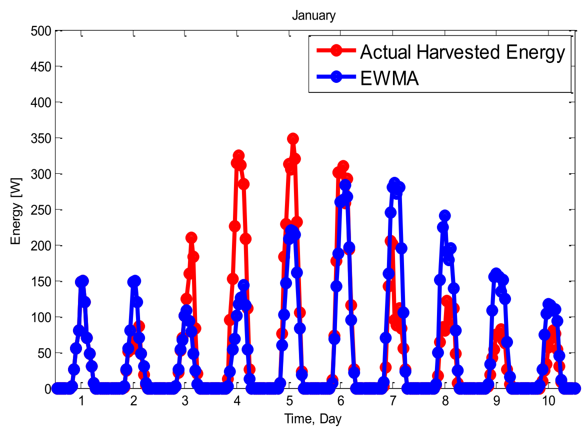

FIGURE 3. EWMA energy prediction in January 2015.

Where d represents the current day and n is the slot number. EWMA sums the last amount of harvested energy (H) and estimated energy (E) with a weighting factor, $0 < \alpha < 1$, arranging the importance of the R and E. Small values of α correspond to higher importance of last-harvested energy and *vice-versa*. An accurate choice of α value would have a significant influence in adapting to seasonal weather variations. It was set to a constant value in all the algorithms described. The main drawback of EWMA is its vulnerability in frequently changing weather conditions. In particular, EWMA produces significant prediction errors when there is a mix of sunny and cloudy days. EWMA can be considered as a baseline scheme which takes seasonal solar energy into consideration, resulting in high levels of incorrect predictions with frequently changing solar conditions. In order to reduce the prediction error rate for non-consistent weather conditions, the current solar conditions should be integrated into the estimation of energy. In order to demonstrate the prediction behavior of EWMA in frequently changing solar conditions, Fig. 3 presents the prediction accuracy of EWMA in January 2015 and we shall discuss the prediction results for the whole year in detail later on.

C. ACCURATE SOLAR ENERGY ALLOCATION (ASEA)

ASEA uses the foundations of EWMA in order to provide optimal allocation of the periodically harvested solar energy in sensor nodes [19]. It is designed to reserve an adequate amount of energy for future use in case the environmental energy is insufficient or unavailable. Operating a sensor node perennially at a constant level requires an accurate prediction of future energy availability. This minimizes the variations in allocated energy in each time slot. To do this, it modifies the EWMA to cope with the drawback of EWMA. ASEA introduces a new parameter, ψ, into Eq. (1) reflecting the current solar conditions. The modified equation can be given as:

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

Where ψ represents the ratio between the actual amount of energy harvested and the energy estimated by EWMA based on the previous slot. The expected energy, $\bar{E}$, is calculated by multiplying the energy expectation by EWMA with the ψ. The value of ψ is calculated at the beginning of each time slot. ASEA considers only the condition in the previous slot, which might result in significant prediction errors for short-term varying weather conditions. A temporary weather change in the current slot would lead to inaccurate prediction for the next slot. The performance of ASEA was evaluated over a period of ten days in the month of July. It is clear that the weather does not change very frequently in the summer. It is believed that a ten-day evaluation might not reflect the actual performance of the scheme. Although the key properties of ASEA have been tested sufficiently, the scale of the experiments has been rather small.

D. WEATHER-CONDITIONED MOVING AVERAGE (WCMA)

WCMA is another algorithm designed to handle the deficiencies of the EWMA and considers both current and past day solar conditions [20]. It collects the energy values of past days and store them in a matrix, E(i, j), where j is a sample on the i^{th} day. Instead of maintaining a weighted-average as in EWMA, WCMA incorporates the energy harvested in the previous slot into the prediction equation. The average of a number of energy values also contributes to the prediction equation. The prediction equation for a particular slot is therefore related to the energy in the previous slot, and the mean value of the corresponding slot for a number of days and current solar conditions is given in Equation 3.

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

Here, M represents the average value of the sample, H is the actual harvested energy in the last slot and GAP is the new weighting factor which reflects the solar condition in the present day. The average value of the n^{th} sample on the d^{th} day is calculated for D past days:

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

The GAP value is a measurement of the current solar conditions, basically observing how the behaviour of a solar energy generation profile in relation to previous days varies for K number of past slots. To compute the GAP value for the past K samples, a vector V with a size of K, $\mathrm{V} = [\mathrm{V}_1, \mathrm{V}_2, \ldots, \mathrm{V}_\mathrm{K}]$, is defined to indicate each value of the past K samples. Each sample denotes the ratio of the harvested energy to the mean value:

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

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, $\mathrm{P} = [\mathrm{p}_1, \mathrm{p}_2, \ldots, \mathrm{p}_\mathrm{K}]$, is defined as follows:

$$p_\mathbf{k} = \frac{\mathrm{k}}{\mathrm{K}} \tag{6}$$

Each element in the P vector is actually inversely proportional to the distance from the current value $\mathrm{p}_\mathbf{k}$. Therefore, GAP value is finally calculated as:

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

E. THE PROFILE ENERGY PREDICTION MODEL (PRO-ENERGY)

Pro-Energy also exploits past days' energy harvesting profile in order to forecast future energy intake. Pro-Energy considers the amount of energy harvested in the previous slot as in WCMA. Similarly, a matrix, E(i, j), maintaining the energy harvested in the past of D days is derived. The distinctive feature of Pro-Energy is that the most similar day to the current day in terms of energy generation is obtained from the E matrix. Therefore, a combination of energy observed in the previous slot and the energy from the most similar day contribute to predicting the current energy as presented in Equation 8.

$$\hat{\mathrm{E}}(d,n) = \alpha\mathrm{H} + (1-\alpha)\mathrm{E}_{\mathrm{MS}} \tag{8}$$

Where H represents the amount of the energy harvested in the previous slot and E_{MS} is the energy observed in slot n in the most similar day. In order to determine the similarity level of D previous days to the current day, the mean absolute error (MAE) in each stored day for K previous slots up to current slot is computed. The day with the lowest MAE is selected as the most similar day. Pro-Energy keeps track of a pool of D typical previous profiles, each of which represents a different solar condition. The stored profile is dynamically updated for the adaptation of predictions against changing seasonal patterns. Pro-Energy makes the decision to update the pool to the present day according to two criteria: (1) a stored profile is allowed to stay in the pool up to A days; the current day profile can be substituted for a day which was stored for longer than A days, and (2) if two similar profiles are detected, the current day is replaced with the one that is most similar to it.

In order to further improve the accuracy of predictions, Pro-Energy suggests combining multiple profiles instead of extracting the value from the most similar day. The purpose of this is to consider potential variations in weather by which a single profile might result in poor performance. To achieve this, the elements of E are sorted with respect to their MAE. The sorted list can be given as E_{s1}, $E_{s2} \ldots$, E_{sP} including P profiles. A weighted profile (WP) is then computed to replace the E_{MS}in Equation 8:

$$WP = \frac{\sum_{j=0}^{P} w_j \cdot E_{sj}}{P-1} \tag{9}$$

Where

$$w_j = 1 - \frac{MAE\left(E_{sj}, C\right)}{\sum_{j=1}^{P} MAE\left(E_{sj}, C\right)} \tag{10}$$

Therefore, the final energy prediction equation with the multiple profile is:

$$\hat{E}(d,n) = \alpha H + (1-\alpha)WP. \tag{11}$$

IV. QL-SEP: A SOLAR ENERGY PREDICTION ALGORITHM WITH Q-LEARNING

In this section, a new solar energy prediction approach is introduced for EH-WSNs which exploits the historical information of past-days' energy generation and the most recent weather conditions in the present day. The proposed approach, a solar energy prediction algorithm with Q-learning (QL-SEP), relies on the assumption that solar energy exhibits a cycle as a periodic energy source in which the time domain is split into equal-length slots repeated daily. This motivates the performance of energy predictions at the onset of each slot. It is believed that EWMA is an efficient way of observing long-term seasonal conditions with no mechanism for adapting to relatively short-term (hourly or daily) variations. QL-SEP takes advantage of the properties of EWMA in that a feature acquiring the status of the current solar condition is employed. To do this, QL-SEP updates Equation 1 with a new parameter, called the daily ratio (DR), as presented in Equation 11.

$$E_{\text{QL-SEP}} = E_{\text{EWMA}} \cdot (1 + \text{DR}) \tag{12}$$

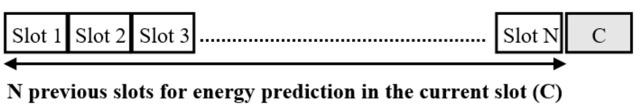

FIGURE 4. QL-SEP energy prediction architecture.

The DR represents the trend in the current solar energy generation, particularly investigating the behavior of the solar energy in the most recent slots. The increase/decrease ratios (either positive or negative) in the harvested energy of previous slots determine the value of DR. In order to simplify this, DR can be considered as the average of energy increase/decrease ratios in the previous slots. For example, if there is an increase of 20% in the previous slots on average, the DR becomes 0.2. The simplified architecture of QL-SEP is shown in Fig. 4.

When forecasting energy in a particular slot, the prediction accuracy in the previous slots is important information. The question of how accurate a prediction is in a previous slot ideally gives us a direction not to only consider the equal contribution of previous slots (the increase/decrease ratio) in relation to the prediction of the current slot. Therefore, each slot in QL-SEP maintains a level of prediction accuracy which represents the reliability of prediction in the slot. This leads to combining the increase/decrease ratios and the reliability of prediction in order to significantly endow the predictions with high reliability. This is achieved by Equation 13:

$$\text{DR} = \frac{\sum_{i=1}^{N} P_e(i) \cdot R(i)}{N} \tag{13}$$

Where P_e indicates the prediction error and R is the reliability level. In order to give greater importance to the closer time slots as the most recent slots would carry the most recent information, this multiplication, similar to WCMA, is weighted by the increasing index (i). Eventually, the daily ratio, DR, is computed as:

$$\text{DR} = \frac{\sum_{i=1}^{N} P_e(i) \cdot R(i) \cdot i}{\sum i} \tag{14}$$

It is obvious that the choice of reliability (R) is a fundamental challenge. It basically represents the goodness level of the prediction and should be explicitly explored in order to identify the best choice. Therefore, exploitation of long-term experience of predictions would sufficiently provide a robust level of R. On the other hand, the mechanism for R is required to respond quickly in non-stationary conditions. Q-learning is an efficient way of exploring the current behavior of an action based on the experience already obtained [22]. It allows determination of an optimum solution using a reward function represented by a numerical value. The solution indicates the desirability of the action in the form of numerical values, referred to as Q-value which is calculated as:

$$Q_{t+1}(s) = Q_t(s) + \gamma(r - Q_t(s)) \tag{15}$$

Where s indicates the slot identifier, r is the current reward function and γ is the learning rate. The R signal typically takes a value of +1 for positive feedback and −1 for negative feedback. Consecutive positive feedback will increase the Q-value to converge to a value very close to +1, whereas a sequence of negative feedback reduces the associated Q-value to −1. The learning rate, γ, has a similar task to that of the weighting factor, α, controlling the speed of Q-value increase/decrease. It is often set at a small value, impacting critically on the Q-value update. The impact of the varying learning rate on the behavior of the Q-value update is presented in Fig. 5. The Q-value of an action is usually set at 0 as a default. The results tell us that it takes longer to converge to +1 whereas the Q-value reduces to 0 more quickly.

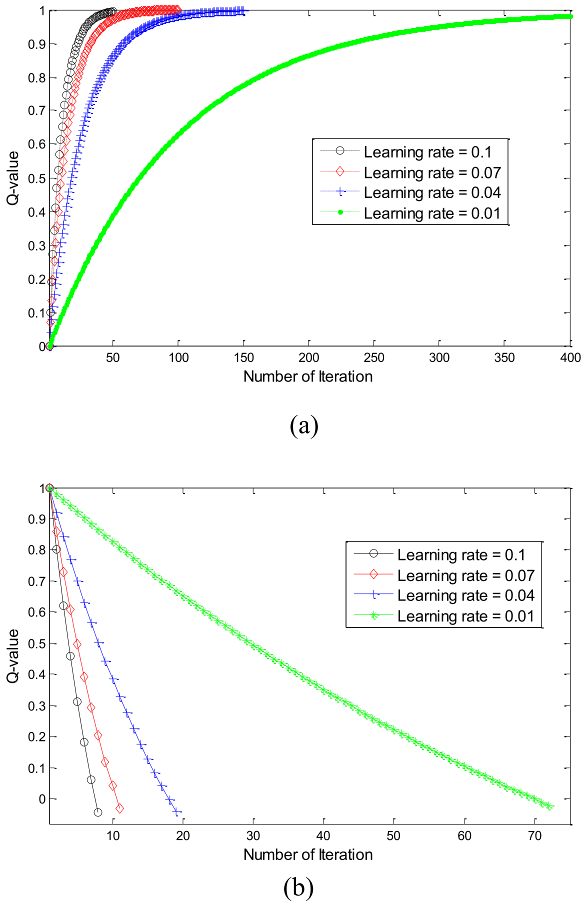

FIGURE 5. Q-value updates in two cases: (a) best case: all positive and (b) worst case: all negative.

This property, the rapid decline of the Q-value, enables a fast response to long-term change. However, this issue may degrade the level of robustness against infrequent changes. For a learning rate of 0.1, only seven consecutive negative feedbacks cause the Q value to return to 0, but there should be fifty sequences of positive feedback to maintain the Q-value at $+1$.

QL-SEP employs a Q-learning approach in which each slot is initiated with a Q-value independently to denote the reliability level of this slot. The Q-value of each slot is initialized to $+1$ on start-up as each slot has had no action so far and has the same reliability. Therefore, the value of R for a slot in Equation 13 is assigned to the Q-value of the slot. The next step is to define the conditions for updating the Q-value, either positive or negative. The Q-value of a slot is updated at the end of the slot in association with the overall prediction error ratio (OPER) in 24 slots. A prediction error ratio (PER) in a slot is compared with OPER. If PER is lower than OPER, R takes a positive value ($+1$), otherwise r takes a negative value (-1). Therefore, a PER higher than OPER is accepted to be a poor prediction. Another important parameter to set is the learning rate, which is typically set at a constant value. However, this is not a practical solution because errors occur at different extents. We therefore introduced a new dynamic modification of the learning rate value. The main motivation behind this modification was to reduce the Q-value more aggressively when the PER is high. In this strategy, the modified learning rate is obtained by multiplying the initial learning rate by the PER, if r has taken the negative value. For example, let the γ be 0.1 and the PER be 0.5: the modified learning rate will be 0.05 (0.1*0.05). Another example with a γ of 1 results in a modified learning rate of 0.1. Therefore, increasing the PER will produce more rapid reduction of the Q-value. The PER for a single slot is calculated as:

$$\mathrm{PER} = \left| \frac{H - P}{P} \right| \tag{16}$$

Where H is the actual harvested energy in the slot and P is the predicted energy value from QL-SEP. Finally, the DR can be calculated as:

$$\mathrm{DR} = \frac{\sum_{i=1}^{N} \left(\frac{H-P}{P}\right) \cdot Q\,(i) \cdot i}{\sum i}. \tag{17}$$

V. PERFORMANCE EVALUATION

The performance of QL-SEP in comparison with that of EWMA, ASEA and Pro-Energy was evaluated using real-life solar data obtained over a one-year period in order to establish the ideal performances of the schemes [10]. WCMA was not considered in the performance comparisons as Pro-Energy already outperforms it. Previous experiments on ASEA performance only covered a period of ten days in July 2008 which may not reflect the actual performance of the scheme. Pro-Energy used the same datasets as in QL-SEP, consisting of 90 days solar data. Therefore, this section also extends the implementations of the schemes by testing their behaviour in all months. Performance evaluations over longer periods would strengthen the accuracy of the schemes.

It was important to set appropriate experiment settings to allow all schemes to achieve their optimum performance. The total number of time slots in a day was set at 24 so that a whole day was represented by 24 time slots each of which corresponded to a one-hour duration. In Pro-Energy, D (the number of previous energy profiles stored), K (the number of previous slots for comparing the stored energy profiles) and P (the number of combined profiles) were set at 10, 7 and 5 respectively, as suggested in the original paper. In QL-SEP, N (the number of previous slots up to the current slot) and γ (the learning rate in Q-learning) were set at 3 and 0.1 respectively. The parameter N had to be carefully assigned in order to balance the effect of past samples in which the effect of earlier slots was lowered. For example, the energy generation pattern during the morning should have no effect in the afternoon.

It is worth noting that the weighting factor has a high influence on prediction accuracy. As the results presented in Fig. 6 show, the performance of all schemes depends deeply on the choice of the weighting factor value. We can see that EWMA, ASEA and QL-SEP exhibited similar curves because they

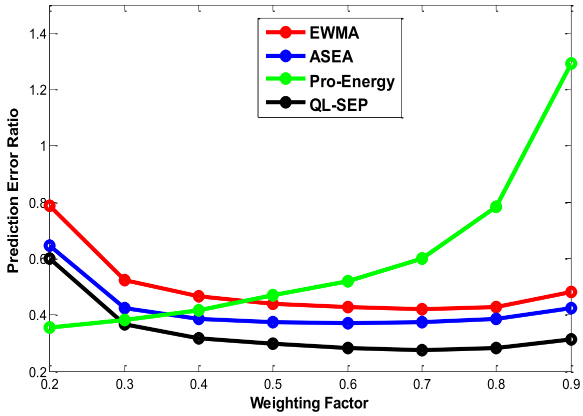

FIGURE 6. Prediction error ratios under various weighting factors.

applied to the same architecture. ASEA improved the performance of EWMA slightly by observing the energy generation in only the last slot. QL-SEP further improves the prediction accuracy of EWMA and ASEA as well as that of Pro-Energy with an exception of the weighting value of 0.2. The results show us that high and low values of α in EWMA, ASEA and QL-SEP provide 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 the harvested energy (H) should contribute closely to achieving accurate predictions. In general, QL-SEP had a superior performance because it carefully observes the current solar conditions. Pro-Energy had opposite performance results as it relies on the energy harvested in the previous slot and the energy trends observed in previous days. Small values of α ensure performance enhancements meaning that low values of α mean a low contribution of energy in the previous slot. Increasing α leads to performance degradations as Pro-Energy does not adapt to current weather conditions, with a reduced contribution of the typical previous profiles in such settings. Therefore, one of the main conclusions of this study in terms of highly accurate energy prediction is to reconcile the past energy generation profile with the current energy pattern.

It is well-understood that solar energy has a low intensity in the morning, increases from morning to afternoon and is almost absent at night. A small prospective increase/decrease in the predicted energy can cause a high prediction error ratio, especially in morning slots. For instance, assume that the estimated energy is 1 energy unit and the harvested energy is 1.5 units. In this case, the prediction error ratio is 50% (0.5). In order to demonstrate this variation, Table 1 presents the average prediction error ratios for four slot ranges. Note that we did not include the night slots as there is no solar energy to be harvested at night. We can see that for slots 6-9 the maximum prediction errors occurred due to insufficient knowledge of past energy generation. ASEA checked the status of the most recent slot which can increase the error ratio for the reason described above (morning slots face high error). QL-SEP had a slightly better performance because

TABLE 1. Prediction error ratios for various slot ranges, $\alpha = 0.7$.

Slot Range	EWMA	ASEA	Pro-Energy	QL-SEP
6-9	0.440	0.458	1.455	0.408
10-12	0.428	0.347	0.316	0.206
13-15	0.415	0.330	0.211	0.201
16-20	0.412	0.374	0.419	0.276

it considered the status of a number of previous slots, in particular more accurate predictions could be obtained in slots 8 and 9 because of the observations in slots 6 and 7. Pro-Energy was the worst scheme as finding the most similar circumstances could not be performed effectively because of an inadequate number of previous slots for comparison. EWMA generally produced similar results for each range on average. During the ranges of the 10-12 and 13-15 slots, all the schemes achieved their best performance as sufficient knowledge about the current solar conditions was gained. Pro-Energy was the second best scheme because it explored the most similar day. It nevertheless experienced a significantly wrong energy profile for a particular slot, even if the most similar day was found with the lowest total prediction error. QL-SEP was able to adapt to temporal change quickly as it checks the status of the most recent slots which makes it the best scheme in all aspects. Similarly, the slot range of 16-20 suffered from the same low solar intensity as in the morning slots.

TABLE 2. Prediction error ratios for months, $\alpha = 0.7$.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
EWMA	0.61	0.57	0.44	0.70	0.42	0.13	0.18	0.19	0.27	0.40	0.40	0.52
ASEA	0.42	0.46	0.40	0.42	0.45	0.16	0.20	0.21	0.30	0.38	0.42	0.46
Pro-Energy	0.79	0.72	0.70	0.62	0.50	0.40	0.35	0.35	0.47	0.61	0.65	0.73
QL-SEP	0.35	0.36	0.32	0.30	0.35	0.15	0.14	0.14	0.22	0.27	0.30	0.36

We next present the overall prediction error ratios for each month in Table 2. The results clearly show that the best predictions were achieved in the summer as weather conditions do not change very often then. EWMA typically outperformed ASEA and Pro-Energy as seasonal variation has a lower impact. A temporary change, such as unexpected cloudy weather for a few slots, would cause high error rates. In the winter, all of the schemes performed badly because of the frequently changing weather conditions.

Another important property is the range of prediction error which can give us an insight and enable us to understand more deeply the behavior of the predictions. Table 3 presents the specifically-ranged prediction errors. QL-SEP and ASEA had more than half of their predictions below an error ratio of 0.2, whereas EWMA and Pro-Energy predicted almost half of the energy below 0.3. The table proves that QL-SEP is the best scheme and that ASEA comes next. Note that Pro-Energy had approximately 8% of its predictions higher than an error ratio of 1, which is why Pro-Energy is prone to finding the wrong energy profile. It can be concluded that high prediction errors

TABLE 3. Range of prediction error ratios, $\alpha = 0.7$.

Error Range	EWMA	ASEA	Pro-Energy	QL-SEP
0.0-0.1	0.2385	0.3053	0.1992	0.3254
0.1-0.2	0.1603	0.2012	0.1771	0.2106
0.2-0.3	0.1195	0.1389	0.1503	0.1586
0.3-0.4	0.0996	0.0957	0.1078	0.1046
0.4-0.5	0.0898	0.0673	0.0691	0.0704
0.5-0.6	0.0804	0.0547	0.0698	0.0557
0.6-0.7	0.0697	0.0322	0.0456	0.0297
0.7-0.8	0.0463	0.0264	0.0366	0.0105
0.8-0.9	0.0288	0.0202	0.0273	0.0104
0.9-1.0	0.0181	0.0196	0.0375	0.0059
>1.0	0.0489	0.0386	0.0798	0.0182

occur when the solar intensity is very low. For instance, a few units of energy are harvested in morning slots but hundreds of energy units can be harvested at noon. Therefore, high prediction errors in terms of the amount of energy harvested may not have a significant impact on the operation of sensor nodes.

VI. CONCLUSION

The energy harvesting (EH) process has the potential to supplement energy to power sensor nodes and allow them to operate perpetually. However, solar energy has an uncertainty about the availability of future energy which makes the optimum use of solar energy a difficult task in sensor nodes. In order to allocate the optimal energy among the sensor nodes in a WSN, energy-prediction algorithms are designed with the aim of maximizing the performance of EH-WSNs. This paper has presented the design and implementation of a novel prediction algorithm which has been shown to outperform all the current state-of-art algorithms. The proposed scheme carefully checks the current solar conditions to adapt to variations in the present day. The performances of the proposed scheme and of the state-of-art approaches have been tested using real–life traces of the harvested energy obtained from the US National Renewable Energy Laboratory. The performance results validate that our algorithm has better performance in long-term evaluations. The proposed algorithm can be incorporated into the development of the current and future MAC protocols in order to forecast the amount of the energy to be harvested within a particular time slot, thereby improving the performance of WSNs through managing the energy level of the sensor nodes intelligently.

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