APPENDIX A
DESCRIPTION OF A TYPICAL SCENARIO.

This section gives the description of a typical scenario in subsection 2.2.

Fig.2 shows a typical scenario to describe the network-induced complexity (i.e. packet dropouts and packet disorders generated from the random transmission delays).

For the i^{th} subsystem, it is assumed that the upper bound of the transmission delays is not more than 5 sample periods (i.e. $N_k \leqslant 5$, and the delay for each step satisfies $N_k \leqslant k$). $\eta(t_k)$ represents the transmission delay, and the sample period is T, while $t \in \{kT,\ k \in \mathbb{N}\}$ denotes the sampling time instant. Depending on the role of the logic ZOH, the packet disorders come from the signals before being transmitted, such as z_3^i and z_2^i, z_8^i and z_7^i, as well as z_{11}^i, z_{10}^i and z_9^i, and then z_3^i, z_8^i and z_{11}^i are held at time instant $k=5$, $k=9$ and $k=12$, respectively.

APPENDIX B
AUGMENTED STATE-SPACE MODEL.

This section gives the definitions and derivations of the augmented state-space model shown in subsection 3.1.

An augmented state-space model combining the systems shown in Eqs.(1) and (17)-(19) is represented as follows:

$$\Psi_t^i = \left(A_{t1}^i + H_{t1}^i F_t E_{t1}^i\right)\tilde{\Psi}_t^i + B_{t1}^i w_t + G_{t1}^i v_t\ , \tag{B.1}$$

and

$$\begin{aligned}\tilde{\Psi}_{t+1}^i = &\left(A_{t2}^i + H_{t2}^i F_t E_{t2}^i + \sum_{\vartheta=1}^{\hbar} A_{\vartheta,t2}\varpi_{\vartheta,t}\right)\tilde{\Psi}_t^i \\ &+ B_{t2}^i w_t + G_{t2}^i v_t\ ,\end{aligned} \tag{B.2}$$

with

$$\begin{aligned}
A_{t1}^i &= \begin{bmatrix} I - K_t^i C_t^i & K_t^i\left(\hat{C}_t^i - C_t^i\right) \\ K_t^i C_t^i & I + K_t^i\left(C_t^i - \hat{C}_t^i\right)\end{bmatrix}\ , \\
H_{t1}^i &= \begin{bmatrix} -K_t^i \mathcal{H}_t^i \\ K_t^i \mathcal{H}_t^i\end{bmatrix}\ ,\ E_{t1}^i = E_{t2}^i = \begin{bmatrix} E_t^i & E_t^i\end{bmatrix}\ , \\
B_{t1}^i &= \begin{bmatrix} -K_t^i B_t^i \\ K_t^i B_t^i\end{bmatrix},\ G_{t1}^i = \begin{bmatrix} -K_t^i G_t^i \\ K_t^i G_t^i\end{bmatrix}, \\
A_{t2}^i &= \begin{bmatrix} A_t - L_t^i C_t^i & A_t - \hat{A}_t^i + L_t^i\left(\hat{C}_t^i - C_t^i\right) \\ L_t^i C_t^i & \hat{A}_t^i + L_t^i\left(C_t^i - \hat{C}_t^i\right)\end{bmatrix}\ ,
\end{aligned}$$

$$\begin{aligned}
H_{t2}^i &= \begin{bmatrix} \mathcal{F}_t - L_t^i \mathcal{H}_t^i \\ L_t^i \mathcal{H}_t^i\end{bmatrix},\ A_{\vartheta,t2} = A_\vartheta \begin{bmatrix} I & I \\ 0 & 0\end{bmatrix}, \\
B_{t2}^i &= \begin{bmatrix} B_t - L_t^i B_t^i \\ L_t^i B_t^i\end{bmatrix},\ G_{t2}^i = \begin{bmatrix} G_t - L_t^i G_t^i \\ L_t^i G_t^i\end{bmatrix}\ .
\end{aligned} \tag{B.3}$$

Based on the augmented system from Eqs.(B.1) and (B.2), we set the covariance matrices to be $\tilde{\Sigma}_t^i = E\left(\tilde{\Psi}_t^i\left(\tilde{\Psi}_t^i\right)^T\right)$ and $\tilde{\Theta}_t^i = E\left(\Psi_t^i\left(\Psi_t^i\right)^T\right)$ under Eqs.(B.1)-(B.3). Then, the Riccati-like equations for the covariance matrices of the estimation errors are derived as follows:

$$\begin{aligned}\tilde{\Theta}_t^i = &\left(A_{t1}^i + H_{t1}^i F_t E_{t1}^i\right)\tilde{\Sigma}_t^i\left(A_{t1}^i + H_{t1}^i F_t E_{t1}^i\right)^T \\ &+ B_{t1}^i E\left(w_t w_t^T\right)\left(B_{t1}^i\right)^T + G_{t1}^i R_t\left(G_{t1}^i\right)^T\ ,\end{aligned} \tag{B.4}$$

and

$$\begin{aligned}\tilde{\Sigma}_{t+1}^i = &\left(A_{t2}^i + H_{t2}^i F_t E_{t2}^i\right)\tilde{\Sigma}_t^i\left(A_{t2}^i + H_{t2}^i F_t E_{t2}^i\right)^T \\ &+ \sum_{\vartheta=1}^{\hbar} A_{\vartheta,t2}\tilde{\Sigma}_t^i A_{\vartheta,t2}^T \theta_{\vartheta,k} + B_{t2}^i E\left(w_t w_t^T\right)\left(B_{t2}^i\right)^T \\ &+ G_{t2}^i R_t\left(G_{t2}^i\right)^T\ .\end{aligned} \tag{B.5}$$

APPENDIX C
PROOF OF THEOREM 1 AND DERIVATION OF THE CONVEX OPTIMIZATION PROBLEM.

This section gives the proof of Theorem 1 shown in Section 3.2.

For the i^{th} subsystem in Eq.(20) with $v_k = 0$, it is derived from Lemma 1 that the requirements (i.e. Conditions 1 and 2) are held, if and only if there exists a matrix $\mathrm{X}_i > 0$ such that

$$\begin{aligned}&\left(A_{t3}^i + \Delta A_{t3}^i\right)^T \mathrm{X}_i\left(A_{t3}^i + \Delta A_{t3}^i\right) + \left(D_{t3}^i\right)^T D_{t3}^i - \mathrm{X}_i \\ &+ \sum_{\vartheta=1}^{\hbar}\varpi_{\vartheta,k} A_{\vartheta,t3}^T \mathrm{X}_i A_{\vartheta,t3} \\ &+ \left(A_{t3}^i + \Delta A_{t3}^i\right)^T \mathrm{X}_i B_{t3}^i\left(\gamma_i^2 - \left(B_{t3}^i\right)^T \mathrm{X}_i B_{t3}^i\right)^{-1} \\ &\times\left(B_{t3}^i\right)^T \mathrm{X}_i\left(A_{t3}^i + \Delta A_{t3}^i\right)\ < 0\ .\end{aligned} \tag{C.1}$$

Thus, the inequality (27) is obtained from Eq.(C.1) using the Schur complement lemma [48]. On the other hand, when the system following Eq.(20) is mean-square stable, the H_2 performance J^i can be expressed as follows [37]:

$$J^i = \lim_{t\to\infty} E\left(\left(\tilde{e}_{k+1}^i\right)^T \tilde{e}_{k+1}^i\right) = Tr\left(R_k\left(G_{t3}^i\right)^T \bar{\mathrm{X}}_i G_{t3}^i\right) \tag{C.2}$$

where $\bar{\mathrm{X}}_i$ is the solution of the following Lyapunov equation:

$$\begin{aligned}&\left(A_{t3}^i + \Delta A_{t3}^i\right)^T \bar{\mathrm{X}}_i\left(A_{t3}^i + \Delta A_{t3}^i\right) - \bar{\mathrm{X}}_i \\ &+ \left(D_{t3}^i\right)^T D_{t3}^i + \sum_{\vartheta=1}^{\hbar}\varpi_{\vartheta,k} A_{\vartheta,t3}^T \bar{\mathrm{X}}_i A_{\vartheta,t3} = 0\ .\end{aligned} \tag{C.3}$$

Meanwhile, it is known from Eq.(27) that

$$\begin{aligned}&\left(A_{t3}^i + \Delta A_{t3}^i\right)^T \mathrm{X}_i\left(A_{t3}^i + \Delta A_{t3}^i\right) - \mathrm{X}_i \\ &+ \left(D_{t3}^i\right)^T D_{t3}^i + \sum_{\vartheta=1}^{\hbar}\varpi_{\vartheta,k} A_{\vartheta,t3}^T \mathrm{X}_i A_{\vartheta,t3} < 0\ .\end{aligned} \tag{C.4}$$

Then, it is concluded that $\bar{\mathrm{X}}_i \leqslant \mathrm{X}_i$. In this case, the upper bound of H_2 performance J^i can be treated as $Tr\left(R_k\left(G_{t3}^i\right)^T \mathrm{X}_i G_{t3}^i\right)$, where X_i is the solution to the matrix inequality based on Eq.(27).

Complete the proof of Theorem 1.

Based on Lemma 2, we define $W_i^T \triangleq \begin{bmatrix} W_{i,1} & 0 \\ W_{i,3} & W_{i,4} \end{bmatrix}$, and the inequality from Eq.(27) will hold. If there exists a matrix W_i, meanwhile, the following inequality

$$\begin{bmatrix} \mathrm{X}_{W_i} & A_{W_i} + F_{W_i} F_k E_{W_i} & B_{W_i} \\ * & \left(D_{t3}^i\right)^T D_{t3}^i + \Upsilon_{t3} - \mathrm{X}_i & 0 \\ * & * & -\gamma_i^2 I \end{bmatrix} < 0 \tag{C.5}$$

holds, and the form of the inequality is similar to Eq.(27). Note that parameters are defined as follows:

Υ_{t3} is defined in Eq.(27), and

$$\begin{aligned} &\mathrm{X}_{W_i} = \mathrm{X}_i - W_i - W_i^T \ , \\ &A_{W_i} = \begin{bmatrix} W_{i,1} A_k & 0 \\ A_{W_{i,3}} & W_{i,4}\left(\hat{A}_k^i - L_k^i \hat{C}_k^i\right) \end{bmatrix} \ , \\ &B_{W_i} = \begin{bmatrix} W_{i,1} B_k \\ \left(W_{i,3} + W_{i,4}\right) B_k - W_{i,4} L_k^i B_k^i \end{bmatrix} \ , \\ &F_{W_i} = \begin{bmatrix} W_{i,1} \mathcal{F}_k \\ W_{i,3} \mathcal{F}_k + W_{i,4}\left(\mathcal{F}_k - L_k^i \mathcal{H}_k^i\right) \end{bmatrix} \ , \ E_{W_i} = \left[E_k \ \ 0\right] \ , \\ &A_{W_{i,3}} = \left(W_{i,3} + W_{i,3}\right) A_k + W_{i,4}\left(L_k^i\left(\hat{C}_k^i - C_k^i\right) - \hat{A}_k^i\right) \ . \end{aligned} \tag{C.6}$$

From Theorem 1, the H_2 performance in Eq.(20) satisfies $J^i \leqslant Tr\left(R_k \left(G_{t3}^i\right)^T \mathrm{X}_i G_{t3}^i\right)$. Then, the upper bound of a symmetric matrix $\rho_{i,0}$ is introduced to conform to $R_k \left(G_{t3}^i\right)^T \mathrm{X}_i G_{t3}^i \leqslant \rho_{i,0}$. Thus, the inequality $\left(G_{t3}^i\right)^T \mathrm{X}_i G_{t3}^i \leqslant R_k^{-1} \rho_{i,0}$ is satisfied. Then, we define $\rho_i \triangleq R_k^{-1} \rho_{i,0}$, based on the Schur complement lemma, the inequality $\left(G_{t3}^i\right)^T \mathrm{X}_i G_{t3}^i \leqslant \rho_i$ is equivalent to

$$\begin{bmatrix} -\mathrm{X}_i & \mathrm{X}_i G_{t3}^i \\ * & -\rho_i \end{bmatrix} < 0 \ . \tag{C.7}$$

It means that the inequality given in Eq.(C.7) is held, if there exists a matrix W_i, which meets the following linear matrix inequalities (LMIs) condition:

$$\begin{bmatrix} \mathrm{X}_{W_i} & G_{W_i} \\ * & -\rho_i \end{bmatrix} < 0 \ , \tag{C.8}$$

where X_{W_i} is given in Eq.(C.6), while $G_{W_i} = \begin{bmatrix} W_{i,1} G_k \\ \left(W_{i,3} + W_{i,4}\right) G_k - W_{i,4} L_k^i G_k^i \end{bmatrix}$.

Remark C.1. Note that for the matrix W_i, if there is no structural constraint, the inequality in Eq.(C.5) is equivalent to Eq.(27), and the inequality in Eq.(C.8) will be equivalent to Eq.(C.7). However, the nonlinear terms in Eqs.(27) and (C.7) are unable to be eliminated in this case. For this reason, an equivalent LMI will be given, which is used to represent the inequality in Eq.(C.5), and then the local estimation parameters will be obtained by solving a convex optimization problem.

Appendix D
Proof of Theorem 3.

This section gives the proof of Theorem 3 shown in Section 4.1.

The solutions of $\bar{\Theta}_t^i$ and $\bar{\Sigma}_{t+1}^i$ are derived from $\bar{\Sigma}_t^i$ in Eqs.(35) and (36), so that the upper bound of Σ_t^i under Eq.(34) can be represented as follows [19, 22]:

$$\Sigma_t^i = \begin{bmatrix} \Sigma_{11,\,t} & \Sigma_{12,\,t} \\ \Sigma_{21,\,t} & \Sigma_{22,\,t} \end{bmatrix} = \begin{bmatrix} \bar{\Sigma}_t^i & 0 \\ 0 & P_t - \bar{\Sigma}_t^i \end{bmatrix} \ . \tag{D.1}$$

To estimate the filter parameters $\hat{C}_t^i$, K_t^i, $\hat{A}_t^i$ and L_t^i, considering the given recursive equations for $\bar{\Sigma}_{t+1}^i$ and P_{t+1} in Eqs.(43) and (44), the approach of optimizing measurement and filtering error covariance matrices is developed based on the local estimators $\hat{x}_{t|t}^i$ and $\hat{x}_{t+1|t}^i$ in Eqs.(17) and (18), respectively. Therefore, the derivation process is shown as follows:

Step 1: Solve the filter parameter $\hat{C}_t^i$.

Due to setting $t = k - \tau^i\left(k_1\right)$, the measurement error $\tilde{y}_k^i$ is defined as:

$$\begin{aligned} \tilde{y}_k^i &= y_k^i - \hat{y}_k^i \\ &= \left(A_{t4}^i + H_{t4}^i F_t E_{t4}^i\right) \tilde{\Psi}_t^i + B_t^i w_t + G_t^i v_t \ , \end{aligned} \tag{D.2}$$

where

$$A_{t4}^i = \begin{bmatrix} C_t^i & C_t^i - \hat{C}_t^i \end{bmatrix} \ , \ H_{t4}^i = \mathcal{H}_t^i, \ E_{t4}^i = \begin{bmatrix} E_t^i & E_t^i \end{bmatrix} \ . \tag{D.3}$$

Next, obtain the upper bound for the covariance of the measurement error from Eq.(D.1), and Lemmas 3 and 4:

$$\begin{aligned} &E\left(\tilde{y}_k^i \left(\tilde{y}_k^i\right)^T\right) \\ &\leqslant A_{t4}^i \Sigma_t^i \left(A_{t4}^i\right)^T + \alpha_t^{-1} H_{t4}^i \left(H_{t4}^i\right)^T \\ &\quad + B_t^i E\left(w_t w_t^T\right) + G_t^i R_t \left(G_t^i\right)^T \\ &\quad + A_{t4}^i \Sigma_t^i \left(E_{t4}^i\right)^T \left(\alpha_t^{-1} I - E_{t4}^i \Sigma_t^i \left(E_{t4}^i\right)^T\right)^{-1} E_{t4}^i \Sigma_t^i \left(A_{t4}^i\right)^T \\ &= \bar{\Pi}_t^i \\ &= C_t^i \bar{\Sigma}_t^i \left(C_t^i\right)^T + \left(C_t^i - \hat{C}_t^i\right)\left(P_t - \bar{\Sigma}_t^i\right)\left(C_t^i - \hat{C}_t^i\right)^T \\ &\quad + \alpha_t^{-1} \mathcal{H}_t^i \left(\mathcal{H}_t^i\right)^T + B_t^i E\left(w_t w_t^T\right) + G_t^i R_t \left(G_t^i\right)^T \\ &\quad + \left(C_t^i \bar{\Sigma}_t^i \left(E_t^i\right)^T + \left(C_t^i - \hat{C}_t^i\right)\left(P_t - \bar{\Sigma}_t^i\right)\left(E_t^i\right)^T\right) \\ &\quad \times \left(\alpha_t^{-1} I - E_t^i P_t \left(E_t^i\right)^T\right)^{-1} \\ &\quad \times \left(C_t^i \bar{\Sigma}_t^i \left(E_t^i\right)^T + \left(C_t^i - \hat{C}_t^i\right)\left(P_t - \bar{\Sigma}_t^i\right)\left(E_t^i\right)^T\right)^T \ . \end{aligned} \tag{D.4}$$

Therefore, we use the first order derivative $\dfrac{\partial \bar{\Pi}_t^i}{\partial \hat{C}_t^i} = 0$ to obtain $\hat{C}_t^i$:

$$\hat{C}_t^i = C_t^i \left(I + \bar{\Sigma}_t^i \left(E_t^i\right)^T \left(M_t^i\right)^{-1} E_t^i\right) \ , \tag{D.5}$$

where $M_t^i = \alpha_t^{-1} I - E_t^i \bar{\Sigma}_t^i \left(E_t^i\right)^T > 0$.

Finally, similar to the derivation of $\hat{C}_t^i$, the other filter parameters such as K_t^i, $\hat{A}_t^i$ and L_t^i are generated.

Step 2: Derive the error covariance matrices $\bar{\Theta}_t^i$, $\bar{\Sigma}_{t+1}^i$ and P_{t+1}, respectively.

Firstly, Theorem 2 defines the solutions of Θ_t^i and Σ_{t+1}^i in Eqs.(32) and (33). Subsequently, the upper bounds for the covariance matrices of the estimation errors $\bar{\Theta}_t^i$ and $\bar{\Sigma}_{t+1}^i$ from Eqs.(35) and (36) are derived as follows:

$$\begin{aligned}\bar{\Theta}_t^i &= \left(I-K_t^iC_t^i\right)\bar{\Sigma}_t^i\left(I-K_t^iC_t^i\right)^T\\&+K_t^i\left(\hat{C}_t^i-C_t^i\right)\left(P_t-\bar{\Sigma}_t^i\right)\left(K_t^i\left(\hat{C}_t^i-C_t^i\right)\right)^T\\&+\alpha_t^{-1}K_t^i\mathcal{H}_t^i\left(K_t^i\mathcal{H}_t^i\right)^T+K_t^iG_t^iR_t\left(K_t^iG_t^i\right)^T\\&+K_t^iB_t^iE\left(w_tw_t^T\right)\left(K_t^iB_t^i\right)^T\\&+\left(\bar{\Sigma}_t^i+K_t^i\left(\hat{C}_t^i\left(P_t-\bar{\Sigma}_t^i\right)-C_t^iP_t\right)\right)\\&\times\left(E_t^i\right)^T\left(\tilde{M}_t^i\right)^{-1}E_t^i\\&\times\left(\bar{\Sigma}_t^i+K_t^i\left(\hat{C}_t^i\left(P_t-\bar{\Sigma}_t^i\right)-C_t^iP_t\right)\right)^T,\end{aligned}\tag{D.6}$$

and

$$\begin{aligned}\bar{\Sigma}_{t+1}^i &= \left(A_t-L_t^iC_t^i\right)\bar{\Sigma}_t^i\left(A_t-L_t^iC_t^i\right)^T\\&+\left(A_t-\hat{A}_t^i+L_t^i\left(\hat{C}_t^i-C_t^i\right)\right)\\&\times\left(P_t-\bar{\Sigma}_t^i\right)\left(A_t-\hat{A}_t^i+L_t^i\left(\hat{C}_t^i-C_t^i\right)\right)^T\\&+\alpha_t^{-1}\left(\mathcal{F}_t-L_t^i\mathcal{H}_t^i\right)\left(\mathcal{F}_t-L_t^i\mathcal{H}_t^i\right)^T\\&+\sum_{\vartheta=1}^{\hbar}A_\vartheta P_t\left(A_\vartheta^T\right)\theta_{\vartheta,t}\\&+\left(\left(A_t-L_t^iC_t^i\right)\bar{\Sigma}_t^i\right.\\&\quad\left.+\left(A_t-\hat{A}_t^i+L_t^i\left(\hat{C}_t^i-C_t^i\right)\right)\left(P_t-\bar{\Sigma}_t^i\right)\right)\\&\times\left(E_t^i\right)^T\left(\tilde{M}_t^i\right)^{-1}E_t^i\\&\times\left(\left(A_t-L_t^iC_t^i\right)\bar{\Sigma}_t^i\right.\\&\quad\left.+\left(A_t-\hat{A}_t^i+L_t^i\left(\hat{C}_t^i-C_t^i\right)\right)\left(P_t-\bar{\Sigma}_t^i\right)\right)^T\\&+\left(B_t-L_t^iB_t^i\right)E\left(w_tw_t^T\right)\left(B_t-L_t^iB_t^i\right)^T\\&+\left(G_t-L_t^iG_t^i\right)R_t\left(G_t-L_t^iG_t^i\right)^T.\end{aligned}\tag{D.7}$$

in which $\tilde{M}_t^i=\alpha_t^{-1}I-E_t^iP_t\left(E_t^i\right)^T$.

According to the above derivation, introducing filter parameters $\hat{C}_t^i$, K_t^i, $\hat{A}_t^i$ and L_t^i derived from Eqs.(45)-(48), and they are substituted into the upper bounds $\bar{\Theta}_t^i$ and $\bar{\Sigma}_{t+1}^i$ from Eqs.(D.6) and (D.7), respectively. Therefore, the error covariance matrices $\bar{\Theta}_t^i$ and $\bar{\Sigma}_{t+1}^i$ are rewritten as:

$$\bar{\Theta}_t^i=\bar{\Sigma}_t^i+\bar{\Sigma}_t^i\left(E_t^i\right)^T\left(\tilde{M}_t^i\right)^{-1}E_t^i\bar{\Sigma}_t^i-\Lambda_t^i\left(\Xi_t^i\right)^{-1}\left(\Lambda_t^i\right)^T,\tag{D.8}$$

and

$$\bar{\Sigma}_{t+1}^i=\tilde{\Delta}_t^i-L_t^i\tilde{\nabla}_t^i,\tag{D.9}$$

where

$$\Lambda_t^i=\left(I+\bar{\Sigma}_t^i\left(E_t^i\right)^T\left(M_t^i\right)^{-1}E_t^i\right)\bar{\Sigma}_t^i\left(C_t^i\right)^T,$$

$$\begin{aligned}\Xi_t^i &= C_t^i\bar{\Sigma}_t^i\left(I+\left(E_t^i\right)^T\left(M_t^i\right)^{-1}E_t^i\bar{\Sigma}_t^i\right)\left(C_t^i\right)^T\\&+\alpha_t^{-1}\mathcal{H}_t^i\left(\mathcal{H}_t^i\right)^T+B_t^iE\left(w_tw_t^T\right)\left(B_t^i\right)^T+G_t^iR_t\left(G_t^i\right)^T,\end{aligned}$$

$$\begin{aligned}\tilde{\Delta}_t^i &= A_t\left(I+\bar{\Sigma}_t^i\left(E_t^i\right)^T\left(M_t^i\right)^{-1}E_t^i\right)\bar{\Sigma}_t^iA_t^T+\alpha_t^{-1}\mathcal{F}_t\mathcal{F}_t^T\\&+B_tE\left(w_tw_t^T\right)B_t^T+G_tR_tG_t^T+\sum_{\vartheta=1}^{\hbar}A_\vartheta P_t\left(A_\vartheta^T\right)\theta_{\vartheta,t},\end{aligned}$$

and

$$\begin{aligned}\tilde{\nabla}_t^i &= C_t^i\left(I+\bar{\Sigma}_t^i\left(E_t^i\right)^T\left(M_t^i\right)^{-1}E_t^i\right)\bar{\Sigma}_t^iA_t^T\\&+\alpha_t^{-1}\mathcal{H}_t^i\mathcal{F}_t^T+B_t^iE\left(w_tw_t^T\right)B_t^T+G_t^iR_tG_t^T.\end{aligned}$$

Subsequently, the covariance for the state with time-varying parametric uncertainty is denoted as follows:

$$\begin{aligned}\tilde{P}_{t+1}&=E\left(x_{t+1}x_{t+1}^T\right)\\&=\left(A_t+\mathcal{F}_tF_tE_t\right)\tilde{P}_t\left(A_t+\mathcal{F}_tF_tE_t\right)^T\\&+\theta_{\vartheta,k}\sum_{\vartheta=1}^{\hbar}A_\vartheta\tilde{P}_tA_\vartheta^T\\&+B_tE\left(w_tw_t^T\right)B_t^T+G_tR_tG_t^T.\end{aligned}\tag{D.10}$$

Afterwards, the upper bound for the covariance matrix of the state is obtained from

$$\begin{aligned}\tilde{P}_{t+1}&\leqslant A_t\left(P_t^{-1}-\alpha_tE_t^TE_t\right)^{-1}A_t^T\\&+\alpha_t^{-1}\mathcal{F}_t\mathcal{F}_t^T+\theta_{\vartheta,k}\sum_{\vartheta=1}^{\hbar}A_\vartheta P_tA_\vartheta^T\\&+B_tE\left(w_tw_t^T\right)B_t^T+G_tR_tG_t^T\\&=P_{t+1}\end{aligned}\tag{D.11}$$

with the initial value $P_0=x_0x_0^T+P_0$, which is similarly calculated using the method reported in [14].

Appendix E
Shown and described for the figures and tables of the numerical simulation.

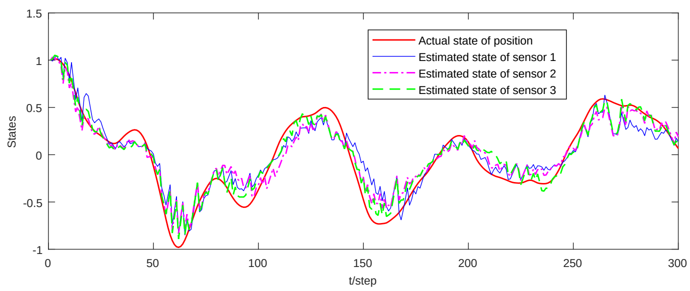
This section shows and describes the distributed estimation results using the logic ZOH presented in Section 5.

The range of the performance indicator is presented in Table E.1.

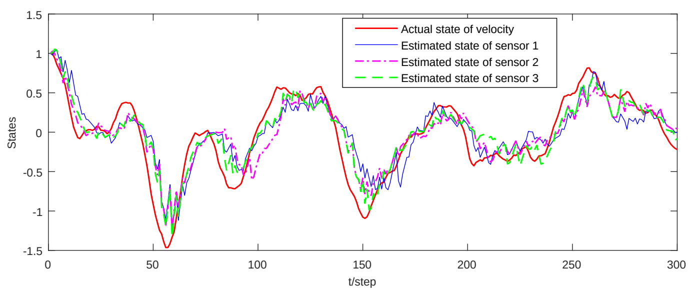
Table E.1 Comparison of the upper and lower bounds for error covariance

Method	Position	Velocity	Acceleration	Trace
RFHDFE 1	0.0096-0.0150	0.0016-0.0100	0.0100-0.0372	0.0300-0.0533
RFHDFE 2	0.0056-0.0100	0.0033-0.0100	0.0100-0.1258	0.0291-0.1313
RFHDFE 3	0.0084-0.0109	0.0004-0.0100	0.0100-0.0823	0.0279-0.0883
IRFHKF	0.0100-0.0267	0.0100-0.0235	0.0100-0.1779	0.0300-0.2280

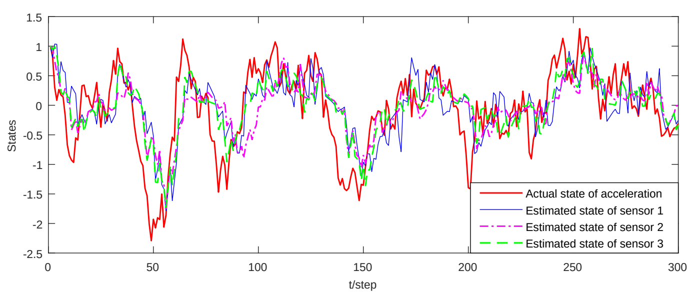
The distributed estimation results for the estimated states are shown in Figs. E.1 (a)-(c), which are obtained from Eqs. (17) and (18), as well as the filter parameters given in Theorems 3. Meanwhile, for the established system model using logic ZOH, the linear compensation method for the packet dropouts, and the weighted fusion criteria obtained from the local estimation are investigated. Based on the preceding discussion, the proposed RFHDFE approach possesses the advantage of the better system performance for target tracking and computational efficiency than the state with packet disorders and one-step prediction estimation schemes.



(a) State estimation for position



(b) State estimation for velocity



(c) State estimation for acceleration

Fig. E.1. Distributed estimation results using RFHDFE.