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A C-LMS Prediction Algorithm for Rechargeable Sensor Networks

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ABSTRACT This paper focuses on the application environment of solar charging in Energy Harvesting Wireless Sensor Networks (EH-WSN), and studies how to effectively use energy prediction to extend the life of sensor networks. Considering the prediction algorithm of the standard Least Mean Square (LMS), the output power error is large when weather changes are fluctuating, and energy collection cannot be accurately predicted. This paper proposes a Correlation Least Mean Square (C-LMS) prediction model that introduces the correlation factor of weather changes. The algorithm has low complexity with a certain flexibility, which can solve it quickly and effectively improve the accuracy of short-term prediction. Experimental results show that the error rate of the C-LMS prediction algorithm is reduced by about 15% compared with the LMS model, and the prediction accuracy is significantly improved dealing with weather fluctuation. At the same time, based on the above lightweight prediction algorithm, the effects of predictive charging and residual energy on the rechargeable sensor network topology are reconsidered. Compared to a routing strategy that does not consider predictive charging, the optimized network lifetime has increased by nearly 31.7%.

INDEX TERMS Rechargeable sensor network, solar energy, energy prediction, network lifetime.

I. INTRODUCTION

Wireless sensor networks (WSN) [1] are one of the hottest research areas that have attracted widespread attention today, involving multidisciplinary cross-fusion and new technologies. Generally, a great number of WSNs form a multi-hop and self-organizing network [2] and transmit object information in the monitoring area in a cooperative manner of sensing, collecting, processing, and wireless communication [3]. The wide application of WSN provides a good technical equipment and information platform for environmental monitoring, resource protection, military monitoring and other related fields [4]. But in the actual environment deployment, WSN has energy limitation due to its own battery power supply drawbacks. And it is difficult to replace the energy supply equipment in special environments, which seriously restricts the application effect of the wireless sensor network in long-term data monitoring and transmission. For the problem of sensor energy limitation, related research around extending the life of the network can be divided into three categories, namely internal energy saving [5], external energy collection [6], [7], and wireless charging [8].

Among them, the external energy collection method refers to using a new energy source in the wireless sensor network to provide energy supply to the sensor. As the development of solar energy collection matures, EH-WSN [9] are gradually applied to the actual. How to make full use of non-constant solar energy supply for energy harvesting is the key.

This paper proposes a C-LMS prediction model that introduces the correlation factor of weather changes, which can improve the accuracy of short-term prediction with low complexity and flexibility. Finally, the optimal effects of predictive charging and residual energy of network topology adjustment is verified by simulation.

The rest of this paper is organized as follows. Section II describes the research status and limitations of EH-WSN energy saving, the hardware measurement of solar energy collection sensor nodes, and proposes the ideas of this paper. Section III introduces the C-LMS prediction model and algorithm design. Section IV compares the stability of the

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TABLE 1. EH-WSN energy prediction algorithm.

Type of prediction algorithm	Prediction Model	Main advantages and disadvantages
Time series prediction model	EWMA [12]	Only based on historical data, but difficult to adapt to the situation of large weather changes; some typical weather matching with subjective factors is difficult to be realistic.
	WCMA [13]	
	UD-WCMA [14]	
Machine learning prediction model	BP neural network [15]	High complexity and requires a large amount of historical training data. The prediction calculation is large, and the sensor memory is limited.
	RNN neural network [16]	
Adaptive filter model	Standard LMS adaptive filter [17]	More accurate on sunny days, but the output power is prone to large fluctuations when faced with cloud occlusion.

prediction algorithm and evaluation of network lifetimes optimization.

II. RELEVANT WORKS AND MOTIVATIONS

At present, the shortage of global energy and the problem of environmental pollution are becoming serious. How to wisely use renewable energy to improve network life is very important in the application of WSN. The current mainstream EH-WSN uses renewable energy (solar, wind, geothermal, vibration, etc.) to supplement the node battery energy. Among them, solar energy is more suitable for providing energy to the WSN node as a clean, stable, and safe energy source. For sensor networks that collect solar energy, the prediction of energy [10], [11] harvesting is critical. The smaller the prediction error, the more stable the entire network can operate, thus extending network life. However, the radiation intensity of solar energy is often accompanied by weather and time changes, and there are many unstable factors. For this irregularity, many methods for energy prediction have emerged.

In the EH-WSN, domestic and foreign scholars have proposed multiple prediction methods for different scales and different scenarios. The current energy prediction algorithms for EH-WSN are shown in Table 1. Among them, there are prediction methods based on short-term historical data. They are usually based on energy data and historical data collected on the same day, including the earliest time series forecasting model such as Exponentially Weighted Moving Average (EWMA) [12], Weather-Conditioned Moving Average (WCMA) [13], and improved Universal Dynamic Weather Condition Moving Average (UD-WCMA) [14]. The EWMA prediction algorithm assumes that the sun's illumination value is similar at each moment of the day, regardless of the weather change. The predicted value depends only on the illumination value of the previous moment and the average of the previous data at that moment. In the case of continuous smooth weather conditions, the prediction accuracy of this method is high, but large prediction errors cannot be avoided when the weather changes occur. The WCMA algorithm introduces the weather factor GAP to scale the average of the days before the predicted time. However, there is a fixed weighting factor α in both models. It is used to adjust the value of the previous moment of the day's forecast and the proportion of the average of the previous few days. α is generally artificially set before the start of the forecast without explicit weather. Therefore, neither of the above two models can adaptively adjust α according to different weather conditions, and cannot adapt to the actual scene with sudden weather and cloud occlusion. Later, the typical weather pattern recognition was added based on Pro-Energy to construct an improved UD-WCMA model. Unfortunately, the extraction of "typical weather" in real-world applications have certain difficulties, and its predictive accuracy is not stable.

Some scholars have proposed using machine learning prediction models for long-term energy harvesting. This usually requires training a large amount of historical data to predict energy harvesting, such as back propagation (BP) neural network [15], Recurrent Neural Network (RNN) [16], etc. However, due to limited sensory memory, a large amount of training data cannot generally apply to the practical application of sensor networks. In addition, some standard-based adaptive filters are used for prediction [17]. The main purpose is to adjust the filter tap weight according to the error between the historical illumination value and the filter output prediction value to obtain the approximation model of the filter for the illumination change prediction. However, the traditional adaptive filter prediction does not fully consider the impact of the recent 24-hour illumination intensity variation of the filter iteration rate. And when facing the cloud occlusion, the output power is prone to large fluctuations, which leads to a standard LMS badly adapted to light intensity mutation.

In summary, these related researches on energy harvesting sensor networks are based on models such as time series models, machine learning models, and standard adaptive filters extend network lifetime, but they all have some limitations. Among them, EWMA and WCMA cannot adapt to large weather changes, and the prediction accuracy of critical time (sunrise and sunset) is low. The improved UD-WCMA is prone to large error points when the weather is stable. Typical weather matching is accompanied by subjective factors. It is difficult to implement in reality, and the load scale that can be achieved is small. The prediction accuracy of the neural network prediction model is improved compared with the time series model. Although the prediction accuracy and prediction range are improved, the prediction process needs to train the prediction model through a large amount of illumination data. It is not applicable to WSNs with less computational capacity and limited memory. It cannot be applied to scenarios with real-time prediction requirements. Based on the short-term accurate solar energy harvesting

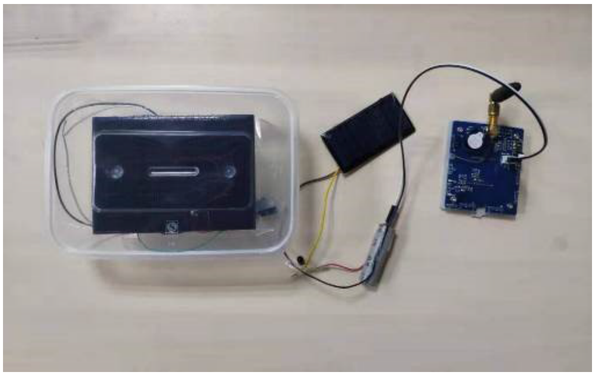

FIGURE 1. **Modified solar panel sensor node equipment diagram.**

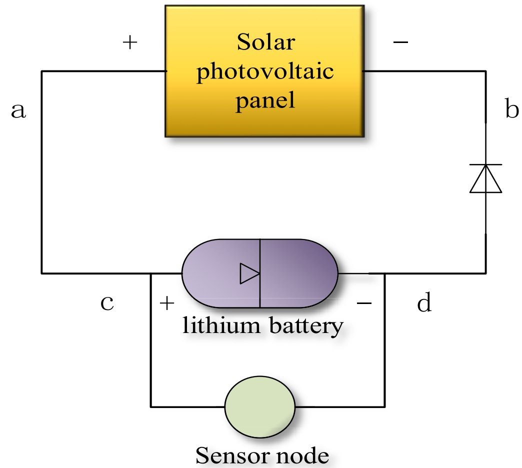

FIGURE 2. **Solar sensor node circuit diagram.**

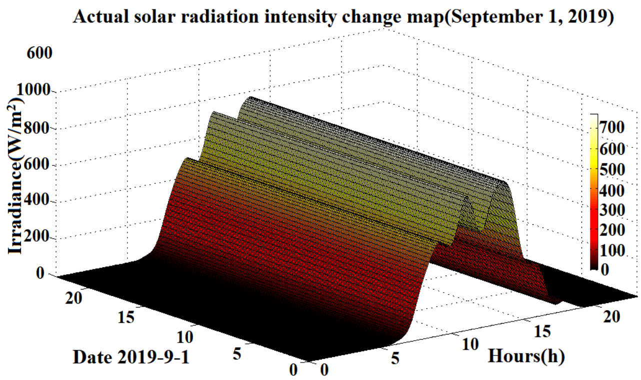

FIGURE 3. **(Sep.1.2019) Actual collection of 24-hour solar irradiance map.**

prediction method, this paper proposes a cloud-based predictive filter C-LMS, which is based on the standard LMS adaptive filter in sunny weather conditions. In a good case, there is a more accurate prediction accuracy, but when the cloud occlusion is faced, the output power is likely to fluctuate greatly, and the cloud mask coefficient is introduced to correct the prediction of the standard adaptive filter to improve the prediction accuracy.

The following analysis based on some preliminary data and examples lead to the idea of this paper. In order to collect the solar energy data in the field, Fig. 1 is based on the existing environment of our lab to build a simple sensor node charging device with solar panels. To improve the credibility of the experiment, we prepare two kinds of solar charging boards with different specifications for the experiment (specification 1:68*36mm; specification 2:110*80mm). The nodes are tested by CC2530 nodes widely used in the market. The nodes and solar panels are powered by ordinary nodes and connected by lithium batteries (3.7v, 650mah). Fig. 2 is the circuit diagram of the modified solar sensor node. The daily solar light data was collected outdoors (the observation period was one month). Figure 3 extracts the 24-hour solar irradiance data collected outdoors on September 1, 2019. The distribution characteristics of solar light intensity can be seen from the figure. Among them, the solar energy data between 6 a.m. and 7 p.m. accounted for 98% of the total energy of the day. Therefore, we define the time slot interval that can collect valid solar energy data as valid data. The valid data in the following parts refers to the valid time slot between 6 a.m. and 7 p.m., which is simplified as [6:19] to represent. In contrast, there is also a period of time during the day basically without sunlight, and the conditions for energy recharge cannot be achieved. The impact of this part of data on the total solar energy in a day is negligible, so we define the energy data time interval of 7 p.m. to 12 p.m., 0 a.m. to 6 a.m. as invalid data, simplified to (19:24] and [0:6) respectively. This article removes invalid data that has a weak impact on the total solar energy of a day, avoiding the interference of invalid data to the subsequent prediction model. Therefore, the subsequent experiments preprocess the collected data in order to provide an accurate source of experimental data for model verification.

III. C-LMS PREDICTION MODEL CONSIDERING WEATHER CORRELATION

A. DISADVANTAGES OF THE STANDARD LMS PREDICTION ALGORITHM

In view of the analysis and summary of the principle, advantages and disadvantages of the existing prediction algorithm in Section II. It can be seen that the performance of the adaptive filter is good and suitable for the deployment of sensor hardware in practice. The LMS prediction algorithm development based on wiener filtering theory not only has better convergence performance and steady-state error performance, but also has simple algorithm structure, low computational complexity, and wide application in linear prediction. The existing traditional adaptive filter prediction principle model is shown in Fig. 4.

As can be seen from Fig. 4, x(k) is the filter input signal, y(k) is the output signal that passes through the adaptive filter, that is the predicted signal value, d(k) is the desired signal, and refers to the actual output value of time k, and e(k) is

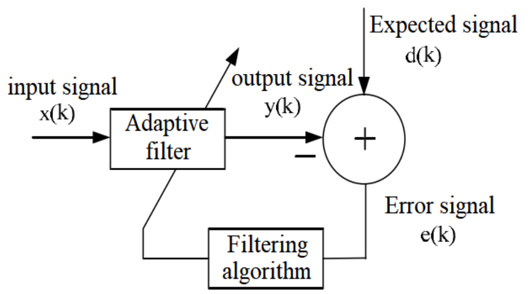

FIGURE 4. Traditional adaptive filter prediction schematic.

the desired signal d(k) and the estimated signal y(k). The error signal between the two is adjusted according to the LMS filtering algorithm to the tap weights ω of the next prediction time, so that the y(k) of the next prediction time is gradually approached to the desired signal d(k). Its prediction algorithm expression is:

$$\begin{cases} y(k) = \omega^T(k)x(k) \\ e(k) = d(k) - y(k) \\ \omega(k+1) = \omega(k) + \mu e(k)x(k) \end{cases} \tag{1}$$

Equation (1) is the standard formula of the LMS algorithm. It shows that the standard prediction algorithm does not need to train the historical data to obtain the statistical characteristics of the data, and only gradually approximates the true value with the iterative adjustment of the input vector and the expected response at each iteration. It can quickly approximate the merit of the weight vector under stationary conditions. But when faced with non-stationary conditions, it does not consider the effect of weather illumination abrupt changes (such as cloud occlusion) on the filter iteration rate. This results in large fluctuations in the output power error of the standard LMS, making it difficult to accurately predict energy harvesting.

B. C-LMS PREDICTION MODEL

Based on the analysis of the standard LMS prediction algorithm, this paper introduces the weather correlation coefficient to correct the prediction of the standard adaptive filter. When updating, the time slot is considered to improve the prediction accuracy, and a new mixed weather correlation coefficient prediction model C-LMS is established, the specific parameter information is shown in Table 2.

1) MODEL DESCRIPTION

$$\begin{cases} \hat{y}(n) = \omega^T(n)U(n) \\ e(n) = d(n) - \hat{y}(n) \\ \hat{\omega}(n+1) = \tilde{\omega}(n) + \mu e(n)U(n) \end{cases} \tag{2}$$

Equation (2) is an improved formula based on (1), as can be seen from (2), $\hat{y}(n)$ is the predicted value of the predicted time n, $\omega^T(n)$ is the Emmett transpose of $\omega(n)$, U(n) = [u(n), u(n-1), u(n-2), u(n-3), u(n-4)..., u(n-N + 1)] is the N × 1 tap input vector at time n, e(n) is the error of the expected response d(n) and the predicted value $\hat{y}(n)$, and $\hat{\omega}(n+1)$ is the n + 1 time prediction The estimated value of the corrected tap vector, C(n) is the weather correlation correction coefficient; μ is the convergence factor step parameter.

TABLE 2. Variable description.

parameters	meaning
u(n)	Solar radiation input at time n
y(n)	Radiation prediction output at time n
w(n+1)	Estimated value of the weight vector at n+1
d(n)	Radiation prediction output at time n
e(n)	Error signal
$\tilde{\omega}(n)$	Weather-related tap weight
μ	Step parameter
$P_{sim}(d)$	weather correlation
ε	Similarity adjustment factor

It is known that the standard LMS algorithm defaults $\omega(n)$ to a constant coefficient and usually takes the value of 1. The C-LMS in this paper introduces dynamic weather correlation to correct the value of *w*, reconsidering the influence factors of the weather correlation degree of the historical reference day and the current predicted time on the iterative value of the tap coefficient. We use the variance of the reference value and the predicted value to indicate the degree of correlation. Among them, the reference value is calculated from the slot tap coefficient of the previous day (or previous days, depending on the specific situation), and the predicted value is calculated from the slot tap coefficient of the predicted day. That is, d = [0, 1, 2,..., D], t = [0, 1, 2,..., T], where d is the number of reference days from the current forecast day, and t is the starting reference time slot of any reference day. According to Section II, the valid data interval is [6:19], so the value of t is 6. And the relevant formula for describing the weather correlation is shown in (3)-(5):

$$P_{sim}(d) = \frac{\frac{1}{T}\sum_{i=t}^{T}[\omega_d(i) - \partial_{pre}]^2}{\frac{1}{T}\sum_{i=t}^{T}[\omega_{now}(i) - \partial_{pre}]^2} \tag{3}$$

$$\partial_{pre} = \frac{1}{T}\sum_{i=t}^{T}\omega_d(i) \tag{4}$$

$$\partial_{now} = \frac{1}{T}\sum_{i=t}^{T}\omega_{now}(i) \tag{5}$$

Among them, T = n − t, represents the time interval of the distance prediction time t; ∂_{pre} and ∂_{now} respectively represent the average value of the reference time slot tap weight ω_d corresponding to the reference day d and the average value of the time slot tap weight ω_{now} of the forecast day; $P_{sim}(d)$ represents the weather correlation between the d reference day and the current prediction time slot n. The weather correlation vector of the historical reference day calculated by (3) is as shown in (6):

$$P_{sim} = [P_{sim}(0), P_{sim}(1), P_{sim}(2), \ldots, P_{sim}(d)] \tag{6}$$

It can be seen from (6) that the smaller the value of $P_{sim}(d)$ (when $P_{sim}(d)$ is 0∼1), the closer the weather correlation of the reference day is to the predicted day, and vice versa (when the value of $P_{sim}(d)$ is greater than 1), the correlation is low, In order to accurately and quickly reduce the impact of low correlation data on the current prediction, a similarity adjustment factor of ε is introduced, and the weight of the reference vector is adjusted based on the value of $P_{sim}(d)$. The value of ε is verified by experiments to be 1∼2. The best adjustment effect can quickly reduce the influence of uncorrelated reference data on the value of tap weight prediction. The specific formula is as shown in (7):

$$\hat{P}_{sim}(d) = \begin{cases} P_{sim}(d), & 0 < P_{sim}(d) < 1 \\ \dfrac{1}{(P_{sim}(d))^{\varepsilon}}, & P_{sim}(d) > 1 \end{cases} \tag{7}$$

The processed weather similarity vector is (8):

$$\hat{P}_{sim} = [\hat{P}_{sim}(0), \hat{P}_{sim}(1), \ldots \hat{P}_{sim}(d)] \tag{8}$$

Use $\hat{P}_{sim}(d)$ to calculate the weighted average of $\omega(n)$. The weather-corrected update weight $\tilde{w}(n)$, as shown in (9):

$$\tilde{w}(n) = \frac{\sum_{i=0}^{d}\sum_{j=t}^{n} \hat{P}_{sim}(i) \cdot w(j)}{T \times \sum_{i=0}^{d} P_{sim}(i)} \tag{9}$$

Bringing (9) into (2) gives the final C-LMS prediction model.

2) ALGORITHMIC PROCESS

The basic idea of C-LMS algorithm is based on the solar radiation value data collected on the day and the days before. Update the tap weight based on the correlation of the reference day reference time slot with the current predicted time slot, calculate the weather correlation by calculating the ratio of the variance of the reference slot to the slot weight of the same day. Performing a power-down processing on the reference data with low correlation, reduce the impact of uncorrelated reference data on the value of the tap weight prediction, the correlation weight vector $\hat{P}_{sim}(d)$ is obtained. Finally, the weighted average of $\omega(n)$ is calculated by $\hat{P}_{sim}(d)$ and the updated weight $\tilde{w}(n)$ is corrected. In summary, after the update weight $\tilde{w}(n)$ is substituted into the C-LMS model, a solar energy quantity prediction model based on weather correlation is constructed.

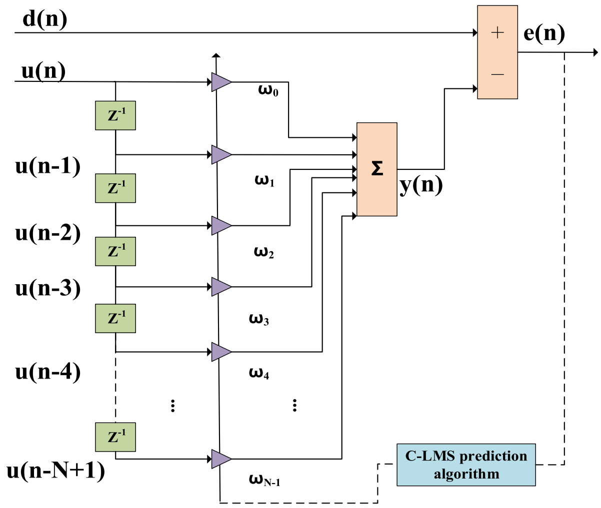

FIGURE 5. C-LMS algorithm iterative block diagram model.

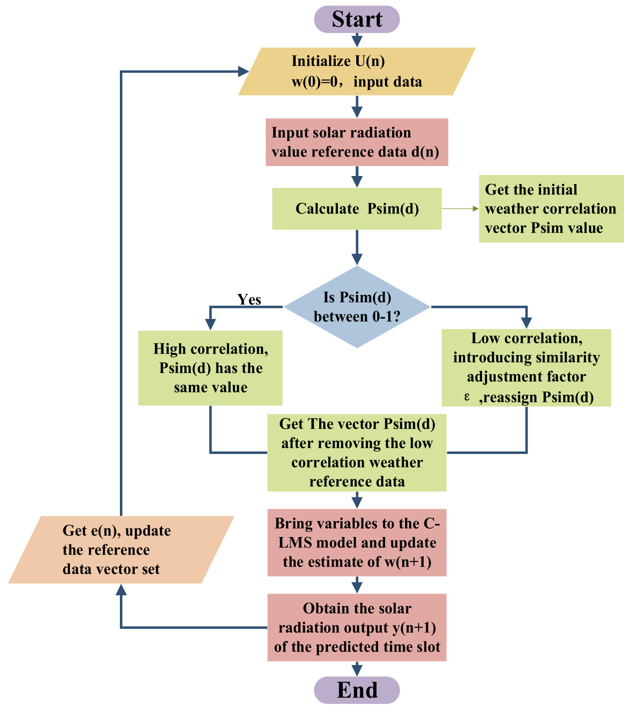

FIGURE 6. C-LMS algorithm flow chart.

The iterative block diagram of the C-LMS algorithm is shown in Fig. 5. Fig. 6 is a simplified flow chart of the C-LMS algorithm.

The detailed prediction model algorithm flow is as follows:

1. Initialize the input data U(n), including the reference data d(n) of the solar radiation value, and bring them into the C-LMS model.
2. Calculate the weather correlation $P_{sim}(d)$ of the d reference day reference time slot and the current predicted time slot n, Get the initial weather correlation vector $P_{sim}(d)$ value.

	A date	B MST	C data Wm2
1	DATE (MM/DD/YYYY)	MST	Global CMP22 (vent/cor) [W/...
2	9/2/2019	00:00	-0.982300
3	9/2/2019	00:01	-1.00388
4	9/2/2019	00:02	-0.998915
5	9/2/2019	00:03	-1.03713
6	9/2/2019	00:04	-1.08544
7	9/2/2019	00:05	-1.10782
8	9/2/2019	00:06	-1.11255

FIGURE 7. Partially collected raw data table.

3. Start to judge whether the value of $P_{sim}(d)$ is between 0-1, if so, the correlation between the reference time slot and the current time slot is high, and the value of $P_{sim}(d)$ is unchanged; if the value of $P_{sim}(d)$ is greater than 1, it means that the correlation is low, use similarity adjustment factor ε to rectify the $P_{sim}(d)$, recalculate the power of $P_{sim}(d)$ and reassign $P_{sim}(d)$.
4. Get the weather correlation vector $P_{sim}(d)$ after removing the low correlation weather reference data, and each variable is brought into the C-LMS model to update the estimated value of $w(n+1)$.
5. Obtain the solar radiation output $y(n+1)$ of the predicted time slot, and calculate the error signal $e(n)$, update the reference data vector set.
6. Start the next iteration of the solution until the desired forecast data set is obtained and the process ends.

IV. EXPERIMENT AND SIMULATION

In order to evaluate the performance of the C-LMS prediction model, the EWMA, WCMA, and the standard LMS prediction algorithms model are selected to compare the prediction accuracy and error. In this paper, from the collected solar power data collected in the field, the current and voltage values collected per second are preprocessed and the total solar radiation intensity value (W/m^2) is calculated. The original data set contains specific dates, acquisition times, and converted solar radiation values. Some of the original data sets are shown in Fig. 7.

It can be seen from the actual data observation in Section II, the valid data interval is [6:19], the experimental setting reference number D is taken as the maximum 4, and the reference time slot t is in the range of $\{t|6 < t < 19\}$. In order to verify the accuracy and stability of the prediction model experiment, four days of representative weather change data were selected from the solar radiation data of the original collected data (the observation period is one month) for experimental verification (August 8, 2019 - cloudy, August 13 - light rain to cloudy, August 16 - sunny, August 28 - cloudy to sunny).The chosen data include sunny days (no cloud cover, low weather fluctuations), cloudy (cloud cover, small weather fluctuations), light rain to cloudy (some clouds cover, weather fluctuations), cloudy, and sunny (some clouds cover, moderate weather fluctuations)) 4 kinds of weather conditions shown in Fig. 8. Meanwhile, the historical data includes reference time data

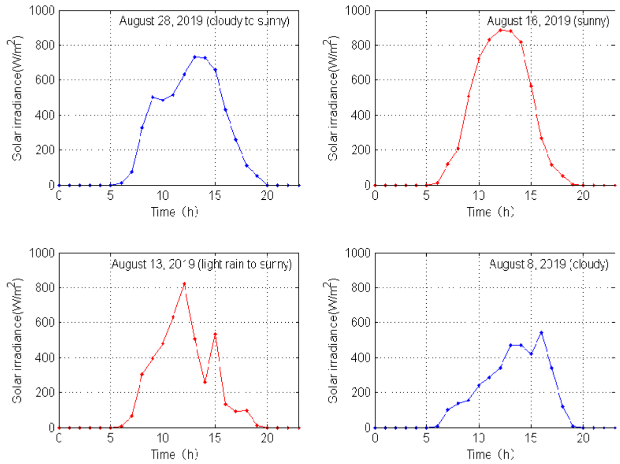

FIGURE 8. Solar irradiance data in 4 different weather conditions.

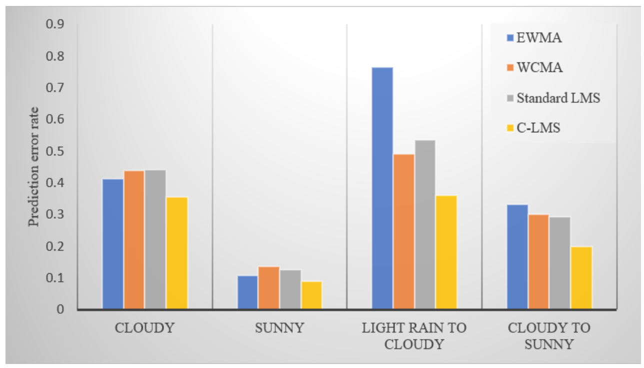

FIGURE 9. Algorithm prediction error rate comparison.

of the current day and reference time slot data of the previous 4 days.

The experiment uses EWMA, WCMA, LMS, and C-LMS prediction algorithm to predict the above four typical weather solar radiation respectively. The comparison results between the prediction result and the true radiation value are shown in Fig. 9.

It can be seen from Fig. 9 that the EWMA algorithm has less error and is slightly better than the WCMA and LMS algorithms when the weather conditions are stable or the fluctuations are small, such as the data on August 8 and August 16, in sunny and cloudy conditions. The performance is good. For weather fluctuations, such as August 13 and August 28, the EWMA algorithm significantly predicts that the error increases, while the WCMA and LMS algorithms have a slightly better prediction error than EWMA. However, the prediction error of C-LMS prediction algorithm in this paper is lower than EWMA, WCMA, and LMS algorithms in four typical weather prediction results, and it has obvious advantages in the case of unstable weather conditions and large fluctuation range. The prediction efficiency has improved by nearly 17.5%, the overall average error rate of

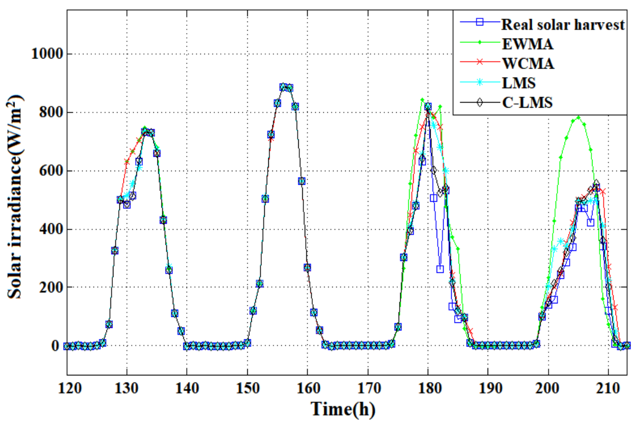

FIGURE 10. Actual fit curve of algorithm prediction result.

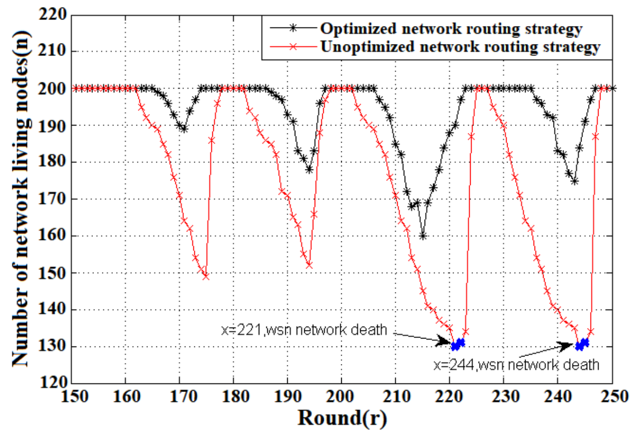

FIGURE 11. Comparison of network node survival rates.

TABLE 3. Parameter settings.

parameters	values
Deployment density	0.025 n/m^2
Number of nodes	200
Initial energy of the node	0.2J
Sink position	Circle center
Maximum communication radius	5m
Acquisition cycle	1 time/s
Node sends data energy consumption	0.6nJ/bit
Node receives data energy consumption	0.4nJ/bit

C-LMS algorithm is 25.21%, which is 15.26%, 8.89%, and 9.76% lower than EWMA, WCMA and LMS respectively.

In order to further analyze the fitting convergence effect of the four prediction effects, the actual illumination data collected is fitted with the prediction curve to visually analyze the prediction accuracy changes of the four algorithms. Fig. 10 is a block diagram of the real illumination data of the interval 120 to 215 and the prediction data of the four prediction algorithms. It can be seen from Fig. 10 that the illumination data of the time slot interval (170, 190) and (200, 210) fluctuates drastically, and the convergence effect of EWMA and WCMA is poor, and the error is large. Compared with the other three prediction algorithms, the C-LMS algorithm converges faster and closer to the real illumination value at the inflection point where solar radiation value changes rapidly, and the prediction curve has the highest fitness fit with the real data. This proves that the prediction accuracy of the C-LMS prediction algorithm in the case of cloud occlusion is more advantageous than the EWMA, WCMA, and LMS algorithms.

In order to evaluate the actual energy saving effect of the C-LMS prediction model on the EH-WSN network, we simulated the network lifetime and data throughput based on the MATLAB simulation platform. The experimental parameters are set as shown in Table 3.

Assume that the initial energy of each node is the same and the SINK node is located at the center of the area. At the same time, in order to reduce the influence of other factors on the simulation effect, the experiment only considers the energy consumption of the node to send data and receive data. Verify network reliability and network life differences and advantages under routing and traffic allocation strategies that consider energy prediction.

The experiment simulates the data transmission and reception when the number of nodes is 200. The network lifetime standard uses 1/3 node death as a sign of network death. It can be seen from Fig. 11 that the routing strategy that does not consider the predicted charging situation has died in the 221 rounds of the WSN network, and the number of remaining nodes in the optimized routing strategy network is increased by nearly 31.7% compared with the original network.

V. CONCLUSION

In this paper, a C-LMS prediction algorithm for introducing weather change correlation is proposed for the rechargeable sensor network, which effectively improves the prediction accuracy when weather fluctuation occurs. Compared with the LMS algorithm, the prediction error is reduced by about 15%. At the same time, the simulation experiment proves that considering the routing strategy under the condition of predicting charging can increase the network lifetime by about 31.7%, which can be generally applied to the practical application scenarios of solar charging sensor networks.

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