Kalman Filtering Based Adaptive Transfer in Energy Harvesting IoT Networks

HU YAO AND WU MUQING
Beijing Laboratory of Advanced Information Networks, Beijing University of Posts and Telecommunications, Beijing 100876, China
Beijing Key Laboratory of Network System Architecture and Convergence, Beijing University of Posts and Telecommunications, Beijing 100876, China
Corresponding author: Hu Yao (huyao81@163.com)

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ABSTRACT In this paper, we investigate an energy prediction algorithm based on Kalman filtering in energy harvesting IoT networks. The IoT nodes harvest renewable energy from nature and powered by green energy only. Owing to the space-time instability and non-uniformity of renewable energy, the IoT nodes may have insufficient energy supply. An unresolved challenge is accurately predicting the available renewable energy, and developing low complexity solutions that incorporate a lossless transfer guarantee. With this in mind, we propose the energy prediction algorithm based on Kalman filtering to bridge the gap between lossless transfer and unstable renewable energy. The energy prediction is performed at the access point in order to dynamically adjust the number of bits to be sent, and the data loss due to receiver energy depletion will be improved. In addition, real solar and wind energy profiles are exploited by simulations. The simulation results show that the proposed energy prediction algorithm can improve transmission efficiency in terms of the rate of drop bits and the number of time slots needed to transmit a given payload, and reduce the wastes of harvested renewable energy.

INDEX TERMS Energy harvesting, IoT networks, Kalman filtering, energy prediction.

I. INTRODUCTION
Recently, the Internet of Things (IoT) has been under the spotlight of attention of the research community and industry. The IoT will be a new paradigm, which links the cyber and the physical world by ubiquitously connecting billions of “things” throughout the Internet [1]. Gartner estimates that the IoT will include 30 billion units installed by 2025 [2]. IoT is expected to provide many services, such as utility meters, vending machines, automotive, medical metering and alerting. To achieve the objective of IoT applications, various objects are connected to the internet through wireless and wired networks, and intelligently transmit data over the network without any manual intervention.

Because of tens of billions units in IoT, a huge power supply is needed. In 2020, it is estimated that the annual carbon emission of the information and communication technology industry will be 235 million tons [3] and the electric energy consumption will be 414 TWh [4]. This not only leads to tremendous network operation costs but also places heavy burdens on the environment. Therefore, it is crucial to reduce the power consumption of the communication devices. Fortunately, energy harvesting enables infrastructures to power their services with energy that harvested from renewable energy sources (e.g., wind, solar, ambient radio power and vibration), which provides an opportunity to address the energy issues for IoT networks. Furthermore, renewable energy is more economical and green than conventional energy [5].

A. MOTIVATIONS AND RELATED WORKS
However, owing to the non-uniformity and space-time instability of renewable energy, it may be difficult to guarantee continuous and sufficient power supplies for IoT. Therefore, to overcome the unreliability and enjoy the benefits of renewable energy, efficient power management is a major challenge [6]–[9]. Fortunately, the problem can be solved by predicting the harvested energy and adjusting the number of bits to be sent accordingly. Therefore, data loss due to receiver energy depletion will be avoided, and the wastes of harvested renewable energy will be reduced.
Several algorithms have been proposed for predicting the amount of energy to be harvested by a node [10]–[17]. An energy prediction algorithm based on Kalman filtering was proposed in [10] for the point-to-point wireless communication, which aims to predict the receiver state of charge and adjust the number of bits to be sent. Reference [11] presents a mobile energy harvesting and data collection platform designed to provide a deeper understanding of energy harvesting dynamics. Two extensions of predictable Kalman filter methods are proposed in [12] to reduce the unnecessary transmission of end devices to the internet. Assuming that the amount of harvested energy during a given period for a day is close to that in the previous days, the exponential weighted moving average (EWMA) algorithm [13] was proposed for solar energy, by performing prediction using an exponentially weighted average of past harvested values. However, since the EWMA algorithm cannot consider weather changes, its performance depends mainly on the stability of the weather. The weather-conditioned moving average (WCMA) is a model issued in [14] based on EWMA that considers weather changes. It performs better when sudden weather changes occur. Some other works are based on EWMA or WCMA models adding more parameters reflecting environmental variations [15]. The normalized least mean square algorithm (NLMS) [16] predicts harvested energy using a weighted average of historical values based on error minimization. And the NLMS algorithm is of lower complexity than EWMA. In addition, the weather-forecast-based prediction (WFBP) algorithm was proposed in [17]. Compared with the aforementioned algorithms, WFBP needs the largest memory to store the weather forecasts, and cannot adapt its parameters simultaneously when the geolocation is changed. Therefore, a low complexity prediction algorithm that with small memory and whose parameters can be dynamically changed is necessary.

Motivated by the encouraging results developed in [10], this paper proposes a low complexity energy prediction algorithm based on Kalman filtering for multiple renewable energy sources, such as solar and wind. The number of bits sent in the next slot is adjusted by the access point (AP) of the IoT. Based on the predicted energy, the number of bits that are lost because of the IoT nodes’ energy depletion is therefore decreased. To minimize the prediction error, the AP can perform dynamic configuration autonomously. Based on some previous values of harvested renewable energy, the AP can estimate the value of harvested energy for the next time slot. Therefore, the proposed algorithm has a low memory requirement.

B. MAIN CONTRIBUTIONS

The main contributions of our work can be summarized as follows:

- A low complexity energy prediction algorithm based on Kalman filtering is proposed to minimize data loss.

Moreover, the proposed algorithm can be used to predict renewable energy, which is space-time instability and non-uniformity.

- Next, we perform the performance analysis to ensure the correctness and advancedness of the proposed algorithm theoretically.

- Finally, by exploiting the practical wind and solar energy profiles, we show that, with renewable energy distributed unevenly, the proposed energy prediction algorithm not only reduces the rate of drop bits and the wastes of harvested renewable energy, but also improve the task completion time.

C. PAPER OUTLINE

The organization of this paper is show as follows. Section II explains the system model and the problem formulation. Section III describes the algorithm used to adapt the number of sent bits based on Kalman filtering. Section IV shows the mean square convergence analysis. Simulation results are provided in section V. Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, this paper considers a typical IoT network composed of one AP and multiple IoT nodes. The number of nodes is \( M (M \in \mathbb{Z} \& M > 1) \). The AP is powered by the grid. All nodes are deployed with both solar panels and wind turbines but no batteries, and powered by renewable energy only. Time is divided into slots of fixed duration denoted by \( \tau \). The AP communicates with the IoT nodes wirelessly. The AP sends data to the nodes in the downlink and receives feedback from the nodes in the uplink. The uplink and downlink work in different frequency bands, such that no interference exists between them. Similar to the Long Term Evolution (LTE) system, we consider the downlink of an orthogonal frequency division multiple access (OFDMA) system and no interference between downlinks. The transmission channel is modeled as a complex Rayleigh fading channel acting on additive white Gaussian noise (AWGN).
FIGURE 2. The communication model at time slot $n$.

In addition, we assume the IoT nodes are static. Due to differences in distribution locations, etc., nodes have different abilities of energy harvesting. It is assumed that para-static time-slotted model for both renewable energy sources and data links. The arrival of renewable energy stays constant during one slot but varies independently from one slot to another. The same goes for channel gain of the data link.

Without loss of generality, we choose one communication block as the reference time slot. Fig. 2 illustrates the communication model at slot $n$, $Q_i$ is the sum of bits sent by the AP to node $i$ in all slots, $Q_i = \sum_{n=1}^{M} Q_i(n)$, $1 \leq i \leq M$. $g(n)$ is the fading channel gain that follows a Rayleigh distribution, $cw(n)$ denotes the AWGN with distribution $N(0, \sigma^2_{aw})$. The harvested renewable energy by node $i$ at time slot $n$ is $E_i^h(n)$. We consider practical wind and solar energy profiles by using the real aggregated solar and wind generations as [7] did. While renewable energy arrives, it will be used by the IoT node immediately, rather than saved in the battery and depleted in the next time slot.

Assume that the energy for sending feedback information is negligible. The energy consumed by node $i$ at slot $n$ is just data receiving, i.e.,

$$E_i^r(n) = B_i(n) E_i^{c,i}$$

$$s.t. E_i^r(n) \leq E_i^h(n), \quad \forall n$$

where $B_i(n)$ is the number of bits received by node $i$ during time slot $n$, $E_i^{c,i}$ is the energy consumed by node $i$ to receive one bit. The value of $E_i^{c,i}$ is known at the AP. The causality constraint that node $i$ cannot use energy that has not been harvested yet in slot $n$ is listed in (2).

The AP predicts as follows. At the beginning of every time slot, each node sends a feedback message to inform the AP the renewable energy it harvested in the previous slot. Then, the AP uses the information to predict the energy that can be harvested by every node for the current slot respectively. According to the predicted values of energy, the AP calculates the numbers of bits that will be sent to each node next without loss. In other words, the AP uses the historical data received from node $i$ about the node’s previous harvested energy $E_i^h(n)$ to predict future energy $E_i^h(n+1)$. By prediction, the reduction of error rate (drop bits, retransmission, etc.) and the fast transfer will be achieved.

Similar to [9], we model the renewable energy harvested by node $i$ with an autoregressive model (ARM) of order $k$,

$$E_i^h(n) = \sum_{j=1}^{k} a_j E_i^h(n-j) + \omega_i(n)$$

where $\omega_i(n)$ is white Gaussian noise that follows a distribution $N(0, \sigma^2_{aw})$, and $\{a_j\}_{j=1,...,k}$ are ARM coefficients that must be updated regularly given the unstable renewable energy sources. The Kalman filter is used for coefficient update. With the historical data, $E_i^h(n+1)$ is estimated, followed by the number of bits that the AP will send to node $i$ at time slot $n+1$.

### III. THE ENERGY PREDICTION ALGORITHM

The proposed energy prediction (EP) algorithm involves two steps. The first one updates the ARM coefficients $\{a_j\}_{j=1,...,k}$ and predicts the renewable energy that will be harvested by node $i$ at time slot $n+1$ with (3). The second one corrects the prediction to improve future performance.

#### A. KALMAN FILTER FORMULATION

Kalman filter estimates the ARM coefficients in (3) based on the assumption that each coefficient satisfies

$$a_j(n+1) = a_j(n) + v_j(n+1), \quad j = \{1, \ldots, k\} \quad (4)$$

in time. Where $v_j(n)$ is white Gaussian noise following $N(0, \sigma^2)$. Then, we have

$$
\begin{align*}
\hat{A}_k(n) &= I_k A_k(n-1) + v(n) \\
E_i^h(n) &= H_i^T(n) A_k(n) + \omega_i(n)
\end{align*}
$$

where $A_k(n) = [a_1(n), \ldots, a_k(n)]^T$ is the state vector, $I_k$ is the identity matrix, $v(n) = [v_1(n), \ldots, v_k(n)]^T$ is the state noise, $H_i(n) = [E_i^h(n-1), \ldots, E_i^h(n-k)]^T$ is the vector of measurement and $\omega_i(n)$ is AWGN as used in (3).

#### B. ARM COEFFICIENT AND LOAD SIZE PREDICTION

With the previous information at time slot $n$, the prediction of $A_k$ is

$$\hat{A}_k(n+1 | n) = I_k \hat{A}_k(n | n)$$

And the covariance matrix $P$ of $A_k$ at time slot $n+1$ is

$$\hat{P}(n+1 | n) = I_k \hat{P}(n | n) I_k^{-1} + \sigma^2_{aw} I_k$$

Then, we have the following prediction for $E_i^h$ at slot $n+1$

$$\hat{E}_i(n+1) = H_i(n+1) \hat{A}_k(n+1 | n)$$

Let the AP sends data to nodes at the same transmission power $P_t$ (watt). Then, the received signal by node $i$ at time slot $n$ is $P_t g(n) d_{AP,i}^{-2}$, where $g(n)$ is the channel gain, $d_{AP,i}$ is the Euclidian distance in meter between node $i$ and the AP, and $\alpha > 2$ is the path loss exponent. Therefore, the signal to noise ratio (SNR) of the data link is $\frac{P_t g(n) d_{AP,i}^{-2}}{\sigma^2_{aw}}$, in which, $\sigma^2_{aw}$ is the background AWGN variance. According to the Shannon expression, with unit bandwidth $1$ Hz, at time slot
In the proposed EP algorithm, the ARM coefficient update consists of the vector \( \frac{P_i g(n+1) d_{AP,n}}{\sigma_{cw}^2} \), and the theoretical number of bits at time slot \( n + 1 \) that will be sent by the AP to node \( i \) is \( r \log_2 \left( 1 + \frac{P_i g(n+1) d_{AP,n}}{\sigma_{cw}^2} \right) \). Hence, under the constraints of data link rate and available energy, the number of bits that will be sent by the AP to node \( i \) at time slot \( n + 1 \) is

\[
Q_i (n + 1) = \text{floor} \left( \min \left( \frac{\bar{E}_i^h (n+1)}{E_{c_i}^c}, r \log_2 \left( 1 + \frac{P_i g(n+1) d_{AP,n}}{\sigma_{cw}^2} \right) \right) \right) \tag{9}
\]

As long as node \( i \) has sufficient energy to receive data and the data link between them is good enough, the AP will send as many bits as possible to the node.

**C. ARM COEFFICIENT UPDATE**

At the beginning of time slot \( n + 2 \), the AP receives the real value of \( E_i^h (n+1) \) from node \( i \), and it updates the predicted ARM coefficients as

\[
\hat{A}_k (n + 1 | n + 1) = \hat{A}_k (n + 1 | n) + K (n + 1) (E_i^h (n + 1) - \hat{E}_i^h (n + 1)) \tag{10}
\]

in which, \( K (n + 1) \) is the Kalman gain denoted as

\[
K (n + 1) = \bar{P} (n + 1 | n) H_i (n + 1) F^{-1} (n + 1) \tag{11}
\]

Finally, the error covariance matrix \( P \) is updated as

\[
\hat{P} (n + 1 | n + 1) = [I_k - K (n + 1) H_i (n + 1)] \bar{P} (n + 1 | n) \tag{13}
\]

**D. ALGORITHM COMPLEXITY ANALYSIS**

Within the proposed EP algorithm, the ARM coefficient update consists of the vector “\( A \)” that embeds the vector “\( H \)”. With (5) we have: \( A (n) = [a_1 (n), \ldots, a_k (n)]^T \) and \( H (n) = [E_i^h (n - 1), \ldots, E_i^h (n - k)]^T \). The number of cycles of coefficient “\( H \)” is depending on \( k \), which is the order of the ARM. And the number of cycles of the coefficient “\( A \)” is depending on \( k \), too. Furthermore, with (10) \sim (12) we get: based on the update of “\( H \)” “\( A \)” is updated. Therefore, the computational complexity of the proposed EP algorithm is \( o (k^2) \).

**IV. MEAN SQUARE CONVERGENCE ANALYSIS**

Similar to [18], [19], the mean square error is used to perform the convergence analysis of the proposed EP algorithm in this section. With the description of Section III and (5), the considered discrete-time system is represented by

\[
A (n) = f (A (n - 1)) + v (n) \tag{14}
\]

\[
E_i^h (n) = H_i (n) A (n) + \omega (n) \tag{15}
\]

where \( f (\cdot) \) is a nonlinear mapping, \( n \in \mathcal{N} \) is discrete-time, \( \mathcal{N} \) denotes the set of non-negative integer, \( A (n) \in \mathbb{R}^k \) is the state of time slot \( n \). Moreover, \( v (n) \) and \( \omega (n) \) are uncorrelated zero-mean Gaussian white sequence and their covariances are

\[
E [v (i) \omega^T (j)] = 0
\]

\[
E [v (i) v^T (j)] = R (i) \sigma_{ij}
\]

\[
E [\omega (i) \omega^T (j)] = Q (i) \sigma_{ij} \tag{16}
\]

Referencing to the standard results in [20], [21] of the boundedness of stochastic processes, the error is analyzed. With reference [21], Lemma 1 is given.

**Lemma 1:** Assume that \( \varphi (n) \) is a stochastic process. There is a stochastic process \( L (\varphi (n)) \) as well as real numbers \( \varepsilon > 0 \), and \( \tau_i, l_{\min}, l_{\max} > 0 \) for \( \forall n \)

\[
l_{\min} \| \varphi (n) \|^2 \leq L (\varphi (n)) \leq l_{\max} \| \varphi (n) \|^2 \tag{17}
\]

\[
E [L (\varphi (n)) | \varphi (n - 1)] - L (\varphi (n - 1)) \leq \varepsilon - \varphi L (\varphi (n - 1)) \tag{18}
\]

are fulfilled. Then the stochastic process is bounded in mean square, i.e.,

\[
E \left[ \| \varphi (n) \|^2 \right] \leq l_{\max} \int_{t_{\min}}^{t_{\max}} E \left[ \| \varphi (0) \|^2 \right] (1 - \varphi)^n + \frac{\varepsilon}{l_{\min}} \sum_{i=1}^{n-1} (1 - \varphi)^i \tag{19}
\]

The lemma and its proof are shown in Theorem 2 of reference [21], at pp. 443.

With reference [22], another lemma is given as follows. Let \( A \) be a real symmetric matrix, \( B \in \mathbb{R}^{k \times j}, C \in \mathbb{R}^{j \times j}, A > 0, C > 0, \)

\[
A^{-1} > B \left( B^T A B + C \right)^{-1} B^T \tag{20}
\]

The proof of Lemma 2 is in Appendix A2 of [22], at pp. 347.

Define the estimation error and the prediction error as

\[
\tilde{A} (n) = A (n) - \hat{A} (n) \tag{21}
\]

\[
\tilde{A} (n + 1 | n - 1) = A (n) - \hat{A} (n | n - 1) \tag{22}
\]

Expanding \( A (n) \) by a Taylor series about \( \hat{A} (n - 1) \), we have

\[
A (n) = f (\hat{A} (n - 1)) + \nabla f (\hat{A} (n - 1)) \hat{A} (n - 1) + \frac{1}{2} \nabla^2 f (\hat{A} (n - 1)) \hat{A}^2 (n - 1) + \cdots + v (n) \tag{23}
\]

where \( \nabla f (\hat{A}) \hat{A}^i = \left( \sum_{j=1}^{k} \hat{A}_j \frac{\partial}{\partial \hat{A}_j} f (\hat{A}) \right)^i \) is the \( j \)-th component of \( A \). Similar to (23), Expanding \( A (n | n - 1) \) given in (22) by a Taylor series about \( \hat{A} (n - 1) \),

\[
\tilde{A} (n | n - 1) = f (\hat{A} (n - 1)) + \frac{1}{2} \nabla^2 f (\hat{A} (n - 1)) P (n - 1) + \cdots \tag{24}
\]
Substituting (23) and (24) into (22) yields

$$\tilde{A}(n|n-1) \approx F(n)\tilde{A}(n-1) + v(n)$$  
(25)

where $F(n) = \frac{\partial f(\lambda)}{\partial \lambda} |_{A = \tilde{A}(n-1)}$. It is evident that the residual of $\tilde{A}(n|n-1)$ always exists. To get accurate results, an unknown vector $\lambda = [\lambda(0), \lambda(1), \cdots, \lambda(n), \cdots]$ is introduced, in which $\lambda(n) \in \mathcal{R}$, and rewrite (25) as

$$\tilde{A}(n|n-1) = \lambda(n)F(n)\tilde{A}(n-1) + v(n)$$  
(26)

The residual of measurement is defined as

$$\tilde{E}_i^h(n) = E_i^h(n) - \tilde{E}_i^h(n)$$  
(27)

Substituting (15) into (27) yields

$$\tilde{E}_i^h(n) = H_i(n)\tilde{A}(n|n-1) + \omega(n)$$  
(28)

With (7) and (16), we have

$$\hat{P}(n|n-1) = I_k\hat{P}(n|n)I_k^{-1} + R(n) + \Delta R(n)$$  
(29)

where $\Delta R(n)$ is an extra positive definite matrix introduced in the calculated covariance matrix. By the original definition, the real prediction error covariance matrix is

$$P(n|n-1) = E\left[ (\tilde{A}(n|n-1) - \hat{A}(n|n-1))^T (\hat{A}(n|n-1) - \hat{A}(n|n-1)) \right]$$  
(30)

Substituting (26) into (30) gives

$$P(n|n-1) = E\left[ (\tilde{A}(n|n-1) + v(n))^T \right] 
\times \left[ (\tilde{A}(n|n-1) + v(n))^T \right] 
\lambda^2(n)F(n)\hat{P}(n-1)F^T(n)$$  
$$+ \lambda^2(n)F(n)\hat{P}(n-1)F^T(n)$$  
$$+ \lambda^2(n)F(n)\hat{P}(n-1)F^T(n) + R(n)$$  
(31)

where $\Delta P(n|n-1)$ is the difference between

$$\lambda^2(n)F(n)\hat{P}(n-1)F^T(n) \text{ and } E\left[ (\tilde{A}(n|n-1) + v(n))^T \right] 
\times \left[ (\tilde{A}(n|n-1) + v(n))^T \right]$$  

Let $\delta P(n|n-1)$ be the difference between $P(n|n-1) \text{ and } I_k\hat{P}(n|n)I_k^{-1} + R(n)$, and (29) can be rewritten as

$$\hat{P}(n|n-1) = P(n|n-1) + \delta P(n|n-1) + \Delta R(n)$$  
$$= \lambda^2(n)F(n)\hat{P}(n-1)F^T(n) + \hat{R}(n)$$  
(32)

where

$$\hat{R}(n) = \Delta P(n|n-1) + R(n) + \delta P(n|n-1) + \Delta R(n)$$  
(33)

Based on Lemma 1, Lemma 2, (26) and (32), Theorem 3 is presented as follows.

**Theorem 3:** Consider the Kalman filter as (5)-(8), (29) and a stochastic system given by (14), (15), if: There are real numbers $r_{max}$, $\hat{r}_{max}$, $r_{min}$, $q_{min}$, $p_{max}$, $p_{min} > 0$, and $\lambda_{max}$, $h_{max}$, $f_{max}$, $\hat{\lambda}_{min}$, $h_{min}$, $f_{min} \neq 0$, such that the following bounds are fulfilled for $\forall n \geq 0$:

$$R(n) \leq r_{max} I$$  
(34)

$$\hat{r}_{min} I \leq \hat{R}(n) \leq \hat{r}_{max} R$$  
(35)

$$q_{min} I \leq Q(n)$$  
(36)

$$p_{min} I \leq \hat{P}(n) \leq p_{max} I$$  
(37)

$$\lambda_{min} I \leq \lambda^2(n) \leq \lambda_{max} I$$  
(38)

$$h_{min}^2 I \leq H_i(n)H_i^T(n) \leq h_{max}^2 I$$  
(39)

$$f_{min}^2 I \leq F(n)F^T(n) \leq f_{max}^2 I$$  
(40)

Then, the estimation error $\tilde{A}(n)$ is bounded in mean square sense.

The proof of Theorem 3 is given in Appendix A. With (68), Setting

$$S_{max} \leq \frac{p_{max}}{p_{min}} E\left[ (\tilde{A}(0)) \right] (1 - \theta_{min})^n + \frac{\hat{r}_{min}^{-1}}{p_{min}} \sum_{i=1}^{n-1} (1 - \theta_{min})^i$$  
(41)

Then, we have $S_{max} \geq 0$. And with (28), we get

$$E\left[ ||\tilde{E}_i^h(n)||^2 \right]$$  
$$\leq E\left[ ||H_i(n)\tilde{A}(n|n-1) + \omega(n)||^2 \right]$$  
$$+ ||\omega(n)||^2$$  
$$\leq h_{max}^2 E\left[ ||\tilde{A}(n)|^2 \right] + 2h_{max} E\left[ ||\tilde{A}(n)|^2 \right] + q_{max}$$  
$$\leq h_{max}^2 S_{max} + 2h_{max} \sqrt{S_{max}} + q_{max}$$  
(42)

The above analysis shows that the mean square error of $E_i^h(n)$ is bounded, and the stability of the proposed EP algorithm is guaranteed.

**V. NUMERICAL SIMULATIONS**

In this section, we will verify the theoretical results derived in Section III and IV, and evaluate the performance of the proposed EP algorithm by simulations. Two parts of the experiments are conducted. The first one evaluates the Kalman filter performance and the second one evaluates the gain obtained in data transmission duration when energy prediction is employed.

The energy model is the same as [7], which is real solar and wind energy harvested record taken from the Elia Group database [23]. Data interception period is from 0:00, Apr. 3, 2016 to 0:00, Apr. 6, 2016 in Belgium. Based on these real data, we get the normalized solar and wind energy harvesting profiles over time, as shown in Fig. 3. Energy sampling is performed every 15 minutes, and 72 hours’ renewable energy data correspond to 288 points. Let the normalized solar and wind energy harvesting profiles in Fig. 3 be denoted as $s = [s_1, \ldots, s_{288}]$ and $w = [w_1, \ldots, w_{288}]$, respectively. With the proposed EP algorithm, Fig. 4 shows the results for a real wind energy profile. Fig. 5 shows the obtained mean square error (MSE) when predicting the values in Fig. 4. The MSE is defined as

$$MSE(n) = \frac{1}{n} \sum_{j=1}^{n} (E_i^h(j) - \tilde{E}_i^h(j))^2$$  
(43)
As Fig.5 shows, the MSE decays to 0 past a short period by the Kalman filter.

After validating the Kalman filter operation, new experiments are conducted to study the impact of using energy prediction for data transmission. In our work, we assume all nodes are deployed with both solar panels and wind turbines of different generation capacities. Let the renewable energy harvesting rate in time slot $n$ at node $i$ be

$$E^h_i(n) = G[c_i s_n + (1 - c_i) w_n],$$

where $G$ is a given constant, and $c_i \in [0, 1]$ is a random number.

We evaluate the performance of the proposed EP algorithm in a typical IoT network with three nodes and one AP, which is $M = 3$. The AP located at the origin of two-dimensional plane. Three nodes located at coordinates $(90, 0), (-30, 40),$ and $(-50, 50)$ respectively. The energy harvesting rate uses the normalized solar and wind energy harvesting profiles. In addition, we give $\alpha = 3$ [7], $P_t = 6$ watt [24], $G = 10$, $c_1 = 0.5, c_2 = 0.2, c_3 = 0.8$. For simplification, $E^r_i(n) = 0.1$ watt for $i = \{1, 2, 3\}$, $\tau = 1$ second, the background noise variance $\sigma^2_{cw}$ in each data link is -100 dB, and the variance of Rayleigh fading is fixed to 1.

For comparison, we introduce the algorithm without prediction as a performance benchmark, in which the number of bits to be sent by the AP at the next time slot $n+1$ depends on the mean of energy that node $i$ can harvest as

$$Q_i(n+1) = \text{floor} \left\{ \min \left( \frac{E^h_i(n)}{E^r_{i}}, \frac{\tau \log_2 \left( 1 + \frac{P_t g (n+1) d_{AP,i}^\alpha}{\sigma^2_{cw}} \right)}{1} \right) \right\}$$

(44)

where $\bar{E}^h_i = \text{mean} (E^h_i (1), \ldots, E^h_i(n))$ is the mean value of the energy harvested by node $i$ in the previous $n$ time slots.

Fig. 6 shows the average rate of drop bits in each node with or without the EP algorithm. Let the AP has enough data to send, that is, $Q_i \to \infty, i = \{1, 2, 3\}$. Under the parameter settings of our work, after more than 1000 simulation operations, we get the total rate of drop bits with or without the proposed EP algorithm is 16.22% and 31.20% respectively. With Fig. 6, it is observed that, firstly, the drop bits rate of the proposed EP algorithm performs better than that without it overall. Secondly, in the first few slots, the drop bits rate of the proposed EP algorithm is much higher than that without it. The main reason is that the energy prediction of the proposed EP algorithm includes two steps: estimation and correction, updating and optimization of the prediction parameters make the prediction result closer to the true value. Thirdly, when
the harvested renewable energy is inadequate (50-63 slot), the rate of drop bits rise rapidly in both algorithms, and the decrease of the harvested energy brings a sharper increase in the rate of drop bits without the EP algorithm (96%) than with the scheme (85%). A few time slots after energy dip (after 50 slots), the drop bits rate of the proposed EP algorithm reduced to 0 quickly, while the drop bits rate without the EP algorithm persistently high. The improvement of the performance is mainly because the energy prediction mechanism of the proposed EP algorithm makes the system adapt to energy fluctuations quickly.

Fig. 7 shows the average wasted renewable energy in each node versus time. The same with Fig. 6, $Q_i \rightarrow \infty, \ i = \{1, 2, 3\}$. Under the parameter settings of our work, after more than 1000 simulation operations, the total rate of wasted renewable energy with or without the EP algorithm is 25.33% and 36.95% respectively. It is visible that, firstly, the wasted renewable energy of the proposed EP algorithm is less than without it overall. Secondly, while the harvested renewable energy is different, the wasted renewable energy is diverse either. On the other hand, when the harvested renewable energy is poor (50-63 slot), with the EP algorithm the wasted renewable energy is higher than that without it. Finally, when the harvested renewable energy is adequate (in the day time, 16-24 and 41-49 slot), the wasted renewable energy rise rapidly in both algorithms, and a few time slots after renewable energy redundancy, the wasted renewable energy of the proposed EP algorithm reduced to 0 quickly, while the wasted renewable energy without the EP algorithm is still high. The main reason is that energy prediction enables the system to quickly adapt to the rapid changes in harvested energy, adjust the number of transmitted data adaptively, and reduce energy waste.

Finally, Fig. 8 shows that as the number of bits to be sent by the AP increasing, algorithm with energy prediction becomes more valuable since it reduces the number of time slot required to complete transmission. The main reason is that energy prediction can decrease the number of drop bit and retransmission, and thus the time needed to carry out the task is improved.

VI. CONCLUSION

This paper proposes a low complex energy prediction algorithm based on Kalman filtering. In the wireless one-to-many communication system, the IoT nodes powered by renewable energy only. With energy prediction, the AP updates the number of sent bit dynamically and autonomously. Analysis and experimental results show that under a practical renewable energy harvesting model, the proposed energy prediction algorithm improves transmission efficiency and reduces the wastes of energy. In future works, simultaneous communication of up and down data links will be proposed.

APPENDIX

A. THE PROOF OF THEOREM 3

proof 4: Choose

$$L_n (\tilde{A} (n)) = \tilde{A}^T (n) \tilde{P}^{-1} (n) \tilde{A} (n)$$

(45)

With (37) we have

$$\frac{1}{p_{\text{max}}} \| \tilde{A} (n) \|^2 \leq L (\tilde{A} (n)) \leq \frac{1}{p_{\text{min}}} \| \tilde{A} (n) \|^2$$

(46)

By (13), we have

$$\tilde{P} (n) = [I_k - K (n) H_i (n)] \tilde{P} (n | n - 1)$$

(47)

Using (11) and (12) yields

$$K (n) = \tilde{P} (n | n - 1) H_i^T (n)$$

$$\times [H_i (n) \tilde{P} (n | n - 1) H_i^T (n) + Q (n)]^{-1}$$

$$= \tilde{P} (n) H_i^T (n) Q^{-1} (n)$$

(48)

Applying the matrix inversion lemma on (47) gives

$$\tilde{P}^{-1} (n) = \tilde{P}^{-1} (n | n - 1) + H_i^T (n) Q^{-1} (n) H_i (n)$$

(49)

From (10) and (21) it can be obtained

$$\tilde{A} (n) = A (n) - \tilde{A} (n)$$

$$= \tilde{A} (n | n - 1) - K (n) \tilde{E}_i^T (n)$$

(50)
With (45) and (50), we have
\[
L_n(\tilde{A}(n)) = \left[\tilde{A}(n | n-1) - K(n) \tilde{E}^h_n(n)\right]^T \times \tilde{P}^{-1}(n) \left[\tilde{A}(n | n-1) - K(n) \tilde{E}^h_n(n)\right] \tag{51}
\]
Inserting (28) into (51) yields
\[
L_n(\tilde{A}(n)) = \tilde{A}^T(n | n-1) \tilde{P}^{-1}(n) \tilde{A}(n | n-1) - [H_i(n) \tilde{A}(n | n-1) + \omega(n)]^T K(n) \tilde{P}^{-1}(n) \times H_i(n) \tilde{A}(n | n-1) + \omega(n) \right] + \left[H_i(n) \tilde{A}(n | n-1) + \omega(n) \right]^T K(n) \left[H_i(n) \tilde{A}(n | n-1) + \omega(n) \right] \tag{52}
\]
Inserting (26), (48), (49) into (52), and taking the conditional expectation we have
\[
E \left\{ L_n(\tilde{A}(n)) \right\} \left[\tilde{A}(n-1)\right] = E \left\{ [\lambda(n) F(n) \tilde{A}(n-1) + v(n)]^T \tilde{P}^{-1}(n | n-1) \times [\lambda(n) F(n) \tilde{A}(n-1) + v(n)] \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [Q^{-1}(n) - Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n)] \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{53}
\]
From (11), (12) and (48), we obtain
\[
\frac{Q^{-1}(n) - Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) = \left[H_i(n) \tilde{P}(n | n-1) H_i^T(n) + Q(n)\right]^{-1}}{\tilde{A}(n-1)} \tag{54}
\]
Substituting (32) and (54) into (53), and applying Lemma 2, (53) is rewritten as
\[
E \left\{ L_n(\tilde{A}(n)) \right\} \left[\tilde{A}(n-1)\right] \leq E \left\{ [\lambda(n) F(n) \tilde{A}(n-1)]^T \times [\lambda(n) F(n) \tilde{A}(n-1)] + v(n) ]^T \times [\lambda(n) F(n) \tilde{A}(n-1)] + v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [Q^{-1}(n) - Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n)] \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{55}
\]
Inequality (40) implies that $[\lambda(n) F(n)]^{-1}$ exists, then, we have
\[
E \left\{ [\lambda(n) F(n) \tilde{A}(n-1)]^T \times [\lambda(n) F(n) \tilde{A}(n-1)] + v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [Q^{-1}(n) - Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n)] \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \leq E \left\{ v(n)^T \times [\lambda^2(n) F(n) \tilde{P}(n) F(n) + Q(n)]^{-1} v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{56}
\]
Subtracting (56) into (55), and moving items yields
\[
E \left\{ L_n(\tilde{A}(n)) \right\} \left[\tilde{A}(n-1)\right] - L_{n-1}(\tilde{A}(n-1)) \leq E \left\{ v(n)^T \times [\lambda^2(n) F(n) \tilde{P}(n) F(n) + Q(n)]^{-1} v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{57}
\]
According to Lemma 2, we have
\[
\tilde{P}^{-1}(n-1) > [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1)] + v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{58}
\]
Since $\tilde{A}(n-1) \neq 0$, we have
\[
\tilde{A}^T(n-1) \tilde{P}^{-1}(n-1) A(n-1) \geq [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1)] + v(n) \right\} - [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)]^T \times [H_i(n) \dot{\lambda}(n) F(n) \tilde{A}(n-1) + v(n)] + \omega^T(n) Q^{-1}(n) H_i(n) \tilde{P}(n) H_i^T(n) Q^{-1}(n) \times \omega(n) \left[\tilde{A}(n-1)\right] \tag{59}
\]
Let
\[
\theta(n) = \frac{\left(\lambda(n) H_i(n) F(n) \tilde{A}(n-1)\right)^T \times [\lambda^2(n) H_i(n) F(n) \tilde{P}(n-1) + Q(n)]^{-1} \times H_i(n) \tilde{R}(n) H_i^T(n) + Q(n)]^{-1} \times \left(\lambda(n) H_i(n) F(n) \tilde{A}(n-1)\right)}{\tilde{A}(n-1) \tilde{P}^{-1}(n-1) \tilde{A}(n-1)} \tag{60}
\]
From (59), we get $\theta(n) < 1$. Under assumption (35) ~ (40) we have

$$
\theta(n) \geq p_{\text{min}}(\lambda_{\text{min}}h_{\text{min}}f_{\text{min}})^2 \times \left[ p_{\text{max}}(\lambda_{\text{max}}h_{\text{max}}f_{\text{max}}) + \hat{r}_{\text{max}}h_{\text{max}}^2 + q_{\text{max}} \right]^{-1} \triangleq \theta_{\text{min}} > 0
$$

(61)

By (59) and (61), we get

$$
-\left(\lambda(n)H_i(n)F(n)\tilde{A}(n-1)\right)^T \times [\lambda^2(n)H_i(n)F(n)\tilde{P}(n-1)[F(n)H_i(n)]^T + H_i(n)\tilde{R}(n)H_i^T(n) + Q(n)^{-1}] \times [\lambda(n)H_i(n)F(n)\tilde{A}(n-1)] \leq -\theta_{\text{min}}L_{n-1}(\tilde{A}(n-1))
$$

(62)

Setting

$$
E[\varepsilon^T(n)\{\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)^{-1} - H_i^T(n)(H_i(n)(\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)) \times H_i^T(n) + Q(n)^{-1}]H_i(n)(\varepsilon(n)v^T(n)) \times \omega^T(n)\} | \tilde{A}(n-1)]
$$

$$
= \varepsilon(n)
$$

(63)

Since both sides of (63) are scalars, taking trace will not change its value. Applying the well-known properties of matrix traces $tr(AB) = tr(BA)$, we have

$$
e(n) = E[tr(\{\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)^{-1} - H_i^T(n)(H_i(n)(\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)) \times H_i^T(n) + Q(n)^{-1}]H_i(n)(\varepsilon(n)v^T(n)) \times \omega^T(n)\} | \tilde{A}(n-1)]
$$

$$
= tr(\{\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)^{-1} - H_i^T(n)(H_i(n)(\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)) \times H_i^T(n) + Q(n)^{-1}]H_i(n)(\varepsilon(n)v^T(n)) \times \omega^T(n)\} | \tilde{A}(n-1)]
$$

(64)

Applying Lemma 2 yields

$$
\{\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)^{-1} - H_i^T(n)(H_i(n)(\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)) \times H_i^T(n) + Q(n)^{-1}]H_i(n) > 0
$$

(65)

Then, we have $\varepsilon(n) > 0$. With (20) and (34) ~ (39), we have

$$
\varepsilon(n) \leq tr\left(\{\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)^{-1} - H_i^T(n)(H_i(n)(\lambda^2(n)F(n)\tilde{P}(n-1)F^T(n) + \tilde{R}(n)) \times H_i^T(n) + Q(n)^{-1}]H_i(n)
$$

$$
+ \frac{r_{\text{max}}}{r_{\text{min}}}k + \frac{p_{\text{max}}h_2^2}{q_{\text{min}}} \triangleq \varepsilon_{\text{max}}
$$

(66)

Therefore, it is able to apply Lemma 1 with (57), (62) and (66). Consequently, the inequality

$$
E\{L_n(\tilde{A}(n))\} - L_{n-1}(\tilde{A}(n-1)) \leq \varepsilon_{\text{max}} - \theta_{\text{min}}L_{n-1}(\tilde{A}(n-1))
$$

(67)

is fulfilled to guarantee the boundedness of $\tilde{A}(n)$, i.e.,

$$
E\left[\|\tilde{A}(n)\|^2\right] \leq \frac{p_{\text{max}}}{p_{\text{min}}}E\left[\|\tilde{A}(0)\|^2\right] (1 - \theta_{\text{min}})^n + \varepsilon_{\text{max}} \sum_{i=1}^{n-1} (1 - \theta_{\text{min}})^i
$$

(68)

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HU YAO received the M.E. degree in information and telecommunication systems from the Chongqing University of Posts and Telecommunications (CQUT), Chongqing, China, in 2008. He is currently pursuing the Ph.D. degree with the School of Information and Telecommunication, Beijing University of Posts and Telecommunications (BUPT), Beijing. His research interests are in the areas of green communications and data center networks.

WU MUQING was born in July 1963. He received the Ph.D. degree. He is currently a Professor with the Beijing University of Posts and Telecommunications (BUPT) and a Senior Member of the China Institute of Communications. His research interests focus on mobile ad hoc networks, UWB, high-speed network traffic control and performance analysis, GPS locating, and services.

**HU YAO**

**WU MUQING**