Sensor Data Forwarding Strategies for State Estimation in Multi-hop Wireless Networks

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Abstract—State estimation is of great importance in various applications based on wireless networked control systems. Since the wireless sensor nodes are typically equipped with power-limited battery, they are only able to emit relatively low-power signal which constrains the reliable communication distance between the transmitter and the receiver. One effective way to tackle such situation is to forward the transmitted packet through relay nodes. In this paper, we investigate the data forwarding strategy design for accurate remote state estimation in multi-hop wireless networks. Based on the computational capability of relay nodes, we first propose two relay strategies, namely, Direct Forwarding Strategy (DFS) and Local Processing and Forwarding Strategy (LFS). Necessary and sufficient conditions of estimation stability are derived for these two strategies respectively. We also prove that LFS is always better than DFS in terms of estimation accuracy at the expense of more energy consumption. We further propose an Event-triggered Forwarding Strategy (EFS) which is able to balance the estimation accuracy and relay energy consumption. Numerical examples are employed to demonstrate the effectiveness of our design.

I. INTRODUCTION

Wireless networked control systems have attracted much interest in the past decade. With rapidly development of electron technology, most modern wireless sensor nodes have the ability to process certain computation tasks in addition to perceiving the area of interest and communicating wirelessly [1]. However, the battery-powered wireless sensor nodes have certain limitations when they are applied in real applications [2], such as small range of communication, short lifetime and so on. Packet drop is one of the main problems in wireless networked control systems, which may cause performance degradation even system instability [3] [4].

State estimation over wireless sensor networks with packet drops has been extensively studied in recent years [5]–[8]. In particular, [5] considered a linear time-invariant (LTI) system with a signal-hop communication, which was subject to independent and identically distributed (i.i.d.) packet drops. The authors gave a lower bound of the packet reception rate above which the expected value of estimation error covariance remains bounded. Similar results were given in [6] for the sequence of random prediction error covariance matrices converging weakly to a unique invariant distribution. The case when the packet drops satisfy a two-state Markov chain was investigated in [7], where a critical packet drop probability was given for mean square stability. Recent results for the one-sensor case with a more general semi-Markov packet drops were presented in [8].

However, most of the previous works focused on single-hop communication. In real world, estimation via multi-hop is more practical in a large scale network, and will be a challenging problem since both the system stability and estimation accuracy rely on the communication quality of each relevant link in the network. [9] designed a sensor data scheduling for optimal state estimation, but this method can not be directly applied to multi-hop case. A predictive control scheme with a delay estimator was proposed to track the delay mean changes over multi-hop wireless networks with packet drops [10]. But in this work, the relay nodes are only responsible of forwarding the received packet, which is different from the condition we consider in this paper that the relay can process the received data. [11] investigated the optimal estimator of a multi-hop tree network with packet drops, where a sensor node will fusion the received data with its own measurement and forward the results to the fusion center.

In this paper, we consider the state estimation over multi-hop wireless networks subject to random packet drops. Specifically, we investigate how the data forwarding strategy design affects the performance of remote state estimation. Based on whether the relay nodes have sufficient computational capability, we propose two typical relay strategies, namely Direct Forwarding Strategy (DFS) and Local Processing and Forwarding Strategy (LFS). We analytically compare the two strategies in terms of the stability condition, estimation performance and energy consumption. Subsequently, motivated by the relationship between the estimation accuracy and the forwarding policy, we further propose a novel Event-Triggered Forwarding Strategy (EFS), which is able to achieve the balance between the estimation accuracy and the energy consumption of relay nodes.

The rest of this paper is organized as follows. We introduce our system framework and formulate the problem in Section II. Two typical relay strategies and the analytical comparison between them are described in Section III. We propose our novel event-triggered data forwarding strategy in Section IV and evaluate its performance by numerical examples in Section V. Finally, the paper is concluded in Section VI.
II. PROBLEM STATEMENT

Consider a discrete linear time-invariant system with the following dynamics

\[ x_k = Ax_{k-1} + w_k, \quad (1) \]
\[ y_k = Cx_k + v_k, \quad (2) \]

where \( x_k \in \mathbb{R}^n \) and \( y_k \in \mathbb{R}^m \) respectively represent the system state and sensor's measurement. \( w_k \in \mathbb{R}^n \) and \( v_k \in \mathbb{R}^m \) are zero-mean Gaussian noises with covariances of \( \mathbb{E}\{w_kw_k^T\} = Q \geq 0 \) and \( \mathbb{E}\{v_kv_k^T\} = R > 0 \), respectively. We assume that \( w_k \) and \( v_k \) are mutually independent. And we further assume that \( A \) is unstable, \( (A, \sqrt{Q}) \) are controllable and \( (C, A) \) are observable.

The sensor is responsible for measuring and estimating the system state, and then communicating the results to the remote estimator periodically via multi-hop networks. We assume that the sensor node has the ability to implement a local Kalman filter according to the system state, and then communicating the results to the remote estimator for further processing via wireless medium with successive forwarding of \( M \) relay nodes, see Fig. 1. Since long-term monitoring is considered in this paper, we assume that the estimation of the sensor has reached its steady state, and further denote the converged estimation error covariance by \( \bar{P} \), which is the unique positive definite solution of the following algebraic Riccati equation

\[ X = Y - YC^T(CYC^T + R)^{-1}CY, \]

where \( Y \triangleq AXA^T + Q \).

In practice, wireless communication quality plays a key role in the overall estimation accuracy since both the packets transmitted from the sensor and from the relay nodes are subject to loss. We denote the arrival process of sensor's packet at time \( k \) by a binary value \( \alpha_k^0 \), where \( \alpha_k^0 = 1 \) represents that relay node \( R_1 \) successfully receives the sensor's packet at time \( k \) and \( \alpha_k^0 = 0 \) otherwise. Similarly, \( \alpha_k^i \) (\( i \in \{1, 2, \ldots, M\} \)) characterizes the arrival process of the packet transmitted by the relay node \( R_i \) at time \( k \). We assume that \( \alpha_k^i \) satisfies i.i.d. for all \( i \in \{0, 1, 2, \ldots, M\} \), and denote the successful packet arrival probability by \( \alpha^+ \triangleq \Pr\{\alpha_k^1 = 1\} \). TCP-like protocol [12] is considered throughout the paper, i.e., successful arrival of packet is acknowledged without error at the receiver. We further assume that in-network processing is much faster than the dynamics of the system, i.e., the time delay that occurs during the multi-hop transmission between the sensor and the remote estimator is neglected.

Due to the random packet drops in the given system, the error covariance on remote estimator, which we denote by \( P_k^e \), is time varying for any given positive initial state [13]. However, note that \( P_k^e \) is bounded with probability 1 if and only if \( \mathbb{E}\{P_k^e\} \) is bounded [14]. Therefore, in the rest of this paper, we will say the estimation on the remote estimator is mean square stable if and only if \( \mathbb{E}\{P_k^e\} < \Gamma \) for some finite \( \Gamma > 0 \) and any \( k > 0 \).

After the network topology is fixed, a relay node will have the knowledge of his parent nodes and son nodes. Considering the framework depicted in Fig. 1, the relay node \( R_i \) will receive a packet only from its parent node \( R_{i-1} \) and transmit a packet only to its son node \( R_{i+1} \). Based on whether the relay nodes have computational capability, different data forwarding strategies can be designed. In this paper, we first propose two typical strategies for the relay nodes with/without computational capabilities, then try to design a novel strategy to forward the sensor’s data in an energy-efficient way.

III. DIRECT FORWARDING STRATEGY v.s. LOCAL PROCESSING AND FORWARDING STRATEGY

A. Direct Forwarding Strategy (DFS)

This strategy is designed for the relay nodes without sufficient computational capability, where every one of them just simply forwards the received packets. It means that if \( \alpha_k^{i-1} = 1 \), then the relay node \( R_i \) will forward the received packet to the node \( R_{i+1} \), otherwise it will remain idle for saving energy. In other words, the remote estimator will receive the current state estimate from the sensor at time \( k \) if and only if \( \alpha_k^1 \triangleq \prod_{i=0}^M \alpha_k^i = 1 \), otherwise it will just make a time update of standard Kalman filter based on its local estimate according to

\[ \hat{x}_k = A\hat{x}_{k-1}. \]

Note that the sensor transmits its current estimate \( \hat{x}_k \) rather than the raw measurement \( y_k \), which means that the error covariance of a receiver can be directly obtained from the packet arrival sequence. As a consequence, the final error covariance of DFS, which we denote by \( P_k^{e1} \), is updated according to

\[ P_k^{e1} = \alpha_k^{e1} \bar{P} + (1 - \alpha_k^{e1})(AP_k^{e1}A^T + Q). \quad (3) \]

**Theorem 3.1:** Consider the system (1)(2) and all the relay nodes run DFS. The estimation on remote estimator is mean
square stable if and only if
\[ \alpha s^1 > 1 - \frac{1}{\max_j |\lambda_j(A)|^2} \]  
(4)

where \( \alpha s^1 \triangleq \prod_{i=0}^{M} \alpha i \) and \( \lambda_j(A) \) is all the eigenvalues of \( A \). Since \( A \) is unstable, the right part of the inequality is strictly positive.

**Proof:** Note that the final estimation error covariance is updated according to (3), then by taking expectations on both sides of which, we have

\[ \mathbb{E}[P_k^{s^1}] = \alpha s^1 \bar{P} + (1 - \alpha s^1)(\mathbb{A}[P_k^{s^1}]A^T + Q) \]

where we have used the independence between \( \{\alpha_0^0, \alpha_1^1, \ldots \alpha_M^M\} \) and \( P_{k-1}^{s^1} \). It is found that \( \mathbb{E}[P_k^{s^1}] \) is bounded if and only if the following equation has a positive definite solution

\[ X = \alpha s^1 \bar{P} + (1 - \alpha s^1)(AXA^T + Q). \]  
(5)

Note that the Lyapunov matrix equation (5) can be rewritten as

\[ X - (\sqrt{1 - \alpha s^1}A)X(\sqrt{1 - \alpha s^1}A)^T = \alpha s^1 \bar{P} + (1 - \alpha s^1)Q, \]

which has a positive definite solution if and only if

\[ 1 - \max_j |\lambda_j(\sqrt{1 - \alpha s^1}A)|^2 > 0, \]  
(6)

where \( \lambda_j(\sqrt{1 - \alpha s^1}A) \) represents the eigenvalues of the matrix \( \sqrt{1 - \alpha s^1}A \).

If there do not exist a positive definite solution for (5), it implies that \( \mathbb{E}[P_k^{s^1}] \) is unbounded such that the estimation on the remote estimator is unstable. So (6) is a necessary and sufficient condition of mean square stability on the remote estimator. By some manipulations on (6), we get (4) and the proof is completed. \( \blacksquare \)

**B. Local Processing and Forwarding Strategy (LFS)**

Different from DFS, relay nodes will buffer the last received data and have sufficient computational capability to implement a local estimation of the system state and buffer the result. More specifically, the estimate on the relay node \( R_i \) under this strategy is given by

\[ \hat{x}_k^i = \begin{cases} \hat{x}_k^{i-1}, & \text{if } \alpha_k^{i-1} = 1 \\ A\hat{x}_k^{i-1}, & \text{if } \alpha_k^{i-1} = 0 \end{cases}, \forall i \in \{1, \ldots, M+1\}, \]  
(7)

while the corresponding estimation error covariance is given by

\[ P_k^i = \begin{cases} P_k^{i-1}, & \text{if } \alpha_k^{i-1} = 1 \\ AP_k^{i-1}A^T + Q, & \text{if } \alpha_k^{i-1} = 0 \end{cases}, \]  
(8)

where with a little abuse of notation, the remote estimator is denoted by \( i = M + 1 \), i.e., \( P_{k+2}^i \triangleq P_{k+1}^{M+1} \). Notice that (7) has been shown to be the optimal least-square estimation under packet-dropping communication [15]. In this case, if one relay node receives a packet at time \( k \), the data will be simply used to replace the buffered estimate without any processing, and meanwhile the node will forward it to its receiver; if no packet has been received, it will make a time update of Kalman filter based on its buffered estimate and transmit the result to its receiver. It means that every relay node tries its best to inform of its son node its newest estimate.

**Property 3.1:** Under LFS, for any given two relay nodes \( R_i \) and \( R_j \), where \( i < j \), their expected estimation error covariances satisfy

\[ \mathbb{E}[P_i^j] \leq \mathbb{E}[P^j]. \]

Property 3.1 naturally follows from (7) and (8), since all the received information of \( R_{i+1} \) is from \( R_i \) and all relay nodes update their local estimate according to the same rule and the local error covariance is likely to increase in absence of a packet reception.

Till now, we are able to figure out that the relay nodes closer to the sensor are likely to own more accurate estimates of system state under LFS. But to track the error covariance on the remote estimator is still nontrivial, because it is jointly determined by the current packet arrival processes along the multi-hop transmission and the buffered estimate on each of relay nodes. Here we give a recursive way to acquire the expected error covariance on the remote estimator.

**Property 3.2:** Under LFS, the expectation of the estimation error covariance on relay node \( R_i \), i.e., \( \mathbb{E}[P^i] \), satisfies the following equation

\[ \mathbb{E}[P^i] = \alpha_i^i \mathbb{E}[P^{i-1}] + (1 - \alpha_i^i)(\mathbb{A}[P^i]A^T + Q), \]

\[ \forall i \in \{1, 2, \ldots, M + 1\} \]  
(9)

which starts with \( \mathbb{E}[P^0] = \bar{P} \) on the sensor and ends with \( \mathbb{E}[P^{M+1}] \) on the remote estimator.

**Remark 3.1:** Note that the estimation error covariance on \( R_i \) is given by (8), which can be rewritten as

\[ P_k^i = \alpha_k^{i-1}P_k^{i-1} + (1 - \alpha_k^{i-1})(AP_k^{i-1}A^T + Q). \]  
(10)

Therefore, by taking expectations on both sides of (10), and using the independence between \( \alpha_k^0, \alpha_k^1, \ldots \alpha_k^{i-1} \) and \( P_k^{i-1} \), we directly obtain (9). It is worth noting that according to (7), \( \hat{x}_k^i \) is determined by all the historical arrival processes in front of the relay node \( R_i \), Thus the expectation of (10) is taken with respect to the random arrival sequence \( \{\alpha_k^0, \alpha_k^1, \ldots \alpha_k^{i-1}\} \).

The stability condition for LFS is given in the following.

**Theorem 3.2:** Consider the system (1)(2) and all the relay nodes run LFS. The estimation on the remote estimator is mean square stable if and only if

\[ \alpha^i > 1 - \frac{1}{\max_j |\lambda_j(A)|^2}, \forall i \in \{0, 1, \ldots, M\}. \]  
(11)

**Proof:** It is not difficult to prove it by induction combining the result of Theorem 3.1. Thus, we skip the detailed proof due to space limitation. \( \blacksquare \)

Given that the packet reception rate sequence \( \{\alpha^0, \alpha^1, \ldots \alpha^M\} \) satisfies (11), we can obtain the expectation of error covariance on the remote estimator by recursively solving (9) with \( \bar{P} = \bar{P} \).
C. Comparison of the Two Strategies

In this section, we compare the previous two strategies in terms of stability, estimation performance and energy consumption. First of all, from Theorem 3.1 and Theorem 3.2, we find that the stability conditions for both strategies are rigidly dependent on the packet arrival rates through the multi-hop link. Furthermore, note that it has 0 ≤ αi ≤ 1, which renders (4) a subset of (11). It implies that the stability condition of LFS is easier to be satisfied than that of DFS, which makes LFS more robust under unreliable wireless networks.

The performance of an estimator is in general characterized by the estimation error covariance. However, it has been shown that the final estimation error covariance is a random process, which will not converge to a steady state [13]. Therefore, in this paper, the accuracy of the remote estimator is evaluated by the expectation of the estimation error covariance. The following theorem shows the different performances between DFS and LFS.

Theorem 3.3: Suppose that the packet reception rates of the transmission links satisfies (4), then the expected estimation error covariances on the remote estimator for DFS and LFS satisfy

$$\mathbb{E}\{P^{s1}\} \geq \mathbb{E}\{P^{s2}\}.$$ 

So far we has shown that LFS achieves a smaller expected error covariance than DFS, and is more robust under unreliable wireless networks. However, LFS requires every relay to transmit periodically regardless whether it has received a packet, while the relay nodes in DFS transmit only when they receive a packet. Therefore, it brings high energy consumption budget to LFS since the battery of a wireless node is in general limited and difficult to replace.

We now are ready to compare the energy consumption between the two strategies. Considering that the energy consumption of data transmission is much greater than that of data processing for a wireless node [16], we will neglect the computational energy consumption of the relay nodes in the rest of this paper. Moreover, the energy consumption of the sensor is not taken into account because the schedule of the sensor will not change with different data forwarding strategies.

Denote the energy consumption of transmitting a packet for a relay node by E, and the total energy consumption of DFS in time period k by $J_{k}^{s1}$ and that of LFS by $J_{k}^{s2}$. Note that for DFS, a relay node $R_j$ will launch a transmission only when $\prod_{i=0}^{j-1} \alpha_i = 1$. Therefore, the expected energy consumption of DFS in time period k is given by

$$\mathbb{E}[J_{k}^{s1}] = \sum_{j=1}^{M} (\prod_{i=0}^{j-1} \alpha_i) E.$$ 

On the other hand, for LFS, $J_{k}^{s2}$ is constantly given by

$$J_{k}^{s2} = ME.$$ 

Obviously, DFS is likely to cost less energy than LFS. As a consequence, we conclude that LFS enhances the robustness of the system and improves the estimation performance at the expense of more energy consumption.

IV. EVENT-TRIGGERED FORWARDING STRATEGY

In this section, we design an energy-efficient data forwarding strategy which takes into account both the estimation performance and energy consumption on relay nodes. Note that in many cases, some transmissions in LFS are needless. For instance, if at time k the estimate is successfully transmitted from the sensor to the remote actuator, i.e., all the relay nodes locally have the current system state estimate $\hat{x}_k$. Suppose that $\alpha_{k+1} = 0$, then according to LFS, the relay node $R_i$ will update the locate estimate to $A\hat{x}_k$ and transmit it to $R_{i+1}$. Then, if $R_{i+1}$ receives the packet, it will update its estimate by $A\hat{x}_k$ and continue the transmission. However, if the packet from $R_i$ is dropped, $R_{i+1}$ will also make a local estimate as $A\hat{x}_k$ which tends to be transmitted. It is of interest that it makes no difference to the result whether the packet from $R_i$ is successfully received or not. This motivates us to design a data forwarding strategy to let a relay node launch a transmission only when it is necessary.

The overall structure of the event-triggered forwarding strategy (EFS) is presented in Algorithm 1. We introduce an indicator $\lambda_{k} \in \{\text{transmit}, \text{update}\}$ to denote the decision made by $R_i$ at time k. First of all, at any time slot, if one relay node receives a packet, it will replace the buffered estimate by the received one and forward it to its son node. It is because the newest received packet is more likely to contain closer estimate of the system state. We emphasize that $R_i$ knows exactly the estimate and error covariance on its son node $R_{i+1}$. That is because the buffered estimate of $R_{i+1}$ is originally from $R_i$, and $R_i$ has full information of the packet reception sequence $\{\alpha_i\}_{i \in [0,N]}$. Based on the error-free acknowledgements. In case of no packet received, it will first implement a time update based on the buffered estimate, then compare the covariance gap with its son node $R_{i+1}$.

$$\Delta_k \triangleq P_{k-1}^{i+1} - P_{k-1}^{i}.$$ 

If it holds that $^{1}|trace(\Delta_k)| \geq \rho$ for a pre-given $\rho$, $\lambda_{k}$ is set as transmit, otherwise $\lambda_{k}$ is set as update.

In the Algorithm 1, a relay node will not launch a transmission if it does not receive a packet at the current time instant and the benefit of a transmission is extremely low, where the benefit is characterized by the tunable value $\rho$. It is interesting to observe that if we set $\rho = 0$, the relay node will always launch a transmission and it becomes the LFS. On the other hand, $\rho = +\infty$ will results in no forwarding for a relay node unless it receives a packet from its parent node, i.e., it becomes DFS.

A. Stability Analysis

Since the proposed EFS will degrade into DFS when $\rho = 0$ and into LFS when $\rho = +\infty$, whose stability conditions are respectively given in Theorem 3.1 and Theorem 3.2, here

$^{1}trace(\Delta_k)$ tends to be positive according to Property 3.1.
we only consider the case when $\rho$ is a finite positive value. Denote the error covariance on the remote estimator in EFS by $P_k^{s3}$, then the following theorem gives the condition for the mean square stability of EFS.

**Theorem 4.1:** Given that $0 < \rho < +\infty$, the estimation on the remote estimation is mean square stable if and only if $\{\alpha^0, \alpha^1, \ldots, \alpha^M\}$ all satisfy (11).

The proof is similar with that of Theorem 3.2. It is of interest to find that the stability condition of EFS is the same with that of LFS, which is independent with the triggered value $\rho$. It is because any finite $\rho$ and a suitable packet reception rate will prevent the error covariance gap between some two neighboring relay nodes from diverging.

**B. Performance Analysis**

In the proposed EFS strategy, every relay node determines whether to transmit its estimate only based on its local information and the acknowledgement from its receiver. The tunable value $\rho$ plays an important role in our algorithm. Typically, $\rho$ provides a tradeoff between the estimation performance and the transmission cost of the relay node. A bigger $\rho$ gives larger tolerance of the estimate differences between neighboring relay nodes but substantially reduce in-network transmissions. On the other hand, a small $\rho$ is beneficial to reducing the estimation error at the expense of more transmissions.

The following theorem gives the estimation performance comparison between DFS, LFS and EFS.

**Theorem 4.2:** Given that $0 < \rho < +\infty$ and the final estimations of DFS, LFS and EFS are all mean square stable, the expected estimation error covariances for the three strategies satisfy

$$E\{P^{s1}\} \geq E\{P^{s3}\} \geq E\{P^{s2}\}$$

where the equalities hold only when $\alpha^i = 1, \forall i \in \{0, 1, \ldots, M\}$.

**Remark 4.1:** Theorem 4.2 can be proofed by following Theorem 3.3, so we omit the detailed proof due to space limitation. Moreover, it can be easily found that the number of transmissions of EFS falls between that of DFS and LFS. So EFS provides a balance between the estimation performance and the energy consumption.

**V. NUMERICAL EXAMPLES**

Consider a example discrete-time system (1)(2) with the dynamics parameters given by

$$A = \begin{bmatrix} 1.3 & 0 \\ 0.2 & 1.1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 1 \end{bmatrix}$$

with process noise covariance $Q = 0.5I$ and measurement noise $R = 2$. Two relay nodes $R_1$ and $R_2$ are employed to construct the multi-hop transmission from the sensor to the remote estimator.

The stabilities of DSF and LFS are investigated in Fig. 2, which verifies the results of Theorem 3.1 and Theorem 3.2. We change one of packet reception rates of the three links in turn and set the other two both 0.8. Only one case for DSF is depicted because the other two exhibit very close performances due to the property of DSF. First of all, we can find that the average error covariance of LFS is smaller than that of DFS for all feasible packet reception rates. However, with the decrease of packet reception rate, the average estimation error covariances of the two strategies will both increase. Especially, for LSF, when the packet reception rate falls to about $1 - \frac{1}{\max |\lambda_i(A)|^2} = 1 - 1/1.3^2 \approx 0.41$, the average estimation error covariance begins to diverge; while for DSF, the average covariance tends to be divergent when the packet reception rate approaches 0.64 which is equivalent to $\alpha^0\alpha^1\alpha^2 \to 1 - \frac{1}{\max |\lambda_i(A)|^2}$.

We compare the estimation performances of DFS, LFS and our proposed EFS in Fig. 3 with average results of 100 repeats. The packet reception rates are set as follows

$$\alpha^0 = 0.7, \quad \alpha^1 = 0.8, \quad \alpha^2 = 0.9.$$

It is easy to verify that in this case, the estimation is stable for all the three strategies, which is also consistent with the obtained stability conditions. It can be observed that LFS achieves the best estimation performance with $E[P^{s2}] \approx 11$, while for EFS with $E[P^{s3}] \approx 12$ which is very close to LFS, and $E[P^{s1}] \approx 15$ for DFS, which supports the result provided by Theorem 4.2. On the other hand, average relay transmission numbers of LFS, EFS and DFS are 200, 172 and 150, which means that with an appropriate $\rho$, EFS achieves a
and Forwarding Strategy (LFS), for two kinds of relay nodes, i.e., nodes with insufficient computation capability, and nodes with sufficient computation capability, respectively. We provide the analytical stability conditions for both forwarding strategies, and show that LFS always achieves better estimation accuracy than DFS but with more costs. Furthermore, we propose a novel Event-triggered Forwarding Strategy (EFS), which exploits the estimate difference between each pair of neighboring relay nodes to reduce the forwarding times while guaranteeing satisfactory estimation accuracy. The effectiveness of EFS is verified by extensive numerical examples. For future work, we plan to implement our design on physical testbed. The forwarding strategy design for closed-loop control performance is another interesting direction.

VI. CONCLUSIONS

In this paper, we considered the design of sensor data forwarding strategies for state estimation in multi-hop wireless networks. We first propose and analyze two typical strategies, i.e., Direct Forwarding Strategy (DFS) and Local Processing satisffactory estimation performance while saving substantial energy.

Fig. 4 depicts the average estimation error covariance and energy consumption of the proposed EFS with varying $\rho$. It illustrates that with the increase of $\rho$, the average expectation of final estimation error covariance will increase while the number of relay transmissions will decrease. It is also very important to observe that when $\rho$ takes a small value, i.e., 1, the performance of EFS is very close to LFS, while the energy consumption reduces dramatically from 200E to about 178E. It means that our strategy discards many unnecessary transmissions of LFS while maintaining satisfactory estimation accuracy. However, when $\rho$ becomes larger, the benefit of algorithm will decrease. It is also important to notice that since DFS is also mean square stable in this case. Therefore, for any pair of neighboring nodes, the difference of estimation error is also bounded. Therefore, when $\rho$ becomes larger than such bound, the benefit of EFS will become less significant which explains the trend with larger $\rho$ in the figure.

REFERENCES