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Optimal sensor scheduling for state estimation over lossy channel

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Abstract: This study studies a sensor scheduling problem for the state estimation of a stochastic discrete-time system where the measurements are to be sent from multiple sensors to a centralised estimator through a lossy channel. By adopting a carrier sense multiple access/collision avoidance (CSMA/CA) protocol, the packet loss rate of the channel increases with the number of competing sensors for data communication. To increase the channel utilisation, it requires to smartly select informative sensors to transmit their measurements. Depending on the availability of the acknowledgment (ACK) messages from the estimator, both online and offline algorithms for scheduling sensor communication are proposed to optimise the expected performance of minimum mean-square error state estimator. Particularly, the online scheduling uses the ACK to trigger the sensor communication while the offline version adopts a random transmission framework and only decides the probability of sending measurements for each sensor in an offline manner. The optimal online scheduler is given by the solution of an integer programming, which is approximated by a practically solvable optimisation. Simulations are included to demonstrate the effectiveness of the proposed algorithms.

1 Introduction

Networked estimation and control systems have received significant interests in recent years [1] due to their great potentials in numerous applications, including autonomous vehicles, large scale monitoring, industrial automation and so on. To increase the channel utilisation, this paper considers a sensor scheduling problem over a lossy network for the networked state estimation of a discrete-time system with multiple sensors. Notably, we focus on a lossy network under the popular CSMA/CA communication protocol [2], which results in a striking property that the more sensors competing for the channel resources for data transmission, the higher the packet loss rate of the channel will be, and vice versa. This essentially suggests that the use of more sensors for simultaneously transmitting their measurements does not always lead to a better estimator. Thus, it is important to design a scheduler to select informative sensors for communication. Under different network scenarios, both online and offline scheduling algorithms are proposed in this work to optimise the expected performance of the minimum mean-square estimation error estimator.

The lossy channel with time-varying packet loss rates has been studied in the literature. For example, Pollin *et al.* [3], Ling *et al.* [4] and Cao *et al.* [5] proposed the SDTMC model to investigate the channel property, while Wang *et al.* [6] adopted a MDTMC model. However, they mainly analysed the throughput capacity of the channel, the power consumption and other channel parameters, and did not work on the state estimation problem. Only Cao *et al.* [5] proposed a model to compute the packet loss rate in data saturated case. While in most applications, especially for the systems under a periodic sampling mechanism, data flow is usually not saturated. Thus we establish a new channel model to compute the packet loss rate for the periodically sampled systems by adopting the CSMA/CA communication protocol [2], and develop a recursive algorithm to compute the minimum mean-square error (MMSE) estimator with multiple sensors.

The state estimation problem over a lossy channel has been investigated in the case of a single sensor. However, these works do not consider the sensor scheduling issue. By modelling the packet loss as an independent and identical distributed (i.i.d.) process, Sinopoli *et al.* [7] derived the MMSE estimator and proved the existence of a critical packet loss rate, above which the mean of the state estimation error covariance matrix will diverge to infinity. This seminal work has ushered an increasing interest in the quantification of the critical packet loss rate. Under the same packet loss model, Mo and Sinopoli [8, 9] exactly quantified the critical value for the system with distinguished eigenvalues and non-degenerate system, respectively. Huang and Dey [10] worked on a similar estimation problem with Markovian packet losses, and a so-called peak stability is introduced. You *et al.* [11] extended this work, and introduced a new concept of stability in stopping times, based on which the necessary and sufficient conditions for the stability of the MMSE estimator of second-order systems and certain higher order systems are explicitly expressed by simple inequalities. Since sensors might be built with some computing capacities, Schenato [12] focused on the stability of the MMSE estimate over the lossy channel by transmitting the output of the Kalman filter in the transmitter side. This leads to a simple characterisation of the necessary and sufficient condition for the stability of the MMSE estimator. The idea was further explored in [13] by transmitting a temporal linear combination of the current and finite previous measurements.

In some networked sensing applications, especially under wireless connections, only limited energy is available for data collection and transmission. Consequently, it is not the best for every sensor to transmit its measurement at each sampling time. Thus, it has to decide whether to send its current packet to the estimator. This decision-making process is referred to as sensor scheduling, which has been a hot research topic for many years. Walsh and Ye [14] studied the stability problem of sensor scheduling for the close-loop control. Gupta *et al.* [15] proposed a stochastic scheduling scheme for the networked state estimation, and provide an 'optimal' probability distribution for selecting sensors at each sampling time. Shi *et al.* [16] considered a system with a single sensor by examining whether to send its data to a remote estimator for the purpose of saving communication energy. They studied two scheduling schemes under different sensor capacities. If the sensor has sufficient computation capability and under a communication constraint,

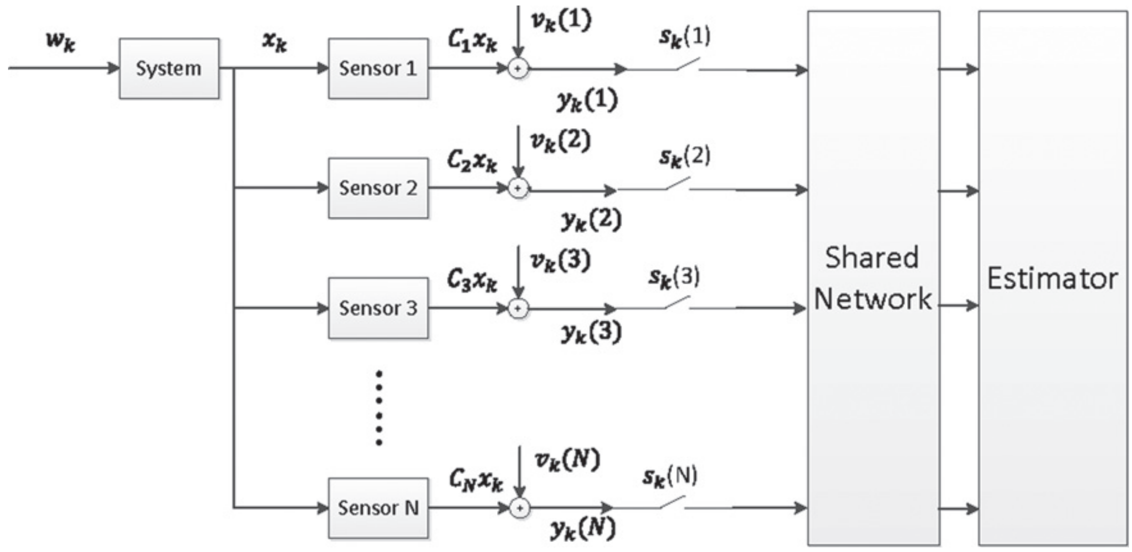

Fig. 1 *N-sensors network*

an optimal scheduling scheme is found to achieve the MMSE. To the contrary, if the sensor has limited computation capability, they provided a scheduling scheme that guarantees the MMSE within a certain level. Similarly, an optimal periodic schedule under both communication and power constrains was given in [17]. Related works include [18–22], to name a few.

However, all the aforementioned works assume that the packet loss process is independent of the channel input. Differently, the packet loss rate of the channel in this work is modelled as an increasing function in the number of active sensors competing for the channel, which is justified by the CSMA/CA protocol. From this perspective, our formulation is novel, but requires a smart design for scheduling the sensor communication. To this purpose, both online and offline scheduling are considered by depending on whether the acknowledgment (ACK) messages is available or not, which covers the most network estimation situations. In comparison, the contribution of this work includes the development of a new model for the lossy channel, the derivation of the corresponding state estimation algorithm, and the design of two types of schedulers to increase the channel utilisation, which is important to the wireless sensor network. It is worth to mentioning that it is N-P hard to find an optimal online scheduler. However, we well approximate the N-P problem by a practically solvable optimisation. The offline scheduling can be obtained by the standard Newton gradient algorithm.

The rest of the paper is organised as follows. In Section 2, the problem under consideration is formulated and the MMSE estimator is derived. In Section 3, the channel model under time-varying packet loss rates is proposed. The online and offline scheduling under different scenarios are given in Section 4 and 5, respectively. To validate the performance of the scheduling schemes, simulations are included in Section 6. Concluding remarks are made in Section 7.

2 Problem statement

Consider a spatially large linear system with distributed sensing as follows

$$\begin{aligned} x_{k+1} &= Ax_k + w_k, \\ y_k(i) &= C_i x_k + v_k(i), \quad i \in \{1, 2, \dots, N\}, \end{aligned} \tag{1}$$

where $x_k \in \mathbf{R}^n$ is the state with initial condition being Gaussian distributed, i.e. $x_0 \sim \mathcal{N}(\bar{x}_0, P_0)$. $w_k \sim \mathcal{N}(0, Q)$ is the process noise, $y_k(i) \in \mathbf{R}^{m_i}$ is the measurement from the ith sensor and $v_k(i) \sim \mathcal{N}(0, R_i)$ is the associated measurement noise. All the sensors are spatially deployed, and are connected to a centralised estimator via a lossy channel. It is assumed that x_0, w_k and $v_k(i)$ are independent for all k and i. To make the problem interesting, (A, C) is observable, where $C = [C_1^{\mathrm{T}} \ \ C_2^{\mathrm{T}} \ \ \dots \ \ C_N^{\mathrm{T}}]^{\mathrm{T}}$.

We are concerned with a networked state estimation problem where all the sensors use a shared communication link to transmit their measurements to a remote state estimator for computing the MMSE state estimate. See Fig. 1 for an illustration where the communication law is based on the CSMA/CA protocol in IEEE 802.15.4 Standard [2]. Due to the limited communication resources, a network manager is deployed to select the ‘informative’ sensor measurements to transmit to the remote estimator at every sampling time, while the rest of sensor measurements are discarded. Since the communication network often operates in uncertain environments, we have to consider some detrimental factors, e.g. packet loss, delay, network congestion and so on, when designing the networked systems. However, we restrict ourselves to the packet loss problem purely caused by the CSMA/CA protocol in this work.

Let $s_k(i)$ be the scheduling switch for the ith sensor node at time k, i.e. $s_k(i) = 1$ if $y_k(i)$ is transmitted; $s_k(i) = 0$ otherwise. Let $\gamma_k(i)$ be the packet loss indicator for the transmission of $y_k(i)$. In particular, $\gamma_k(i) = 1$ if $y_k(i)$ is received, and 0 otherwise. When $y_k(i)$ is not transmitted, we take the convention that $\gamma_k(i) = 0$. It is clear that $y_k(i)$ is both transmitted and received if and only if $\xi_k(i) = \gamma_k(i) s_k(i) = 1$.

Define the packets receiving matrix Υ_k as

$$\Upsilon_k = \mathrm{diag}\{\xi_k(1) \cdot I_1, \dots, \xi_k(N) \cdot I_N\} \tag{2}$$

where $I_i \in \mathbf{R}^{m_i \times m_i}$ is an identity matrix and $\sum_{i=1}^{N} m_i = m$. Furthermore, the sensor observations are collectively written as $y_k = [y_k(1)^{\mathrm{T}}, \dots, y_k(N)^{\mathrm{T}}]^{\mathrm{T}}$.

At time k, it is clear that the remote state estimator obtains the following information

$$\mathcal{F}_k = \{\Upsilon_t y_t, \Upsilon_t, t \le k\}.$$

Denote by $\hat{x}_{k+1|k}$ an estimate of x_{k+1} conditioned on $\mathcal{F}_k$, i.e. $\hat{x}_{k+1|k} := \mathcal{E}\{x_{k+1} | \mathcal{F}_k\}$, and the corresponding estimation error covariance by

$$P_{k+1} := P_{k+1|k} = \mathcal{E}\{(x_{k+1} - \hat{x}_{k+1|k})(x_{k+1} - \hat{x}_{k+1|k})^{\mathrm{T}} | \mathcal{F}_k\},$$

where the expectation $\mathcal{E}\{\cdot\}$ is taken over the distributions of x_0, w_k and $v_k(i)$. It is obvious that P_{k+1} is a random matrix depending on all $\{\Upsilon_t, t \le k\}$.

In fact, the above quantities can be recursively computed by a Kalman-like algorithm.

Theorem 1: The MMSE estimate of the networked system in (1) is recursively computed by

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \Upsilon_k (y_k - C\hat{x}_{k|k-1}); \tag{3}$$

$$P_{k|k} = P_{k|k-1} - K_k \Upsilon_k C P_{k|k-1}, \tag{4}$$

where the Kalman gain

$$K_k = P_{k|k-1} C^{\mathrm{T}} \Upsilon_k (\Upsilon_k C P_{k|k-1} C^{\mathrm{T}} \Upsilon_k + R)^{-1} \tag{5}$$

and $R = \mathrm{diag}(R_1, \ldots, R_N)$.

Proof: As in [7], the absence of observation corresponds to the limiting case that the measurement noise level goes to infinity. This implies that the measurement noise distribution can be given by

$$p(v_k^i | \gamma_k^i) \sim \begin{cases} \mathcal{N}(0, R_i), & \text{if } \xi_k(i) = 1; \\ \mathcal{N}(0, \sigma^2 I_i), & \text{if } \xi_k(i) = 0, \end{cases} \tag{6}$$

where σ is arbitrarily large. Then, the MMSE estimator is computed by

$$\begin{aligned} \hat{x}_{k|k} &= \hat{x}_{k|k-1} + P_{k|k-1} C^{\mathrm{T}} (C P_{k|k-1} C^{\mathrm{T}} + \Upsilon_k R \\ &\quad + (I - \Upsilon_k)\sigma^2)^{-1} (y_k - C\hat{x}_{k|k-1}), \end{aligned} \tag{7}$$

$$\begin{aligned} P_{k|k} &= P_{k|k-1} - P_{k|k-1} C^{\mathrm{T}} (C P_{k|k-1} C^{\mathrm{T}} + \Upsilon_k R \\ &\quad + (I - \Upsilon_k)\sigma^2)^{-1} C P_{k|k-1}. \end{aligned} \tag{8}$$

Without loss of generality, suppose that $\xi_k(1) = 1, \ldots, \xi_k(i) = 1$ and $\xi_k(i+1) = 0, \ldots, \xi_k(N) = 0$. Rewrite $\begin{bmatrix} C_1^{\mathrm{T}} & \ldots & C_i^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$ and $\begin{bmatrix} C_{i+1}^{\mathrm{T}} & \ldots & C_N^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}$ as $\bar{C}_1$ and $\bar{C}_2$, respectively. Similarly, we rewrite $\mathrm{diag}(R_1, \ldots, R_i)$ as $\bar{R}_1$ and $\mathrm{diag}(R_{i+1}, \ldots, R_N)$ as $\bar{R}_2$.

It follows that

$$\begin{aligned} & C P_{k|k-1} C^{\mathrm{T}} + \Upsilon_k R + (I - \Upsilon_k)\sigma^2 \\ &= \begin{bmatrix} \bar{C}_1 P_{k|k-1} \bar{C}_1^{\mathrm{T}} + \bar{R}_1 & \bar{C}_1 P_{k|k-1} \bar{C}_2^{\mathrm{T}} \\ \bar{C}_2 P_{k|k-1} \bar{C}_1^{\mathrm{T}} & \bar{C}_2 P_{k|k-1} \bar{C}_2^{\mathrm{T}} + \sigma^2 I_2 \end{bmatrix}. \end{aligned}$$

One can easily derive that

$$\begin{aligned} & \lim_{\sigma \to \infty} (C P_{k|k-1} C^{\mathrm{T}} + \Upsilon_k R + (I - \Upsilon_k)\sigma^2)^{-1} \\ &= \begin{bmatrix} (\bar{C}_1 P_{k|k-1} \bar{C}_1^{\mathrm{T}} + \bar{R}_1)^{-1} & 0 \\ 0 & 0 \end{bmatrix} \\ &= \Upsilon_k (\Upsilon_k C P_{k|k-1} C^{\mathrm{T}} \Upsilon_k + R)^{-1} \Upsilon_k. \end{aligned} \tag{9}$$

Letting $\sigma \to \infty$ in (7) and (8), the rest of the proof is trivial. □

The difficulty in computing the MMSE estimator above is that the estimator gains K_k becomes random and depends on Υ_k. To simplify state estimation, the sub-optimal estimates can be obtained by using a constant estimator gain $K_s = [K_s(1), K_s(2), \ldots, K_s(N)]$ which can be computed in an offline manner and is independent of Υ_k. Similar to that of [7, 23], two common choices of K_s are shown below:

i. The first one is the steady-state Kalman gain without packet loss, i.e. $K_s = P_\infty C^{\mathrm{T}} (C P_\infty C^{\mathrm{T}} + R)^{-1}$, where $P_\infty = A P_\infty A^{\mathrm{T}} + Q - A P_\infty C^{\mathrm{T}} (C P_\infty C^{\mathrm{T}} + R)^{-1} C P_\infty A^{\mathrm{T}}$.

ii. The second one is the steady-state gain from a modified algebraic Riccati equation. Since there are 2^N cases of packet receiving process for N sensors at each sampling time, then

$$K_s = \sum_{i=1}^{2^N} \alpha_i P_\infty^s \bar{C}_i^{\mathrm{T}} (\bar{C}_i P_\infty^s \bar{C}_i^{\mathrm{T}} + \bar{R}_i)^{-1},$$

where α_i denotes the probability of the ith case, and $\bar{C}_i, \bar{R}_i$ are the measurement matrix and the noise level correspond to the ith case. Moreover

$$P_\infty^s = A P_\infty^s A^{\mathrm{T}} + Q - \sum_{i=1}^{2^N} \alpha_i A P_\infty^s \bar{C}_i^{\mathrm{T}} (\bar{C}_i P_\infty^s \bar{C}_i^{\mathrm{T}} + \bar{R}_i)^{-1} \bar{C}_i P_\infty^s A^{\mathrm{T}}.$$

Then, the resulting estimate is given below

$$\hat{x}_{k+1|k} = A\hat{x}_{k|k-1} + \sum_{i=1}^{N} \xi_k(i) K_s(i) (y_k(i) - C_i \hat{x}_{k|k-1}), \tag{10}$$

$$\begin{aligned} P_{k+1} &= \sum_{i=1}^{N} K_s(i) R_i K_s^{\mathrm{T}}(i) + \left(A - \sum_{i=1}^{N} \xi_k(i) K_s(i) C_i \right) P_k \\ &\quad \times \left(A - \sum_{i=1}^{N} \xi_k(i) K_s(i) C_i \right)^{\mathrm{T}} + Q. \end{aligned} \tag{11}$$

To differentiate from the steady-state estimator gain K_s, the estimator gains K_k in (5) is called time-varying Kalman gains. Denote the probability of packet loss rate when M sensors simultaneously access the communication link within one sampling period by $P_1(M)$, i.e.

$$P_1(M) = \mathrm{Prob} \left\{ \gamma_k(i) = 0 | s_k(i) = 1, \quad \sum_{j=1}^{N} s_k(j) = M \right\}$$

for all $i \in \{1, 2, \ldots, N\}$.

Consider that $P_1(M)$ is a monotonically increasing function of M, the total throughput of the communication link is given by

$$\theta(M) = M \cdot (1 - P_1(M)).$$

Clearly, it increases in M when M is small, but decreases when M is large. This property is consistent with the popular CSMA/CA protocols.

To optimally utilise the channel for the above state estimation problem, the sensors need to be scheduled for competing the channel. In this paper, the following two scheduling schemes are proposed, respectively.

(a) Online scheduling: In this case, the communication link has an acknowledgement (ACK) message for every transmitted packet and the ACK message is successfully broadcast back to all the sensors, i.e. the ith sensor knows $\xi_{k-1}(j)$ at time k for all $j \in \{1, \ldots, N\}$. With the ACK messages, every sensor can recursively compute P_k at time k.

At every time, an optimal scheduler $s_k = [s_k(1), s_k(2), \ldots, s_k(N)]$ is designed to minimise the trace of the mean of the estimation error covariance matrix at time $k+1$ as defined below

$$\pi_{k+1} = \mathrm{Tr}(\mathcal{E}\{P_{k+1} | P_k, s_k\}), \tag{12}$$

where the expectation is taken over the packet loss processes $\gamma_k(i)$, and $\mathrm{Tr}(\cdot)$ denotes the trace operation of a matrix. Since each sensor can receive the ACK, they know the whole packet receiving information Υ_k, and will reach a consensus on the decision s_k.

(b) Offline scheduling: The online scheduling method requires a feedback channel to transmit ACK message from the estimator to all sensors. This might not be feasible in some applications. For example, in wireless sensor networks, the ACK broadcasting is usually avoided to save energy or might be lost. Without ACK, the sensors cannot execute the online scheduling. Instead, we resort to an offline scheduling by using either a deterministic or probabilistic schedule, which can be designed in an offline manner for a given communication link.

The offline scheduling problem we consider here assumes that a constant estimator gain is used and that $s_k(i)$ are both temporally and spatially independent across k and i. The objective is to compute the transmitting probability vector $p = \{p_1, p_2, \ldots, p_N\}$ with

$$p_i = \text{Prob}\{s_k(i) = 1\}$$

to minimise the trace of the mean of the steady-state estimation error covariance matrix

$$\pi = \text{Tr}(\bar{P}_\infty), \tag{13}$$

where p_i denotes the probability for selecting sensor i for communication and

$$\bar{P}_\infty = \lim_{k\to\infty} \mathcal{E}\{P_k\}.$$

3 Channel modelling under IEEE 802.15.4 standard

If the packet loss rate is independent of the channel input, it is obviously optimal for all the sensors transmitting their measurements at each sampling period. However, it generically does not hold, and the packet loss should be dependent on the channel input due to the possible packet congestion and collision. In this section, we adopt the CSMA/CA protocols to establish a new packet loss model, and focus on the often used IEEE 802.15.4 wireless communication standard [2]. Then, an interesting phenomenon is that the packet loss rate of the channel increases with the number of competing sensors for data communication. This implies that the sensor scheduling is required for the data communication.

To formalise the problem, the CSMA/CA protocol for this standard is depicted in Fig. 2 [24]. Now, we evaluate the packet loss rate $P_l(M)$ when M sensors are competing for the communication channel and need the following assumptions. Note that the variable d in this section means the backoff time (the number of backoffs).

A1: A star topology is considered in Fig 1, which means that only one sensor is allowed to transmit at the same time.
A2: All the sensors compete for the channel synchronously.
A3: In a sampling period, each sensor has only one measurement (packet) to transmit.
A4: The sampling interval is greater than the maximum transmission delay.
A5: When the studied sensor has experienced d times of mandatory backoffs, all other competing sensors' mandatory backoff time is d [This assumption comes from the statistic point of view: when the studied sensor has experienced d times of mandatory backoffs, the expected backoff time for the rest sensors is also d.].

Following notations will be used in modelling as well.

- M_{BK} is the maximum number of mandatory backoffs;
- S_d is the probability of successful transmission with d times of mandatory backoffs;
- N_d is the number of sensors that still in competition after d times of mandatory backoffs;
- $P_{\text{sens}}(d)$ is the probability of making a CCA after d times of mandatory backoffs;
- $P_{\text{CCA}}(d)$ is the probability of successful transmission after d times of mandatory backoffs;
- min BE is the Mac-layer's minimum CSMA backoff exponent;
- max BE is the Mac-layer's maximum CSMA backoff exponent;
- L is the length of a packet.

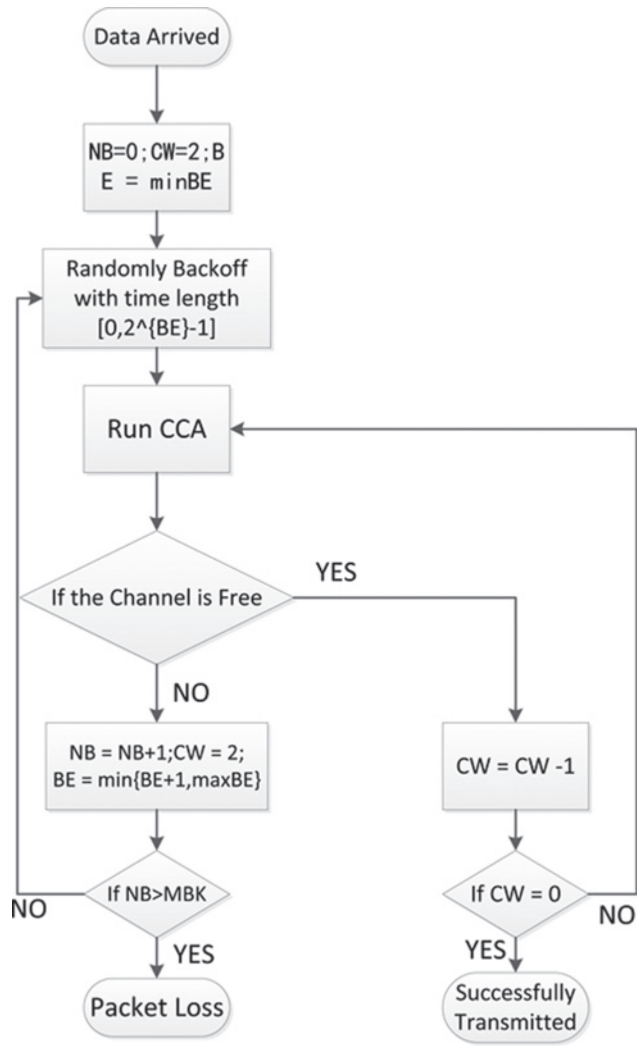

Fig. 2 *Principle of Mac-layer's CSMA/CA protocol*

Since the sensors quit the channel competition after a successful transmission or packet loss, the number of sensors in competition decreases with the increment of mandatory backoffs times. Thus $P_{\text{sens}}(d)$, $P_{\text{CCA}}(d)$, N_d and S_d change as d increases, and are computed in the following way:

(a) Evaluation of $P_{\text{sens}}(d)$. After d times of mandatory backoffs, there are $2^{\min\{\min \text{BE}+d, \max \text{BE}\}}$ time slots to make a CCA. The probability of making a CCA after k times of mandatory backoffs is

$$P_{\text{sens}}(d) = 2^{-\min\{\min \text{BE}+d, \max \text{BE}\}}. \tag{14}$$

(b) Evaluation of $P_{\text{CCA}}(d)$. Suppose that a competing sensor has experienced d times of mandatory backoffs till time t. Usually, there are two situations for another mandatory backoff.
i. There is another sensor starting transmission at time $t' \in \{t - L + 1, t - L + 2, \ldots, t, t + 1\}$. Then, the transmission will fail due to channel occupation.
ii. There are more than one sensors starting CCA at time t. Then, the transmission will fail for packet collision.
Using Assumption A5, it follows that

$$\begin{aligned}1 - P_{\text{CCA}}(d) &= (L+1)[1 - (1 - P_{\text{sens}}(d))^{N_d - 1}]P_{\text{CCA}}(d) \\ &\quad + \{1 - (L+1)[1 - (1 - P_{\text{sens}}(d))^{N_d - 1}] \\ &\quad \times P_{\text{CCA}}(d)\}(1 - (1 - P_{\text{sens}}(d))^{N_d - 1}).\end{aligned} \tag{15}$$

Remark 1: The first term in the right side of (15) is the probability of case (i), and the second term denotes the probability of case (ii).

Solving (15) results in that

$$P_{\text{CCA}}(d) = \frac{P_{ns}}{1 + (L+1)(1-P_{ns})P_{ns}}, \tag{16}$$

where $P_{ns} = (1 - P_{\text{sens}}(d))^{N_d - 1}$.
(c) Evaluation of N_d. N_d denotes the expected number of sensors that are still in competition after d times of mandatory backoffs. By A5, the sensors that quit competition can be viewed as completing their transmission. Moreover, for $d \in \{0, \dots, M_{\text{BK}}\}$,

$$T_d = 2^{\min\{\min \text{BE}+d, \max \text{BE}\}-1}$$

is the expected time interval between the dth mandatory backoff and next CCA. The number of senors quit competition during time interval T_d is $N_d - N_{d+1}$. Let

$$Q_d = \left(1 - (1 - P_{\text{sens}}(d))^{N_d - 1}\right) P_{\text{CCA}}(d)$$

be the probability that a sensor successfully transmits its packet after d times of mandatory backoffs. Base on the Mac-layer's law, the time interval required by transmitting a packet is $L+2$. Thus the maximum packet flow rate is $(1/L+2)$, and N_{d+1} is given by [This is the expected number of competing sensors.]

$$N_{d+1} = \begin{cases} N_d - \dfrac{T_d}{L+2} & \text{if } Q_d > \dfrac{1}{L+2} \\ N_d - T_d Q_d & \text{if } Q_d \le \dfrac{1}{L+2}, \end{cases} \tag{17}$$

where $N_0 = M$.
(e) Evaluation of S_d. The probability of successful transmission with exact d times of mandatory backoffs is simply given by

$$S_d = P_{\text{CCA}}(d) \prod_{j=0}^{d} (1 - P_{\text{CCA}}(j)). \tag{18}$$

(e) Evaluation of $P_1(M)$. The packet loss rate $P_1(M)$ is computed by

$$P_1(M) = 1 - \sum_{d=0}^{M_{\text{BK}}} S_d. \tag{19}$$

In the sequel, the above quantities will be used to design the scheduling algorithms.

4 Online scheduling

In this section, we solve the online scheduling problem under a constant estimator gain. To this purpose, we compute $\mathcal{E}\{P_{k+1} | P_k, s_k\}$ in the following result.

Lemma 1: Given an arbitrary scheduling s_k, let $M = \sum_{i=1}^{N} s_k(i)$. Then,

$$\begin{aligned} \mathcal{E}\{P_{k+1}|P_k, s_k\} = {} & AP_kA^{\mathrm{T}} + Q + (1 - P_1(M)) \sum_{i=1}^{N} s_k(i)(K_{\mathrm{s}}(i) \\ & \times (C_iP_kC_i^{\mathrm{T}} + R_i)K_{\mathrm{s}}^{\mathrm{T}}(i) - K_{\mathrm{s}}(i)C_iP_kA^{\mathrm{T}} \\ & - AP_kC_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i)) + (1 - P_1(M))^2 \sum_{i=1}^{N} \sum_{j \ne i} \\ & \times s_k(i)s_k(j)K_{\mathrm{s}}(i)C_iP_kC_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j) \end{aligned} \tag{20}$$

Proof: If $s_k(i) = s_k(j) = 1$, then $\gamma_k(i)$ and $\gamma_k(j)$ are uncorrelated for $i \ne j$ and thus

$$\begin{aligned} & \mathcal{E}\{\xi_k(i)\xi_k(j) | s_k(i), s_k(j)\} \\ & \quad = s_k(i)s_k(j)\text{Prob}(\gamma_k(i) = \gamma_k(j) = 1 | s_k(i) = s_k(j) = 1) \\ & \quad = s_k(i)s_k(j)(1 - P_1(M))^2. \end{aligned} \tag{21}$$

It is clear that the above also holds if $s_k(i) = 0$ or $s_k(j) = 0$. Similarly, we have that

$$\mathcal{E}\{\xi_k(i) | s_k(i)\} = s_k(i)(1 - P_1(M)). \tag{22}$$

In light of (11), we obtain that

$$\begin{aligned} & \mathcal{E}\{P_{k+1}|P_k, s_k\} \\ & \quad = AP_kA^{\mathrm{T}} + Q + \sum_{i=1}^{N} \mathcal{E}\{\xi_k(i)|s_k(i)\}K_{\mathrm{s}}(i)R_iK_{\mathrm{s}}^{\mathrm{T}}(i) \\ & \qquad - \sum_{i=1}^{N} \mathcal{E}\{\xi_k(i)|s_k(i)\}(K_{\mathrm{s}}(i)C_iP_kA^{\mathrm{T}} \\ & \qquad + AP_kC_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i)) + \sum_{i=1}^{N} \mathcal{E}\{\xi_k^2(i)|s_k(i)\}K_{\mathrm{s}}(i)C_iP_kC_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i) \\ & \qquad + \sum_{i=1}^{N}\sum_{j \ne i} \mathcal{E}\{\xi_k(i)\xi_k(j)|s_k(i), s_k(j)\}K_{\mathrm{s}}(i)C_iP_kC_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j). \end{aligned} \tag{23}$$

Since $\xi_k^2(i) = \xi_k(i)$, substituting (21) and (22) into (23), we obtain (20). □

Using Lemma 1 and $s_k(i) = s_k^2(i)$, we can write π_{k+1} as a quadratic function of s_k, i.e. $\pi_{k+1} = s_k^{\mathrm{T}}\mathbf{A}_k s_k + \mathbf{c}_k$ for some $N \times N$ matrix $\mathbf{A}_k$ and a scalar $\mathbf{c}_k$ (cf. Theorem 2). Since $P_1(M)$ depends only on the sum of $s_k(i)$, we can minimise π_{k+1} in two steps. For each $M \in \{1, \dots, N\}$, we minimise π_{k+1} under the constraint that $\sum_{i=1}^{N} s_k(i) = M$. Then, the minimum of π_{k+1} is obtained by ranging all feasible M. The first step needs to be solved using a relaxation by converting the integer optimisation problem to a real-valued optimisation problem. One difficulty, as far as relaxation is considered, is that the matrix $\mathbf{A}_k$ may have negative diagonal elements. This is fixed by adding a sufficiently large positive diagonal matrix $\alpha_k \cdot I$ to $\mathbf{A}_k$. We formally write the result in the following theorem.

Theorem 2: Under a constant estimator gain $K_{\mathrm{s}} = [K_{\mathrm{s}}(1), K_{\mathrm{s}}(2), \dots, K_{\mathrm{s}}(N)]$, the optimal s_k for minimising π_{k+1} in (12) can be obtained by solving the following optimisation problem

$$\min_{1 \le M \le N} \left\{ \min_{\sum_{i=1}^{N} s_k(i) = M} s_k^{\mathrm{T}}(\mathbf{A}_k + \alpha_k I)s_k \right\} + (\mathbf{c}_k - \alpha_k M) \tag{24}$$

where $\mathbf{c}_k = \mathbf{Tr}(AP_kA^{\mathrm{T}} + Q)$, I is an $N \times N$ identity matrix, $\mathbf{A}_k$ is an $N \times N$ symmetric matrix with elements

$$\begin{aligned} \mathbf{a}_{k,ij} &= (1 - P_1(M))^2 \text{Tr}(K_{\mathrm{s}}(i)C_iP_kC_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j)), \quad i \ne j \\ \mathbf{a}_{k,ii} &= (1 - P_1(M))\text{Tr}(K_{\mathrm{s}}(i)C_iP_kC_i^{\mathrm{T}} + R_i)K_{\mathrm{s}}^{\mathrm{T}}(i) \\ & \quad - 2K_{\mathrm{s}}(i)C_iP_kA^{\mathrm{T}}) \end{aligned}$$

and $\alpha_k = -\min\{0, \mathbf{a}_{k,11}, \mathbf{a}_{k,22}, \dots, \mathbf{a}_{k,NN}\}$ which guarantees the non-negativeness of all the elements of $\mathbf{A}_k + \alpha_k I$.

Proof: By Lemma 1 and $s_k(i) = s_k^2(i)$, we can write $\pi_{k+1} = \mathcal{E}\{P_{k+1}|P_k, s_k\}$ as

$$\pi_{k+1} = s_k^{\mathrm{T}} \mathbf{A}_k s_k + \mathbf{c}_k$$

with $\mathbf{a}_{k,ij}$ and $\mathbf{c}_k$ defined above. It is clear that

$$s_k^{\mathrm{T}} \mathbf{A}_k s_k + \mathbf{c}_k = s_k^{\mathrm{T}} (\mathbf{A}_k + \alpha_k I) s_k + \mathbf{c}_k - \alpha_k M$$

when $\sum_{i=1}^N s_k(i) = M$ since $s_k^{\mathrm{T}}(\alpha_k I) s_k = \alpha_k s_k^{\mathrm{T}} s_k = \alpha_k M$. One can easily verify that the selected α_k can guarantee the non-negativeness of all elements of $\mathbf{A}_k + \alpha_k I$. □

Unfortunately, the inner optimisation problem is known to be NP-hard [25]. Thus, a brute force computation is feasible only for a relatively small N. For a large N (say $N > 10$), sub-optimal solutions seems more sensible. Indeed, various effective relaxation algorithms are available [25], with the basic idea of replacing the terms $s_k(i)s_k(j)$ by another variable, say, $s_k(ij) \in \{0, 1\}$ and relaxing the integer constraint on $s_k(i)$ and $s_k(j)$ to an interval [0, 1]. This results in $O(N^2)$ number of variables and thus the corresponding optimisation problem is large.

In the sequel, we adopt a more efficient relaxation algorithm in [25] and obtain a mixed integer programming problem with $O(N)$ variables.

Lemma 2: Consider the following quadratic zero-one programming problem

$$\begin{aligned} &\min f(x) = x^{\mathrm{T}} Q x \\ &\text{s.t.} \sum_{i=1}^n x_i = M, \ x \in \{0, 1\}^n \end{aligned} \tag{25}$$

where Q is an $n \times n$ matrix with each element $q_{i,j} \geq 0$, and $x = [x_1 \ x_2 \ \ldots \ x_n]^{\mathrm{T}}$. Then, it is equivalent to the following mixed integer programming problem

$$\begin{aligned} &\min_{x,y,z} g(z) = \sum_{i=1}^n z_i \\ &\text{s.t.} \sum_{i=1}^n x_i = M; Qx - y - z = 0; y \leq \mu(e - x); y_i \geq 0, \\ &\qquad z_i \geq 0, x_i \in \{0, 1\} \text{ for any } i = 1, 2, \ldots, n, \end{aligned} \tag{26}$$

where $e = [1 \ 1 \ \ldots \ 1]^{\mathrm{T}}$ and μ is a constant.

We will demonstrate via simulation in Section 6 that the above relaxation method is effective in practice.

5 Offline scheduling

Note that the receiving probability is given by

$$\tau_i = \mathrm{Prob}\{\xi_k(i) = 1\} = \mathrm{Prob}\{s_k(i) = 1, \gamma_k(i) = 1\}.$$

Under the assumption that $s_k(i)$ are independent and $\mathrm{Prob}\{s_k(i) = 1\} = p_i$, the above probability is computed in the following result.

Theorem 3: Given $p = \{p_1, p_2, \ldots, p_N\}$, it follows that τ_i is independent of time k and

$$\tau_i = p_i \sum_{M=0}^{N-1} (1 - P_1(M + 1)) \rho_i(M), \tag{27}$$

where $\rho_i(M)$ is the probability that M sensors, not including sensor i, are transmitting, i.e.

$$\rho_i(M) = \sum_{|V_i|=M} \left(\prod_{v \in V_i} p_v \right) \left(\prod_{v \in \bar{V}_i} (1 - p_v) \right). \tag{28}$$

In the above, V_i is any subset of $\{1, 2, \ldots, N\}$ not containing i, $\bar{V}_i = \{1, 2, \ldots, N\} \backslash \{V_i \cup \{i\}\}$, and the sum is done over all such V_i with a cardinality M.

Furthermore, for any $j \neq i$, the probability for both ith and jth sensors' messages are received at time k is given by

$$\tau_{ij} = p_i \, p_j \sum_{M=0}^{N-2} (1 - P_1(M + 2)) \rho_{i,j}(M), \tag{29}$$

where $\rho_{i,j}(M)$ is the probability that M sensor nodes, not including nodes i and j, are transmitting, i.e.

$$\rho_{i,j}(M) = \sum_{|V_{i,j}|=M} \left(\prod_{v \in V_{i,j}} p_v \right) \left(\prod_{v \in \bar{V}_{i,j}} (1 - p_v) \right), \tag{30}$$

where $V_{i,j}$ is any subset of $\{1, 2, \ldots, N\}$ not containing i and j, $\bar{V}_{i,j} = \{1, 2, \ldots, N\} \backslash \{V_{i,j} \cup \{i, j\}\}$, and the sum is done over all such $V_{i,j}$ with a cardinality M.

Proof: Since $s_k(i)$ are independent in different k and i, it is clear that

$$\tau_i = p_i \mathrm{Prob}\{\gamma_k(i) = 1 | s_k(i) = 1\}$$

To compute $\mathrm{Prob}\{\gamma_k(i) = 1 | s_k(i) = 1\}$, we take $0 \leq M \leq N - 1$ and consider the event E_M that M sensors, in addition to sensor node i, are transmitting. It is clear that different events E_M for different values of M are exclusive. For each M, the probability ρ_M for E_M to occur is obtained by listing all elements of the set $\{s_k(j), \, j \neq i\}$ such that M elements are equal to 1 and the rest equal to 0. Denote by V_i the index set of such $\{s_k(j), \, j \neq i\}$, i.e. $v \in V_i$ if and only if $s_k(v) = 1$. Note that $|V_i| = M$. Using $\mathrm{Prob}\{s_k(j) = 1\} = p_j$, it follows that $\rho_i(M)$ is given in (28). Finally, if sensor node i and M other sensor nodes are transmitting, the probability of receiving packet is given by $1 - P_1(M + 1)$. Combining all the results above, we obtain (27).

The expression of τ_{ij} in (29) can be worked out similarly. Namely, the term $p_i p_j \rho_{i,j}(M)$ is the probability that nodes i and j, and M additional nodes are transmitting, thus its contribution to τ_{ij} is $(1 - P_1(M + 2)) p_i p_j \rho_{i,j}(M)$. Putting all the i,j together, we get (29). The derivation of $\rho_{i,j}(M)$ is similar to $\rho_i(M)$, and the detail is omitted. □

Next, we compute $\bar{P}_\infty(i)$ for any probability of receiving packet τ_i in the following result.

Theorem 4: Let the receiving probabilities τ_i, $i \in \{1, \ldots, N\}$ be given and a constant estimator gain $K_s = [K_s(1), K_s(2), \ldots, K_s(N)]$ is used. Let $A_c = A - \sum_{i=1}^N \tau_i K_s(i) C_i$, then $\mathcal{E}\{P_k\}$ obeys the following linear recursion

$$\begin{aligned} \mathcal{E}\{P_{k+1}\} &= A_c \mathcal{E}\{P_k\} A_c^{\mathrm{T}} + \sum_{i=1}^N \tau_i (1 - \tau_i) K_s(i) C_i \mathcal{E}\{P_k\} C_i^{\mathrm{T}} K_s^{\mathrm{T}}(i) \\ &\quad + \sum_{i \neq j}^N \sum_{j=1}^N (\tau_{ij} - \tau_i \tau_j) K_s(i) C_i \mathcal{E}\{P_k\} C_j^{\mathrm{T}} K_s^{\mathrm{T}}(j) \\ &\quad + \sum_{i=1}^N \tau_i K_s(i) R_i K_s^{\mathrm{T}}(i) + Q. \end{aligned} \tag{31}$$

Moreover, suppose that A_c is stable and τ_i, τ_{ij} are sufficiently large, there is a positive definite matrix $\bar{P}_\infty$ solving the following *linear* equation

$$\bar{P}_\infty = A_c\bar{P}_\infty A_c^{\mathrm{T}} + \sum_{i=1}^{N}\tau_i(1-\tau_i)K_{\mathrm{s}}(i)C_i\bar{P}_\infty C_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i) + \sum_{i\neq j}^{N}\sum_{j=1}^{N}(\tau_{ij}-\tau_i\tau_j)K_{\mathrm{s}}(i)C_i\bar{P}_\infty C_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j) + \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)R_i K_{\mathrm{s}}^{\mathrm{T}}(i) + Q. \quad (32)$$

Proof: Using (11) with a constant estimator gain K_{s}, and the independence of $\xi_k(i) - \tau_i$, we get that

$$\begin{aligned}\mathcal{E}\{P_{k+1}|P_k\} &= \mathcal{E}\left\{\left(A_c - \sum_{i=1}^{N}(\xi_k(i)-\tau_i)K_{\mathrm{s}}(i)C_i\right)\cdot P_k\left(A_c - \sum_{i=1}^{N}(\xi_k(i)-\tau_i)K_{\mathrm{s}}(i)C_i\right)^{\mathrm{T}}\right\} \\ &\quad + \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)R_i K_{\mathrm{s}}^{\mathrm{T}}(i) + Q \\ &= \left(A - \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)C_i\right)P_k\left(A - \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)C_i\right)^{\mathrm{T}} \\ &\quad + \sum_{i=1}^{N}\mathcal{E}\{(\xi_k(i)-\tau_i)^2\}K_{\mathrm{s}}(i)C_iP_kC_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i) \\ &\quad + \sum_{i\neq j}^{N}\sum_{j=1}^{N}(\xi_k(i)-\tau_i)(\xi_k(j)-\tau_j)K_{\mathrm{s}}(i)C_iP_kC_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j) \\ &\quad + \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)R_i K_{\mathrm{s}}^{\mathrm{T}}(i) + Q \\ &= \left(A - \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)C_i\right)P_k\left(A - \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)C_i\right)^{\mathrm{T}} \\ &\quad + \sum_{i=1}^{N}\tau_i(1-\tau_i)K_{\mathrm{s}}(i)C_iP_kC_i^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(i) \\ &\quad + \sum_{i\neq j}^{N}\sum_{j=1}^{N}(\tau_{ij}-\tau_i\tau_j)K_{\mathrm{s}}(i)C_iP_kC_j^{\mathrm{T}}K_{\mathrm{s}}^{\mathrm{T}}(j) \\ &\quad + \sum_{i=1}^{N}\tau_i K_{\mathrm{s}}(i)R_i K_{\mathrm{s}}^{\mathrm{T}}(i) + Q. \end{aligned} \quad (33)$$

Since the right-hand side above is linear in P_k, the above leads to (31). Furthermore, as (31) is a linear recursion (in $\mathcal{E}\{P_k\}$), its steady-state solution is naturally given in (32). Using the assumption that $A - \sum_{i=1}^{N}K_{\mathrm{s}}(i)C_i$ is stable, $\bar{P}_\infty$ exists when $\tau_i = 1$ and $\tau_{ij} = 1$ for all i,j. Note that $\bar{P}_\infty$ in (32) is a continuous function of τ_i and τ_{ij}. Therefore, by continuity, $\bar{P}_\infty$ exists as long as all τ_i and τ_{ij} are sufficiently large. □

Remark 2: In [7], the single sensor case ($N = 1$) is analysed and it is shown that there exists a critical value for the receiving probability τ to ensure the boundness (existence) of $\bar{P}_\infty$. In particular, it is shown in [7] that the boundness of $\bar{P}_\infty$ is guaranteed if A is stable or, in the case of unstable A, if $(1-\tau)|\lambda_{\max}(A)|^2 < 1$. The multi-sensor case ($N > 1$) is much more involved in terms of determining a similar condition on τ_i and τ_{ij} for the boundness of $\bar{P}_\infty$. For a simpler channel model, the stability condition is studied in [26]. In this section, we only focus on the optimal design of transmitting probability $\{p_1, p_2, \ldots, p_N\}$, which minimises $\mathrm{Tr}(\bar{P}_\infty)$ and guarantees the maximal stability margin.

The term $\mathrm{Tr}(\bar{P}_\infty)$ can be optimised by standard Newton Gradient method (see, e.g. [27]), thus is omitted here.

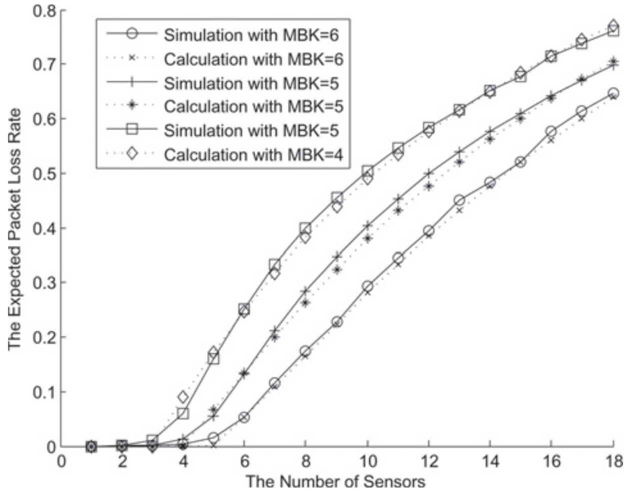

Fig. 3 *Expected packet loss rate comparison*

6 Simulation

In this section, we demonstrate the proposed packet loss model and scheduling algorithms via simulation.

6.1 Packet loss model

To verify the packet loss model in Section 3, we consider a series of simulations with a set of common parameters for the IEEE 802.15.4 Standard: $\min \mathrm{BE} = 3, \max \mathrm{BE} = 3, L = 3$, but different parameters $M_{\mathrm{BK}} = 4, 5, 6$, respectively. The simulations are done by running 10, 000 Monte Carlo tests, and the comparison between model and simulation is shown in Fig. 3. We see that our model matches the simulated result very well.

6.2 Scheduling optimisation

To illustrate performance of the two proposed scheduling algorithms, a networked system with following parameters is

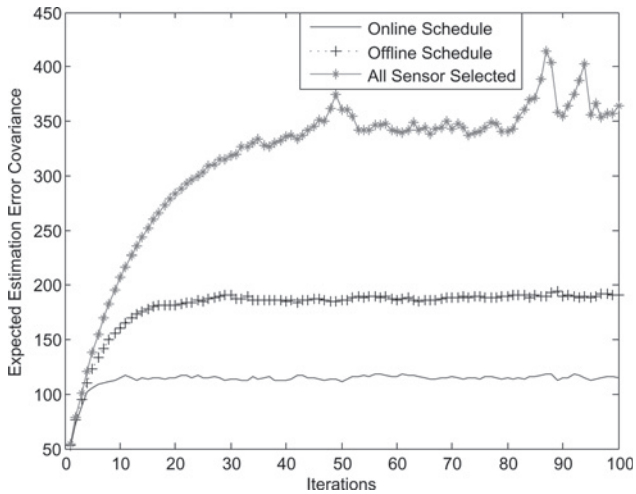

Fig. 4 *Simulation of online scheduling and offline scheduling*

considered

$$A = \mathrm{diag}\{1.2, 1.1, 1.1, 1.15, 1.2, 1.05, 1.2, 1.1, 1, 1.2, 1.2, 1.2, 1.2, 1.2, 1.2\};$$
$$C = Q = R = P_0 = I_{15},$$

where I_{15} is a 15×15 identical matrix.

Base on the same Mac-layer parameters as in packet loss model, online scheduling, offline scheduling and non-scheduled are simulated with the same steady-state estimator gain, which is shown in Fig. 4.

It is clear that online scheduling gives a lower level of the estimation error covariance matrix than that of offline scheduling, and non-scheduled case has the worst performance.

7 Conclusion

In this paper, a sensor scheduling problem under dynamic packet lossy network was studied. Firstly, the MMSE estimator for the multiple sensors observed system under a packet lossy network was given. In addition, the network is further modelled as a dynamic packet lossy network, which has the property that the more sensors are transmitting their measurements to the centralised estimator, the higher packet loss rate it has. To quantify the dynamic nature of network, CSMA/CA protocol was chosen and we built a packet loss model to calculate the expected packet loss rate under different number of sensors. Then, under the assumption that the estimator broadcast ACK message after receiving a packet from sensor, an online scheduling was proposed, and the expected estimation error covariance was minimised step by step. Without the ACK message, the packets receiving results are unknown to the sensors, thus an offline schedule was introduced. The offline schedule assigns each sensor a constant packet transmitting rate in a random framework. Finally, we included simulation results to verify the effectiveness of the packet loss model, and compare the estimation performance under the two schedulers to the case without a scheduler.

8 References

1 Hespanha, J., Naghshtabrizi, P., Xu, Y.: ‘A survey of recent results in networked control systems’, *Proc. IEEE*, 2007, **95**, (1), pp. 138–162

2 Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs). IEEE Std. 802.15.4, 2006

3 Pollin, S., Ergen, M., Ergen, S., *et al.*: ‘Performance analysis of slotted carrier sense ieee 802.15.4 medium access layer’, *IEEE Tran. Wirel. Commun.*, 2008, **7**, (9), pp. 3359–3371

4 Ling, X., Cheng, Y., Mark, J., *et al.*: ‘A renewal theory based analytical model for the contention access period of ieee 802.15.4 mac’, *IEEE Tran. Wirel. Commun.*, 2008, **7**, (6), pp. 2340–2349

5 Cao, X., Chen, J., Sun, Y., *et al.*: ‘Maximum throughput of ieee 802.15. 4 enabled wireless sensor networks’. Global Telecommunications Conf., 2011, pp. 1–5

6 Wang, W., Xu, Q., Fang, S., *et al.*: ‘Performance analysis of unsaturated slotted ieee802.15.4 medium access layer’. CCWMC, 2009, pp. 53–56

7 Sinopoli, B., Schenato, L., Franceschetti, M., *et al.*: ‘Kalman filtering with intermittent observations’, *IEEE Trans. Autom. Control*, 2004, **49**, (9), pp. 1453–1464

8 Mo, Y., Sinopoli, B.: ‘A characterization of the critical value for Kalman filtering with intermittent observations’. 47th IEEE Conf. on Decision and Control, 2008, pp. 2692–2697

9 Mo, Y., Sinopoli, B.: ‘Towards finding the critical value for Kalman filtering with intermittent observations’, 2010, http://arxiv.org/abs/1005.2442

10 Huang, M., Dey, S.: ‘Kalman filtering with Markovian packet losses and stability criteria’. Proc. 45th IEEE Conf. on Decision and Control, 2006, pp. 5621–5626

11 You, K., Fu, M., Xie, L.: ‘Mean square stability for Kalman filtering with Markovian packet losses’, *Automatica*, 2011, **47**, (12), pp. 2647–2657

12 Schenato, L.: ‘Optimal estimation in networked control systems subject to random delay and packet drop’, *IEEE Trans. Autom. Control*, 2008, **53**, (5), pp. 1311–1317

13 Sui, T., You, K., Fu, M.: ‘Kalman filtering with intermittent observations using measurements coding’. 10th IEEE Int. Conf. on Control and Automation, 2013, pp. 1127–1132

14 Walsh, G., Ye, H.: ‘Scheduling of networked control systems’, *IEEE Control Syst. Mag.*, 2002, **21**, (1), pp. 57–65

15 Gupta, V., Chung, T., Hassibi, B., *et al.*: ‘On a stochastic sensor selection algorithm with applications in sensor scheduling and sensor coverage’, *Automatica*, 2006, **42**, (2), pp. 251–260

16 Shi, L., Cheng, P., Chen, J.: ‘Sensor data scheduling for optimal state estimation with communication energy constraint’, *Automatica*, 2011, **47**, (8), pp. 1693–1698

17 Shi, L., Cheng, P., Chen, J.: ‘Optimal periodic sensor scheduling with limited resources’, *IEEE Trans. Autom. Control*, 2011, **56**, (9), pp. 2190–2195

18 Hovareshti, P., Gupta, V., Baras, J.: ‘Sensor scheduling using smart sensors’. 46th IEEE Conf. on Decision and Control, 2007, pp. 494–499

19 Shi, L., Epstein, M., Sinopoli, B., *et al.*: ‘Effective sensor scheduling schemes in a sensor network by employing feedback in the communication loop’. IEEE Int. Conf. on Control Applications, 2007, pp. 1006–1011

20 Savage, C., Scala, B.: ‘Optimal scheduling of scalar Gauss–Markov systems with a terminal cost function’, *IEEE Trans. Autom. Control*, 2009, **54**, (5), pp. 1100–1105

21 You, K., Xie, L.: ‘Kalman filtering with scheduled measurements’, *IEEE Trans. Signal Process.*, 2013, **61**, (6), pp. 1520–1530

22 You, K., Xie, L., Song, S.: ‘Asymptotically optimal parameter estimation with scheduled measurements’, *IEEE Trans. Signal Process.*, 2013, **61**, (14), pp. 3521–3531

23 Deshmukh, S., Natarajan, B., Pahwa, A.: ‘State estimation over a lossy network in spatially distributed cyber-physical systems’, *IEEE Trans. Signal Process.*, 2014, **62**, (15), pp. 3911–3923

24 Khanafer, M., Guennoun, M., Mouftah, H.: ‘A survey of beacon-enabled ieee 802.15. 4 mac protocols in wireless sensor networks’, *IEEE Commun. Surv. Tutorials*, 2014, **16**, (2), pp. 856–876

25 Chaovalitwongse, W., Pardalos, P., Prokopyev, O.: ‘A new linearization technique for multi-quadratic 0-1 programming problems’, *Oper. Res. Lett.*, 2004, **32**, (6), pp. 517–522

26 Quevedo, D.E., Ahlén, A., Johansson, K.H.: ‘State estimation over sensor networks with correlated wireless fading channels’, *IEEE Trans. Autom. Control*, 2013, **58**, (3), pp. 581–593

27 Kincaid, D., Cheney, W.: Numerical analysis: mathematics of scientific computing (China Machine Press, 2003)