Copyright © 2021 Elsevier Ltd. All rights reserved. This is the accepted manuscript version of an article which has been published in final form at https://doi.org/10.1016/j.inffus.2021.12.005, archived on this repository under a Creative Commons CC BY-NC-ND attribution licence.

Multi-Sensor Multi-Rate Fusion Estimation for Networked Systems: Advances and Perspectives

Yuxuan Shen, Zidong Wang, Hongli Dong and Hongjian Liu

***Abstract*—In industrial systems, the multi-rate sampling strategy has been widely used due to the advantage in balancing cost and performance as well as the psychical characteristics of the hardware. Accordingly, the analysis and synthesis problems of the multi-rate systems (MRSs) have received considerable research attentions owing to the significant engineering background. Among others, the state estimation problem, aims to estimate the system state based on the contaminated measurement signals, is one of the most important topics in the area of signal processing. In the past decades, plenty of research results have been obtained on the state estimation problems for MRSs. The intent of this survey is to provide a timely and systematic review with respect to the available state estimation algorithms for networked MRSs and the corresponding fusion methods. First, a general state-space model of the MRSs is given and the methods that transform the MRSs into single-rate ones are introduced. Then, the recent advances on the state estimation as well as fusion estimation problems for MRSs are discussed based on the performance indices used. Finally, some future research topics are given in the MRS state estimation problems.**

***Index Terms*—Multi-rate systems, networked systems, H_∞ state estimation, Kalman filtering, multi-sensor information fusion.**

I. Introduction

With the rapid development of the wireless communication technology and the digital technology, the networked systems have been widely applied in the practical applications such as process monitoring, power grids, industrial control systems, traffic systems, and etc [24], [30], [45], [86], [107], [118], [126]. In the networked systems, the signals generated by the system components, including the sensors, the underlying plant, and the controllers, are first sampled and then transmitted through the communication networks. Compared to the traditional systems, the networked systems provide the advantages of low cost, easy maintenance, and high reliability. Nevertheless, the introduction of the communication network largely increases the complexity of the networked systems, and hence brings major challenges to the state estimation of the networked systems. Consequently, the problem of state estimation for networked systems has been attracting ever-increasing research interest [5], [15], [40], [78], [141], [142].

Due to the large scale, it is often the case that the networked system contains numerous spatially distributed system components (including multiple sensors). As mentioned before, the continuous signals from the system components are first sampled into discrete signals with fixed sampling periods before being transmitted. Traditionally, to simplify the design of the state estimation algorithms, it is assumed that a unified sampling period is chosen for different signals [20], [70], [94], [95], [117]. Unfortunately, such an assumption is not realistic in real practice. Since different system components own different physical characteristics, it is quite difficult (if not impossible) to unify the sampling periods for different components. Furthermore, setting different sampling periods for different system components (i.e., multi-rate sampling) according to the importance of their signals is preferable in engineering practice [4], [88], [98], [99]. As such, the state estimation problems for networked multi-rate systems (MRSs), which reflect the real situation in the practical engineering, have stirred attentions form researchers.

In the state estimation problems for MRSs, due to the existence of the multiple time sequences, it is quite difficult to directly design state estimators for the considered MRSs. In other words, the state estimation methods developed for single-rate systems (SRSs) can not be directly applied to MRSs. Therefore, much research effort has been devoted to solving state estimation problems for MRSs [1], [17], [19], [73], [97], [100], [106], [108], [116], [145]. In literature, a widely accepted way to deal with the state estimation problems for MRSs is that we first transmit the MRSs into equivalent SRSs, and then design state estimators for the equivalent SRSs by using the renowned state estimation methods such as the H_∞ estimation method, the Kalman filtering method, and the set-membership filtering method. Once the estimate of the state of the transmitted SRSs is obtained, the estimate of the state of the MRSs can be easily obtained by some simple matrix operations.

The multiple sensors in the networked systems provide complementary or redundant information about the plant of interest. To achieve an accurate estimation performance, it is suggested to utilize the multi-sensor information fusion methods to fuse the information from the multiple sensors.

This work was supported in part by the National Natural Science Foundation of China under Grants 62103095, 61873058, 61873148 and 61933007, the AHPU Youth Top-notch Talent Support Program of China under Grant 2018BJRC009, the Natural Science Foundation of Anhui Province of China under Grant 2108085MA07, the Royal Society of the UK, and the Alexander von Humboldt Foundation of Germany. (*Corresponding author: Hongjian Liu*)

Y. Shen and H. Dong are with the Artificial Intelligence Energy Research Institute, Northeast Petroleum University, Daqing 163318, China, and is also with the Heilongjiang Provincial Key Laboratory of Networking and Intelligent Control, Northeast Petroleum University, Daqing 163318, China. (Emails: shenyuxuan5973@163.com; shiningdhl@vip.126.com)

Z. Wang is with the Department of Computer Science, Brunel University London, Uxbridge, Middlesex, UB8 3PH, United Kingdom. (Email: Zidong.Wang@brunel.ac.uk)

H. Liu is with the Key Laboratory of Advanced Perception and Intelligent Control of High-end Equipment, Ministry of Education, Anhui Polytechnic University, Wuhu 241000, China, and is also with the School of Mathematics and Physics, Anhui Polytechnic University, Wuhu 241000, China. (Email: hjliu1980@gmail.com)

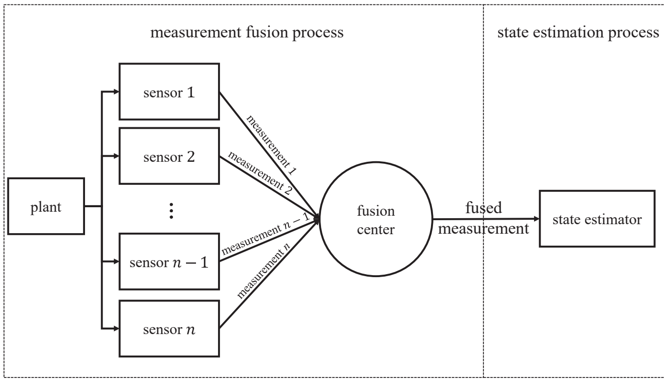

Fig. 1: The architecture of the centralized fusion process

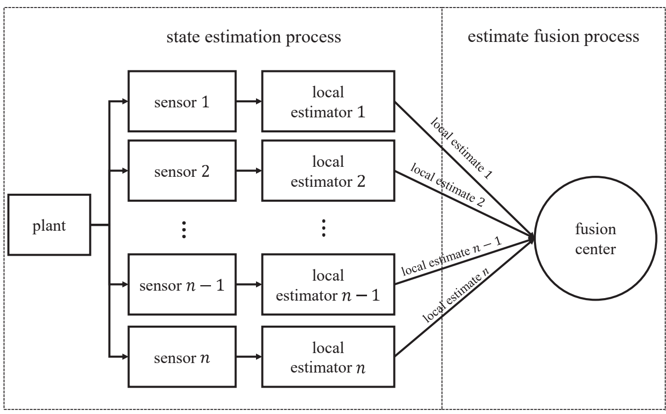

Fig. 2: The architecture of the distributed fusion process

In general, the multi-sensor information fusion methods can be categorized into two types: the centralized fusion methods and the distributed fusion methods [6], [7], [23], [72], [114]. In the centralized fusion methods, the measurements from the multiple sensors are transmitted to a fusion center where the measurements are fused to a new measurement. Then, the system state is estimated based on the obtained new measurement. In the distributed fusion methods, each local estimator first gives a local estimate based on its measurement and then transmits the estimate to a fusion center where the local estimates are fused to an optimal/suboptimal global estimate. The architectures of the centralized fusion process and the distributed fusion process are shown in Fig. 1 and Fig. 2, respectively.

On the other hand, due to the limited communication resources of the communication networks, some network-induced phenomena arise inevitably in the networked systems. Such network-induced challenges include, but are not limited to, the missing measurements, the communication delays, the channel fading, and the packet disorders. If not properly handled, these network-induced phenomena would deteriorate the estimation performance in the state estimation of the networked systems. Therefore, it is of great importance to find effective solutions to handle the above mentioned network-induced problems. Up to now, plenty of results have been obtained for state estimation problems for networked systems under network-induced phenomena, see [46], [85], [101], [124] for missing measurements, see [14], [60], [111], [125] for communication delays, see [35], [38], [77], [136] for channel fading, and see [18], [21], [75] for packet disorders.

Generally speaking, in the existing literature, there are mainly two ways to deal with the network-induced challenges in the state estimation problems. The first one is to passively design state estimation algorithms that are robust to the network-induced phenomena. That is, with the existence of the network-induced phenomena, designing state estimation algorithms such that the desired performance requirement is achieved, see for examples [13], [53], [66], [110]. The other way is to actively introduce communication protocols into the communication networks to alleviate/aviod the network-induced phenomena, and then develop state estimation algorithms whilst considering the influence of the introduced communication protocols. Some of the widely used communication protocols are the static event-triggered protocol [115], [122], [123], [154], the dynamic event-triggered protocol [8], [90], [138], [149], the self-triggered protocol [127], [128], the Round-Robin protocol [104], [156], the weighted Try-Once-Discard protocol [54], [148], and the random access protocol [25], [58], [147], [155].

In this paper, we aim to provide a systematic review of the existing results on the state estimation problems for networked MRSs and the applied multi-sensor information fusion methods. The remainder of this paper is outlined as follows. In Section II, a general state-space model of the MRSs is presented and various methods that transform the MRSs into SRSs are surveyed. In Section III, research results are discussed on the state estimation problems for MRSs where the methods in Section II are used to transmit the MRSs. Moreover, the multi-sensor information fusion methods applied are also reviewed. Section IV provides the conclusion and the future research topics.

II. Multi-rate systems

In this section, we first introduce a general state-space model of the discrete-time MRSs. Then, some effective methods that transform the MRSs into SRSs are presented. Moreover, the corresponding estimators are designed for the transformed SRSs.

A. State-space model of the MRSs

Consider a discrete-time multi-sensor MRS described as follows:

$$\begin{cases} x(s_{k+1}) = A(s_k)x(s_k) + B(s_k)w(s_k), \\ y_i(t_k^i) = C_i(t_k^i)x(t_k^i) + D_i(t_k^i)v_i(t_k^i) \end{cases} \tag{1}$$

where $x(s_k) \in \mathbb{R}^{n_x}$ and $y_i(t_k^i) \in \mathbb{R}^{n_y}$ $(i \in [1, N])$ are the system state and the measurement output from the i-th sensor, respectively. $w(s_k)$ and $v_i(t_k^i)$ are the process noise and the measurement noise on the i-th sensor, respectively. $A(s_k)$, $B(s_k)$, $C_i(t_k^i)$, and $D_i(t_k^i)$ are constant matrices with compatible dimensions.

The state update period of the system (1) is $h \triangleq s_{k+1} - s_k$ and the sampling period of the i-th sensor is $b_i h \triangleq t_{k+1}^i - t_k^i$

where $b_i \geq 1$ $(i \in [1, N])$ are allowed to be different. That is, in the MRS (1), the state update period of the system is allowed to be different with the sampling period of the sensor, while the sampling periods of different sensors are also allowed to be different. An illustration of the multi-rate sampling scheme is given in Fig. 3. Moreover, the MRS (1) can be seen as a combination of N multi-rate subsystems where the i-th subsystem consists of the state equation and the measurement equation of the i-th sensor.

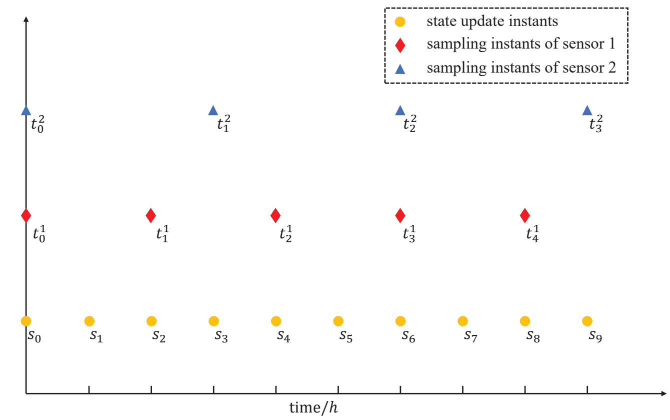

Fig. 3: An illustration of the multi-rate sampling scheme with $b_1 = 2$ and $b_2 = 3$

B. Transformation from MRSs to SRSs

After presenting the state-space model of the MRSs, in this subsection, we are going to introduce some effective methods that convert the MRSs into single-rate ones.

1) Using the lifting technique: The lifting technique proposed in [87] is one of the popular methods that are used to transform the MRSs. The main idea of the lifting technique is to obtain equivalent SRSs by increasing the state update period. Taking the i-th multi-rate subsystem of (1) as an example, the states $x(t_{k-1}^i + h), \ldots, x(t_k^i - h), x(t_k^i)$ in the interval $(t_{k-1}^i, t_k^i]$ are first augmented into a vector $\bar{x}_i(t_k^i)$. Then, a new state equation with the state update period $b_i h$ is obtained by the aid of the original state equation. Accordingly, the MRSs are transformed into SRSs. In the following, the detailed process is presented.

Denote $\bar{x}_i(t_k^i) \triangleq \mathrm{col}\{x(t_{k-1}^i + h), \ldots, x(t_k^i - h), x(t_k^i)\}$. By recurring to (1), it is derived that

$$x(t_k^i + mh) = \tilde{A}_m^i(t_k^i)x(t_k^i) + \tilde{B}_m^i(t_k^i)\tilde{w}_i(t_k^i)$$

where

$$\begin{aligned}
&\tilde{A}_m^i(t_k^i) \triangleq \prod_{l=1}^{m} A(t_k^i + (m-l)h), \ \tilde{B}_m^i(t_k^i) \triangleq \tilde{F}_m^i(t_k^i)\breve{B}_i(t_k^i), \\
&\tilde{F}_m^i(t_k^i) \triangleq \begin{bmatrix} \tilde{A}_{m-1}^i(t_k^i) & \tilde{A}_{m-2}^i(t_k^i) & \cdots & A_1^i(t_k^i) & 0 & \cdots & 0 \end{bmatrix}, \\
&\breve{B}_i(t_k^i) \triangleq \mathrm{diag}\{B(t_k^i), B(t_k^i + h), \cdots, B(t_{k+1}^i - h)\}, \\
&\tilde{w}_i(t_k^i) \triangleq \mathrm{col}\{w(t_k^i), w(t_k^i + h), \ldots, w(t_{k+1}^i - h)\}.
\end{aligned}$$

Then, it is obtained that

$$\begin{cases} \bar{x}_i(t_{k+1}^i) = \bar{A}_i(t_k^i)\bar{x}_i(t_k^i) + \bar{B}_i(t_k^i)\tilde{w}_i(t_k^i), \\ y_i(t_k^i) = \bar{C}_i(t_k^i)\bar{x}_i(t_k^i) + D_i(t_k^i)v_i(t_k^i) \end{cases} \tag{2}$$

where

$$\begin{aligned}
&\bar{A}_i(t_k^i) \triangleq \begin{bmatrix} 0 & \cdots & 0 & \tilde{A}_1^i(t_k^i) \\ 0 & \cdots & 0 & \tilde{A}_2^i(t_k^i) \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & \tilde{A}_{b_i}^i(t_k^i) \end{bmatrix}, \\
&\bar{B}_i(t_k^i) \triangleq \mathrm{col}\{\tilde{B}_1^i(t_k^i), \tilde{B}_2^i(t_k^i), \cdots, \tilde{B}_{b_i}^i(t_k^i)\}, \\
&\bar{C}_i(t_k^i) \triangleq \begin{bmatrix} 0 & \cdots & 0 & C_i(t_k^i) \end{bmatrix}.
\end{aligned}$$

Following the similar process, the MRS (1) is transformed into N SRSs with uniform periods $b_i h$ $(i = 1, 2, \ldots, N)$. For the i-th SRS, the i-th local estimator is designed as

$$\hat{x}_i(t_{k+1}^i) = \bar{A}_i(t_k^i)\hat{x}_i(t_k^i) + K_i(t_k^i)(y_i(t_k^i) - \bar{C}_i(t_k^i)\hat{x}_i(t_k^i))$$

where $\hat{x}_i(t_k^i)$ is the estimate of $\bar{x}_i(t_k^i)$ and $K_i(t_k^i)$ is the estimator gain to be designed.

From the above process, we can see that the lifting technique is able to transform the linear MRSs to equivalent linear SRSs. Nevertheless, due to the augmentation of the states, the designed estimation algorithm will have a high computational cost. On the other hand, when applying the lifting technique to the nonlinear MRSs, the transformation will be complicated due to the iteration of the nonlinear function.

2) Iterating the state equation: By simply iterating the state equation in (1), we have the following new state equation with a state update period $b_i h$:

$$x(t_{k+1}^i) = \tilde{A}_{b_i}^i(t_k^i)x(t_k^i) + \tilde{B}_{b_i}^i(t_k^i)\tilde{w}_i(t_k^i).$$

Accordingly, we have the following SRS:

$$\begin{cases} x(t_{k+1}^i) = \tilde{A}_{b_i}^i(t_k^i)x(t_k^i) + \tilde{B}_{b_i}^i(t_k^i)\tilde{w}_i(t_k^i), \\ y_i(t_k^i) = C_i(t_k^i)x_i(t_k^i) + D_i(t_k^i)v_i(t_k^i). \end{cases} \tag{3}$$

For the SRS (3), the i-th local estimator is designed as

$$\hat{x}_i(t_{k+1}^i) = \tilde{A}_{b_i}^i(t_k^i)\hat{x}_i(t_k^i) + K_i(t_k^i)(y_i(t_k^i) - C_i(t_k^i)\hat{x}_i(t_k^i))$$

where $\hat{x}_i(t_k^i)$ is the estimate of $x(t_k^i)$ and $K_i(t_k^i)$ is the estimator gain to be designed.

By iterating the state equation, the i-th multi-rate subsystem of (1) is transformed into the SRS (3). Compared to the SRS (2) obtained by using the lifting technique, the computational cost of the estimation algorithm designed for the SRS (3) is low. Nevertheless, the designed estimation algorithm only estimates the states at the measurement sampling instants (i.e., t_k^i $(k = 0, 1, 2, \ldots)$) and other states are not estimated.

3) Compensating measurements with zero: In the above two approaches, the MRSs are transformed into SRSs by increasing the state update period of the state equation. Intuitively, we can also complete the transformation by decreasing the sampling period of the measurement equation. A method to achieve this goal is compensating the measurements at non-sampling instants with zero.

By introducing a variable

$$\lambda_i(s_k) = \begin{cases} 1, & \text{if } \mathrm{mod}(s_k, b_i h) = 0; \\ 0, & \text{otherwise} \end{cases}$$

with $\mathrm{mod}(x, y)$ being the unique nonnegative remainder on division of x by y, the compensated measurement is formulated as

$$y_i(s_k) = \lambda_i(s_k)C_i(s_k)x(s_k) + \lambda_i(s_k)D_i(s_k)v_i(s_k).$$

Then, a SRS is derived as follows:

$$\begin{cases} x(s_{k+1}) = A(s_k)x(s_k) + B(s_k)w(s_k), \\ y_i(s_k) = \lambda_i(s_k)C_i(s_k)x(s_k) + \lambda_i(s_k)D_i(s_k)v_i(s_k). \end{cases} \quad (4)$$

For the SRS (4), the i-th local estimator is designed as

$$\begin{aligned} \hat{x}_i(s_{k+1}) =& A(s_k)\hat{x}_i(s_k) \\ &+ K_i(s_k)(y_i(s_k) - \lambda_i(s_k)C_i(s_k)\hat{x}_i(s_k)) \end{aligned}$$

where $\hat{x}_i(s_k)$ is the estimate of $x(s_k)$ and $K_i(s_k)$ is the estimator gain to be designed.

The advantages of such an approach are that the computational cost is low and the designed estimation algorithm can estimate the state at all state update instants. Unfortunately, the estimation accuracy may be low since the estimate is obtained by prediction at non-measurement-sampling instants.

4) Compensating measurements with the zero-order holder: Suppose that a zero-order holder is used to compensate the measurements at the non-sampling instants. After the compensation, the measurement available is

$$\bar{y}_i(s_k) \triangleq y_i(t_m^i), \quad t_m^i \le s_k < t_{m+1}^i.$$

Inspired by the input delay approach which has been used to transform the discrete-time control input into delayed control input [29], we define a variable $\rho_{s_k}^i$ as follows:

$$\rho_{s_k}^i \triangleq s_k - t_m^i, \quad t_m^i \le s_k < t_{m+1}^i.$$

Noting that $t_m^i = s_k - (s_k - t_m^i) = s_k - \rho_{s_k}^i$ holds for $t_m^i \le s_k < t_{m+1}^i$, the measurement $\bar{y}_i(s_k)$ is reformulated as

$$\begin{aligned} \bar{y}_i(s_k) &= y_i(s_k - \rho_{s_k}^i) \\ &= C_i(s_k - \rho_{s_k}^i)x(s_k - \rho_{s_k}^i) \\ &\quad + D_i(s_k - \rho_{s_k}^i)v_i(s_k - \rho_{s_k}^i). \end{aligned}$$

Therefore, the i-th multi-rate subsystem of (1) is transformed into a SRS

$$\begin{cases} x(s_{k+1}) = A(s_k)x(s_k) + B(s_k)w(s_k), \\ \bar{y}_i(s_k) = C_i(s_k - \rho_{s_k}^i)x(s_k - \rho_{s_k}^i) \\ \qquad\qquad + D_i(s_k - \rho_{s_k}^i)v_i(s_k - \rho_{s_k}^i). \end{cases} \quad (5)$$

For the SRS (5), the i-th local estimator is designed as

$$\begin{aligned} \hat{x}_i(s_{k+1}) =& A(s_k)\hat{x}_i(s_k) \\ &+ K_i(s_k)(\bar{y}_i(s_k) - C_i(s_k - \rho_{s_k}^i)\hat{x}(s_k - \rho_{s_k}^i)) \end{aligned}$$

where $\hat{x}_i(s_k)$ is the estimate of $x(s_k)$ and $K_i(s_k)$ is the estimator gain to be designed.

Remark 1: In this section, for simplification of the formulas, we only consider the case that the system state update period and the sampling period are different. Note that, the transformation methods provided in this section can be easily extended to the case where the system state update period, the sampling period and the estimate update period are mutually different.

III. Estimation problems for multi-rate systems

Due to the practical engineering significance of the multi-rate sampling, the state estimation problem for MRSs has become an active research topic. Up to now, a number of estimation approaches have been applied on MRS state estimation problems. According to the performance indices used, the applied estimation approaches can be categorized into the H_∞ estimation approach [49], [50], [62], [63], [82], the Kalman filtering approach and its variants [43], [121], [133], the set-membership filtering approach [12], [76], [151], the moving horizon estimation approach [134] and etc. On the other hand, in the state estimation problems for MRSs, the multi-sensor information fusion methods are widely used that include the weighted by matrix fusion method, the weighted by scalar fusion method, the covariance intersection fusion method, the sequential covariance intersection fusion method and so on [7], [31], [37], [81], [113]. The weighted by matrix fusion method and the weighted by scalar fusion method can obtain the optimal fused estimate but need the cross-covariances among local estimation errors. The covariance intersection fusion method and the sequential covariance intersection fusion method can avoid the calculation of the cross-covariances but can not obtain optimal fused estimate.

In the following, the available results on state estimation problems for MRSs are reviewed and the corresponding fusion methods are also discussed.

A. H_∞ estimation approach

In the past few decades, the H_∞ estimation approach has received particular research interest since it is able to attenuate the influence of the energy-bounded external disturbances on the estimation performance. The core idea of the H_∞ estimation is to design an estimator such that a predefined disturbance attenuation level (i.e. the H_∞ performance index) is achieved. Based on the methods like the linear matrix inequality, the Hamilton-Jacobi inequality as well as the Riccati equation, the H_∞ state estimation problems have been concerned for various systems [41], [61].

In the MRS state estimation problems, the H_∞ estimation approach has been widely used and a large body of literature has been available [28], [71], [79], [105], [109], [120]. In [105], the H_2 and H_∞ filtering problems have been studied for multi-rate linear time-invariant systems with a state update period h and a sampling period nh. First, a standard filter with a periodic filter gain and an update period h has been proposed to cater for the multi-rate sampling. Then, the state update period, the sampling period and the estimate update period have been uniformed by iterating the system state equation and the filter equation. Finally, the H_2 and H_∞ filters have been designed by solving certain linear matrix inequalities where nonconvex constraints have been introduced due to the multi-rate sampling. Subsequently, the authors of [105] has extended the results to multi-rate linear time-invariant systems with packet dropouts in [71] where the state update period, the sampling period as well as the estimate update period are different. A sufficient condition has been provided on the existence of a stable filter. In [109], the

H_∞ estimation problem has been concerned for multi-sensor multi-rate linear time-invariant systems where the estimate update period is integer multiple of the sampling period/state update period. The measurements of the sensors have been transmitted to a fusion centre in a competitive way. By fusing the measurements received in one estimate update period, the estimator in the fusion centre has estimated the system state. A sufficient condition has been obtained on the mean-square stability as well as the H_∞ performance and the H_∞ estimator has been characterized.

For time-varying MRSs, the quantized finite-horizon H_∞ filtering problem has been studied in [79] under the stochastic communication protocol. The lifting technique has been first applied to handle the MRSs, and then the desired H_∞ filter has been designed by solving certain Riccati different equations. Similar to [79], the variance-constrained finite-horizon H_∞ state estimation problem has been considered in [120] for time-varying MRSs. In [28], the sequential fusion H_∞ filtering problem has been investigated for time-varying MRSs where p asynchronous sensors are used to measure the system and send the measurements to a fusion center asynchronously. In the fusion center, the estimator updates the estimate once a measurement is received. With such a multi-rate sampling strategy, a sequential fusion H_∞ filter has been designed based on the Krein-space approach.

The fault detection problem is a long-standing research topic that has been widely studied [51], [55], [137], [150], [153]. In the MRSs, due to reasons like sensor aging, random sensor failure, or harsh environment, the fault may occur which largely degrades the system performance. Therefore, it is of great importance to design fault detection algorithm to detect the fault. Recently, the H_∞ fault detection problems for MRSs have received initial research interest. In [146], the H_∞ fault detection problem has been investigated for MRSs with asynchronous state update rate and sampling rate. By iterating the state equation, the equivalent SRSs have been derived, and then an observer-based fault detection filter has been designed. With the help of the linear matrix inequality method, sufficient conditions have been developed such that the H_∞ norm from the noises and faults to the fault estimation error is less that a given attenuation level. In [143], the intermittent fault detection problem has been concerned for a class of nonuniformly sampled MRSs. The nonuniform sampling interval is governed by a Markov process with partly unknown and uncertain transition probabilities. Due to the existence of the Markov process, the MRSs has been transformed into SRSs with Markovian jumping parameters. Sampling-interval-dependent fault detection filters have been designed such that the residual estimation error satisfies the H_- and H_∞ performances simultaneously.

B. Kalman filtering approach and its variants

The classic Kalman filtering approach is one of the most celebrated filtering approaches. For linear systems with Gaussian noises whose statistics are exactly known, the classic Kalman filtering is an optimal filtering approach under which the filtering error covariance is minimized at each time instant. Nevertheless, when applied to nonlinear systems or systems with non-Gaussian noises, the classic Kalman filtering is no longer applicable. Therefore, some modified Kalman filtering approaches have been developed that includes the extended Kalman approach [64], [119], the unscented Kalman approach [69], [112], the cubature Kalman approach [11], [57] and so on.

For state estimation problems concerning the MRSs, the classic Kalman filtering approach is another popular approach that has been widely studied [22], [33], [47], [56], [84], [129], [130]. In [129], the fusion estimation problem has been studied for multi-sensor systems by using the traditional Kalman filtering approach where the sampling periods of the sensors are asynchronous. By using the lifting technique, the multi-sensor MRS has been transformed into synchronous single-rate single-sensor systems. Local Kalman filters has been first designed to obtain the local estimates which have been then fused to a global estimate with the help of the fusion method in [9]. In [130], the problem in [129] has been reconsidered and a novel fusion estimation algorithm has been proposed which fuses the local estimates in a recursive form and is optimal in the linear minimum variance sense. In [47], the result in [129] has been extended to multi-sensor systems with arbitrary number of sensors and arbitrary sampling rates. Both the centralized asynchronous fusion estimation algorithm and the distributed asynchronous fusion estimation algorithm have been developed based on the Kalman filtering. It has been verified that the estimation performances of both fusion estimation algorithms are equivalent under the full-rate communication assumption, while the centralized one outperforms the distributed one when the communications are constrained. In [132], the federated Kalman filtering problem has been investigated for asynchronous multi-sensor MRSs with random missing measurements.

The Kalman fusion estimation algorithm has been developed in [140] for MRSs over the sensor networks. The system state update period, the measurement transmission period, and the estimate update period have been allowed to be different. The local Kalman filters have been first designed based on the SRSs derived by the lifting technique. Then, the local estimates have been fused with the weighted by matrix fusion method. Due to the asynchronism of the local estimates, at a certain time instant, only the available estimates have been fused. In [139], the hierarchical fusion estimation problem has been coped with for MRSs over sensor networks. The underlying sensor network consists of N sensor clusters and each sensor cluster contains multiple sensors and a cluster head. First, the estimator in the cluster head has generated a local estimate based on the fused measurement which has been obtained by fusing the available measurements from the sensors in this cluster with the sequential fusion method. Then, the cluster head has communicated with other cluster heads to generate the fused estimate. In the estimate fusion process, only the available local estimates have been used also due to the asynchronism of the local estimates. In [92], the Kalman fusion estimation problem has been also investigated for MRSs over sensor networks where the state update period and the sampling period are different. Different from [140], the estimates at the non-sampling instants have been obtained through prediction based on the state equation. Therefore, the estimates from all local estimators have been available in the estimation fusion process at each time instant. The distributed fusion estimation problem has been considered in [52] for multi-rate linear systems where the estimation process and the fusion process are similar to those in [140].

The fault detection problems for MRSs based on the Kalman filtering approach have received little research attentions. In [68], the Kalman filtering problem has been investigated for a class of non-uniformly sampled MRSs. After transforming the MRSs into SRSs with the lifting technique, a filter has been designed for the obtained SRSs and the stability as well as the convergence of the filtering error has been analyzed. Then, the fault detection and isolation problems have been concerned for the underlying non-uniformly sampled MRSs.

Other than the classic Kalman filtering approach, the modified Kalman filtering approaches have also been widely used in the state estimation problems for MRSs. In [34], the extended Kalman filtering problem has been discussed for nonlinear systems where the availability of the *primary* and the *secondary* measurements are asynchronous. Several methods that effective for the asynchronous measurements have been discussed and modified in the extended Kalman filtering framework. In [131], the state estimation problem has been dealt with for nonlinear multi-sensor MRSs by using the modified sigma point Kalman filtering approach. A modified unscented Kalman filter has been proposed in [27] for the multi-rate INS/GPS integrated navigation systems. The state estimation problem has been investigated in [39] for nonlinear systems with a normal measurement and an infrequent integral measurement. The systems have been first reformulated to equivalent variable dimension systems. Then, a variable dimension unscented Kalman filter has been designed. In [89], a joint-unscented Kalman filtering algorithm has been proposed for a continuous stirred-tank reactor system with asynchronous sensors.

C. Other estimation approaches

In the state estimation problems for MRSs, the moving horizon estimation approach, the particle filtering approach, the l_2-l_∞ filtering approach and the set-membership filtering approach have been taken into consideration either [2], [3], [26], [74], [83], [157]. In the moving horizon estimation, the estimate is generated by solving a predefined optimization problem based on the measurements in a moving time interval with fixed length. Due to its efficiency in handling nonlinear systems, the moving horizon estimation has received ever-increasing research interest in the past decade [36], [74], [157]. In [74], the state estimation problem has been solved for mobile robot systems with asynchronous sensors according to the moving horizon estimation. The sampling rates of the sensors have been uniformed by compensating the measurements from the slow-rate sensor with a prediction value. Then, a moving horizon estimation algorithm has been developed by solving a regularized least-squares problem. The moving horizon estimation problem has been concerned in [157] for linear systems with multi-rate measurements and correlated noises. By introducing a switching variable, the multi-rate measurements have been combined in a new measurement model. Based on the obtained SRSs, the desired moving horizon estimator has been designed.

The particle filtering approach, roots on the sampling-based approximation techniques, is an effective filtering approach for nonlinear systems or systems with non-Gaussian noises. In [42], both the particle filtering and extended Kalman filtering have been applied to an intensified chemical process subject to asynchronous measurements. The l_2-l_∞ filtering problem has been studied in [135] for MRSs. The lifting technique has been used to handle the MRSs and the l_2-l_∞ filter has been designed according to the solution of linear matrix inequalities with a nonconvex constraint. The set-membership filtering problem has been concerned in [80] for MRSs over sensor networks. A set of local filters have been designed such that the filtering errors have been constrained in a given ellipsoid. In [91], the zonotopes-based distributed set-membership filtering problem has been investigated for MRSs where the state estimates belong to the computed sets.

D. Handling the network-induced challenges

In the networked systems, due to the limited resources of the communication networks, the network-induced phenomena inevitably occur [44], [96]. Up to now, considerable research attentions have been paid on the state estimation problems for networked MRSs subject to network-induced phenomena and plenty of results have been available. In the following, some typical network-induced phenomena are introduced and the corresponding state estimation problems for networked MRSs are summarized.

The packet dropout is one of the most frequently occurred network-induced phenomena which may be caused by many reasons such as intermittent sensor failures, network congestion and so on. In [32], the linear-minimum-mean-square-error observer design problem has been considered for multi-sensor MRSs with multiple packet dropouts. The observer has been designed by minimizing the estimation error covariances. In [152], the almost surely state estimation problem has been studied for MRSs subject to both Markovian packet dropouts and random packet dropouts characterized by the bernoulli distributed random variables. An estimator has been designed such that the estimation error is almost surely exponentially stable. The non-fragile distributed H_∞ filtering problem has been concerned in [102] for MRSs with packet dropouts characterized by the Gilbert-Elliott model. A sufficient condition has been derived on the exponential stability and the H_∞ performance.

The signal quantization and saturation are two ubiquitous network-induced phenomena due to the inherent nature of the digital transmission and the physical constraints of the hardware, respectively [10], [16], [93]. In [144], the variance-constrained H_∞ state estimation problem has been studied for MRSs subject to measurement quantization. The quantization effect has been characterized by a logarithmic quantizer and transformed to sector-bounded uncertainties. The desired H_∞

filter has been designed by resorting to the stochastic analysis approach and the Lyapunov theory. In [59], the multi-objective filtering problem has been concerned for MRSs with random sensor saturations. The saturation function has been rewritten as a combination of a linear term and a nonlinear function satisfying the sector condition.

In the above results, the state estimation algorithms have been developed such that, with the existence of the network-induced phenomena, the estimation performance still satisfies given performance requirements. In another way, we can also introduce certain communication protocols to reduce the occurrence of the network-induced phenomena. In [48], the event-triggered protocol has been introduced in the fusion estimation problem for MRSs with sensor degradations. In [79], the stochastic communication protocol has been considered in H_∞ state estimation for MRSs. The round-robin protocol has been discussed in [104] and [80] where the recursive state estimation problem and the distributed set-membership filtering problem have been coped with for MRSs, respectively. The weighted try-once-discard protocol has been introduced in [103] for recursive filtering problem of MRSs.

IV. Conclusions and Future Work

In this survey, the state estimation approaches developed for MRSs and the corresponding multi-sensor information fusion methods have been discussed and reviewed. First, a general state-space model has been given to characterize the MRSs. The methods that transform the MRSs into SRSs have been summarized. Then, the recent advances on the fusion estimation problems for MRSs have been reviewed based on the applied estimation approach. According to the literature review, some future research topics are given as follows:

1) In the existing literature, the state estimation problems are mostly investigated for linear MRSs or nonlinear MRSs with strict assumption on the nonlinear function. It would be an interesting and challenging topic to investigate the state estimation problems for MRSs with general nonlinearities.
2) The complex networks can characterize plenty of real-world dynamical systems and have received consistent research interest in the past decades [65], [67]. Unfortunately, the studies on the state estimation problems for complex networks with multi-rate sampling strategy are quite few. Therefore, the state estimation problem for multi-rate complex networks will be an attractive area.
3) Other than the communication protocols discussed in this survey, there are also some effective communication protocols, e.g. the FlexRay protocol, introduced in the networked systems and the corresponding state estimation algorithms have been developed. Nevertheless, how to modify the existing results to make them applicable to MRSs or how to develop novel estimation algorithms suitable for MRSs with above-mentioned protocols remain open and challenging.
4) In the estimate fusion process, due to the asynchronism of the local estimates, only the estimates available at the current time instant are fused. As such, the valuable estimate information are not fully used which would lead to deterioration of the estimation accuracy. To this end, a trend for future research is to propose novel fusion strategies that make full use of the asynchronous estimates.
5) Another promising research topic is to study the fault detection, diagnosis, and isolation problems for MRSs. Although some initial results have been obtained, the corresponding theories for MRSs are far from mature. Hence, it is of great importance to develop fault detection, diagnosis, and isolation theories for MRSs.

References

[1] D. Andrisani and C.-F. Gau, Estimation using a multirate filter, *IEEE Transactions on Automatic Control*, vol. 32, no. 7, pp. 653–656, 1987.
[2] L. Armesto, J. Tornero and M. Vincze, On multi-rate fusion for non-linear sampled-data systems: Application to a 6D tracking system, *Robotics and Autonomous Systems*, vol. 56, no. 8, pp. 706–715, 2008.
[3] J. Bae, Y. Kim and J. M. Lee, Multirate moving horizon estimation combined with parameter subset selection, *Computers & Chemical Engineering*, vol. 147, art. no. 107253, 2021.
[4] T. Bonargent, T. Ménard, O. Gehan and E. Pigeon, Adaptive observer design for a class of Lipschitz nonlinear systems with multirate outputs and uncertainties: Application to attitude estimation with gyro bias, *International of Robust and Nonlinear Control*, vol. 31, no. 8, pp. 3137–3162, 2021.
[5] R. Caballero-Águila, A. Hermoso-Carazo and J. Linares-Pérez, Optimal state estimation for networked systems with random parameter matrices, correlated noises and delayed measurements, *International Journal of General Systems*, vol. 44, no. 2, pp. 142–154, 2015.
[6] R. Caballero-Águila, A. Hermoso-Carazo and J. Linares-Pérez, Fusion estimation using measured outputs with random parameter matrices subject to random delays and packet dropouts, *Signal Processing*, vol. 127, pp. 12–23, 2016.
[7] R. Caballero-Águila, A. Hermoso-Carazo and J. Linares-Pérez, Networked fusion estimation with multiple uncertainties and time-correlated channel noise, *Information Fusion*, vol. 54, pp. 161–171, 2020.
[8] Z. Cao, Y. Niu, H.-K. Lam and J. Zhao, Sliding mode control of Markovian jump fuzzy systems: A dynamic event-triggered method, *IEEE Transactions on Fuzzy Systems*, in press, doi:10.1109/TFUZZ.2020.3009729.
[9] N. A. Carlson, Federated square root filter for decentralized parallel processors, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 26, no. 3, pp. 517–525, 1990.
[10] L. Chen, Y. Chen and N. Zhang, Synchronization control for chaotic neural networks with mixed delays under input saturations, *Neural Processing Letters*, in press, doi: 10.1007/s11063-021-10577-9.
[11] Q. Chen, C. Yin, J. Zhou, Y. Wang, X. Wang and C. Chen, Hybrid consensus-based cubature Kalman filtering for distributed state estimation in sensor setworks, *IEEE Sensors Journal*, vol. 18, no. 11, pp. 4561–4569, 2018.
[12] S. Chen, L. Ma and Y. Ma, Distributed set-membership filtering for nonlinear systems subject to round-robin protocol and stochastic communication protocol over sensor networks, *Neurocomputing*, vol. 385, pp. 13–21, 2020.
[13] W. Chen, J. Hu, Z. Wu, X. Yu and D. Chen, Finite-time memory fault detection filter design for nonlinear discrete systems with deception attacks, *International Journal of Systems Science*, vol. 51, no. 8, pp. 1464–1481, 2020.
[14] Y. Chen, Z. Chen, Z. Chen and A. Xue, Observer-based passive control of non-homogeneous Markov jump systems with random communication delays, *International Journal of Systems Science*, vol. 51, no. 6, pp. 1133–1147, 2020.
[15] Y. Chen, J. Ren, X. Zhao and A. Xue, State estimation of Markov jump neural networks with random delays by redundant channels, *Neurocomputing*, vol. 453, pp. 493–501, 2021.
[16] Y. Chen, Z. Wang, B. Shen and Q.-L. Han, Local stabilization for multiple input-delay systems subject to saturating actuators: The continuous-time case, *IEEE Transactions on Automatic Control*, in press, doi:10.1109/TAC.2021.3092556.

[17] X. Chi, X. Jia, F. Cheng and M. Fan, Networked H_∞ filtering for Takagi-Sugeno fuzzy systems under multi-output multi-rate sampling, *Journal of the Franklin Institute*, vol. 356, no. 6, pp. 3661–3691, 2019.
[18] M. B. G. Cloosterman, L. Hetel, N. van de Wouw, W. P. M. H. Heemels, J. Daafouz and H. Nijmeijer, Controller synthesis for networked control systems, *Automatica*, vol. 46, no. 10, pp. 1584–1594, 2010.
[19] R. Cristi and M. Tummala, Multirate, multiresolution, recursive Kalman filter, *Signal Processing*, vol. 80, no. 9, pp. 1945–1958, 2000.
[20] Y. Cui, Y. Liu, W. Zhang and F. E. Alsaadi, Sampled-based consensus for nonlinear multiagent systems with deception attacks: The decoupled method, *IEEE Transactions on Systems, Man and Cybernetics: Systems*, vol. 51, no. 1, pp. 561–573, 2021.
[21] Y. Cui, L. Xu and Y. Shen, H_2/H_∞ filtering for networked systems with data transmission time-varying delay, data packet dropout and sequence disorder, *Journal of the Franklin Institute*, vol. 354, no. 13, pp. 5443–5462, 2017.
[22] N. Davari and A. Gholami, Variational Bayesian adaptive Kalman filter for asynchronous multirate multi-sensor integrated navigation system, *Ocean Engineering*, vol. 174, pp. 108–116, 2019.
[23] Z. Deng, P. Zhang, W. Qi, J. Liu and Y. Gao, Sequential covariance intersection fusion Kalman filter, *Information Sciences*, vol. 189, p-p. 293–309, 2012.
[24] D. Ding, Q.-L. Han, X. Ge and J. Wang, Secure state estimation and control of cyber-physical systems: A survey, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 1, pp. 176–190, 2021.
[25] Y. Dong, Y. Song and G. Wei, Efficient model-predictive control for networked interval type-2 T-S fuzzy system with stochastic communication protocol, *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 2, pp. 286–297, 2021.
[26] M. Elsheikh, R. Hille, A. T.-Codrean and S. Krämer, A comparative review of multi-rate moving horizon estimation schemes for bioprocess applications, *Computers & Chemical Engineering*, vol. 146, art. no. 107219, 2021.
[27] M. Enkhtur, S. Y. Cho and K.-H. Kim. Modified unscented Kalman filter for a multirate INS/GPS integrated navigation system, *ETRI Journal*, vol. 35, no. 5, pp. 943–946, 2013.
[28] X. Feng, C. Wen and J. H. Park, Sequential fusion H_∞ filtering for multi-rate multi-sensor time-varying systems–A Krein-space approach, *IET Control Theory & Applications*, vol. 11, no. 3, pp. 369–381, 2017.
[29] E. Fridman, A. Seuret and J.-P. Richard, Robust sampled-data stabilization of linear systems: An input delay approach, *Automatica*, vol. 40, no. 8, pp. 1441–1446, 2004.
[30] H. Geng, Y. Liang and Y. Cheng, Target state and Markovian jump ionospheric height bias estimation for OTHR tracking systems, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 50, no. 7, pp. 2599–2611, 2020.
[31] H. Geng, Y. Liang, Y. Liu and F. E. Alsaadi, Bias estimation for asynchronous multi-rate multi-sensor fusion with unknown inputs, *Information Fusion*, vol. 39, pp. 139–153, 2018.
[32] H. Geng, Y. Liang and X. Zhang, Linear-minimum-mean-square-error observer for multi-rate sensor fusion with missing measurements, *IET Control Theory & Applications*, vol. 8, no. 14, pp. 1375–1383, 2014.
[33] M. Ghosal and V. Rao, Fusion of multirate measurements for nonlinear dynamic state estimation of the power systems, *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 216–226, 2019.
[34] A. Gopalakrishnan, N. S. Kaisare and S. Narasimhan, Incorporating delayed and infrequent measurements in Extended Kalman Filter based nonlinear state estimation, *Journal of Process Control*, vol. 21, no. 1, pp. 119–129, 2011.
[35] X. Gu, T. Jia and Y. Niu, Consensus tracking for multi-agent systems subject to channel fading: A sliding mode control method, *International Journal of Systems Science*, vol. 51, no. 14, pp. 2703–2711, 2020.
[36] Y. Gu, Y. Chou, J. Liu and Y. Ji, Moving horizon estimation for multirate systems with time-varying time-delays, *Journal of the Franklin Institute*, vol. 356, no. 4, pp. 2325–2345, 2019.
[37] Q. Guan, G. Wei, L. Wang and Y. Song, A novel feature points tracking algorithm in terms of IMU-aided information fusion, *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5304–5313, 2021.
[38] X. Guan, J. Hu, J. Qi, D. Chen, F. Zhang and G. Yang, Observer-based H_∞ sliding mode control for networked systems subject to communication channel fading and randomly varying nonlinearities, *Neurocomputing*, vol. 437, pp. 312–324, 2021.
[39] Y. Guo and B. Huang, State estimation incorporating infrequent, delayed and integral measurements, *Automatica*, vol. 58, pp. 32–38, 2015.
[40] C. Han, H. Zhang and M. Fu, Optimal filtering for networked systems with Markovian communication delays, *Automatica*, vol. 49, no. 10, pp. 3097–3104, 2013.
[41] F. Han, Z. Wang, H. Dong and H. Liu, Partial-nodes-based scalable H_∞-consensus filtering with censored measurements over sensor networks, *IEEE Transactions on Systems, Man and Cybernetics: Systems*, vol. 51, no. 3, pp. 1892–1903, 2021.
[42] D. Haßkerl, M. Arshad, R. Hashemi, S. Subramanian and S. Engell, Simulation study of the particle filter and the EKF for state estimation of a large-scale DAE-system with multi-rate sampling, *IFAC-PapersOnLine*, vol. 49, no. 7, pp. 490–495, 2016.
[43] G. Hu, B. Gao, Y. Zhong and C. Gu, Unscented Kalman filter with process noise covariance estimation for vehicular ins/gps integration system, *Information Fusion*, vol. 64, pp. 194–204, 2020.
[44] J. Hu, G.-P. Liu, H. Zhang and H. Liu, On state estimation for nonlinear dynamical networks with random sensor delays and coupling strength under event-based communication mechanism, *Information Sciences*, vol. 511, pp. 265–283, 2020.
[45] J. Hu, H. Zhang, H. Liu and X. Yu, A survey on sliding mode control for networked control systems, *International Journal of Systems Science*, vol. 52, no. 6, pp. 1129–1147, 2021.
[46] J. Hu, H. Zhang, X. Yu, H. Liu and D. Chen, Design of sliding-mode-based control for nonlinear systems with mixed-delays and packet losses under uncertain missing probability, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 5, pp. 3217–3228, 2021.
[47] Y. Hu, Z. Duan and D. H. Zhou, Estimation fusion with general asynchronous multi-rate sensors, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 46, no. 4, pp. 2090–2102, 2010.
[48] C. Huang and B. Shen, Event-based fusion estimation for multi-rate systems subject to sensor degradations, *Journal of the Franklin Institute*, in press, doi:10.1016/j.jfranklin.2021.08.011.
[49] H. Huang, T. Huang and X. Chen, Guaranteed H_∞ performance state estimation of delayed static neural networks, *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 60, no. 6, pp. 371–375, 2013.
[50] H. Huang, T. Huang and X. Chen, Further result on guaranteed H_∞ performance state estimation of delayed static neural networks, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 6, pp. 1335–1341, 2014.
[51] K. Huang, S. Wu, F. Li, C. Yang and W. Gui, Fault diagnosis of hydraulic systems based on deep learning model with multirate data samples, *IEEE Transactions on Neural Networks and Learning Systems*, in press, doi:10.1109/TNNLS.2021.3083401.
[52] L. Jiang, L. P. Yan, Y. Q. Xia and M. Y. Fu, Optimal distributed fusion for state estimation in multirate wireless sensor networks, in *processdings of the 34th Chinese Control Conference*, Hangzhou, China, Jul. 28-30, 2015.
[53] Y. Ju, Y. Liu, X. He and B. Zhang, Finite-horizon H_∞ filtering and fault isolation for a class of time-varying systems with sensor saturation, *International Journal of Systems Science*, vol. 52, no. 2, pp. 321–333, 2021.
[54] Y. Ju, G. Wei, D. Ding and S. Liu, A novel fault detection method under weighted try-once-discard scheduling over sensor networks, *IEEE Transactions on Control of Network Systems*, vol. 7, no. 3, pp. 1489–1499, 2020.
[55] L. Ke, Y. Zhang, B. Yang, Z. Luo and Z. Liu, Fault diagnosis with synchrosqueezing transform and optimized deep convolutional neural network: An application in modular multilevel converters, *Neurocomputing*, vol. 430, pp. 24–33, 2021.
[56] M. Kordestani, M. Dehghani, B. Moshiri and M. Saif, A new fusion estimation method for multi-rate multi-sensor systems with missing measurements, *IEEE Access*, vol. 8, pp. 47522–47532, 2020.
[57] M. V. Kulikova and G. Y. Kulikov, SVD-based factored-form cubature Kalman filtering for continuous-time stochastic systems with discrete measurements, *Automatica*, vol. 120, art. no. 109110, 2020.
[58] D. Li, J. Liang, F. Wang and X. Ren, Observer-based H_∞ control of two-dimensional delayed networks under the random access protocol, *Neurocomputing*, vol. 401, pp. 353–363, 2020.
[59] H. Li, M. Lyu and B. Du, Event-based multi-objective filtering for multi-rate time-varying systems with random sensor saturation, *Kybernetika*, vol. 56, no. 1, pp. 81–106, 2020.
[60] J. Li, H. Dong, Z. Wang and X. Bu, Partial-neurons-based passivity-guaranteed state estimation for neural networks with randomly occurring time-delays, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 9, pp. 3747–3753, 2020.

[61] J. Li, G. Wei, D. Ding and E. Tian, Protocol-based H_∞ filtering for piecewise linear systems: A measurement-dependent equivalent reduction approach, *International Journal of Robust and Nonlinear Control*, vol. 31, no. 8, pp. 3163–3178, 2021.

[62] J.-Y. Li, B. Zhang, R. Lu and Y. Xu, Robust distributed H_∞ state estimation for stochastic periodic systems over constraint sensor networks, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 50, no. 11, pp. 4396–4407, 2020.

[63] J.-Y. Li, B. Zhang, R. Lu, Y. Xu and T. Huang, Distributed H_∞ state estimator design for time-delay periodic systems over scheduling sensor networks, *IEEE Transactions on Cybernetics*, vol. 51, no. 1, pp. 462–472, 2021.

[64] L. Li, T. Wang, Y. Xia and N. Zhou, Trajectory tracking control for wheeled mobile robots based on nonlinear disturbance observer with extended Kalman filter, *Journal of the Franklin Institute*, vol. 357, no. 13, pp. 8491–8507, 2020.

[65] N. Li, Q. Li and J. Suo, Dynamic event-triggered H_∞ state estimation for delayed complex networks with randomly occurring nonlinearities, *Neurocomputing*, vol. 421, pp. 97–104, 2021.

[66] Q. Li, J. Liang and H. Qu, H_∞ estimation for stochastic semi-Markovian switching CVNNs with missing measurements and mode-dependent delays, *Neural Networks*, vol. 141, pp. 281–293, 2021.

[67] Q. Li, Z. Wang, J. Hu and W. Sheng, Simultaneous state and unknown input estimation for complex networks with redundant channels under dynamic event-triggered mechanisms, *IEEE Transactions on Neural Networks and Learning Systems*, in press, doi:10.1109/TNNLS.2021.3070797.

[68] W. Li, S. L. Shah and D. Xiao, Kalman filters in non-uniformly sampled multirate systems: For FDI and beyond, *Automatica*, vol. 44, no. 1, pp. 199–208, 2008.

[69] W. Li, G. Wei, F. Han and Y. Liu, Weighted average consensus-based unscented Kalman filtering, *IEEE Transactions on Cybernetics*, vol. 46, no. 2, pp. 558–567, 2015.

[70] X. Li, F. Han, N. Hou, H. Dong and H. Liu, Set-membership filtering for piecewise linear systems with censored measurements under Round-Robin protocol, *International Journal of Systems Science*, vol. 51, no. 9, pp. 1578–1588, 2020.

[71] Y. Liang, T. Chen and Q. Pan, Multi-rate stochastic H_∞ filtering for networked multi-sensor fusion, *Automatica*, vol. 46, no. 2, pp. 437–444, 2010.

[72] H. Lin and S. Sun, Distributed fusion estimation for multi-sensor asynchronous sampling systems with correlated noises, *International Journal of Systems Science*, vol. 48, no. 5, pp. 952–960, 2017.

[73] H. Lin and S. Sun, An overview of multirate multisensor systems: Modelling and estimation, *Information Fusion*, vol. 52, pp. 335–343, 2019.

[74] A. Liu, W.-A. Zhang, M. Z. Q. Chen and L. Yu, Moving horizon estimation for mobile robots with multirate sampling, *IEEE Transactions on Industrial Electronics*, vol. 64, no. 2, pp. 1457–1467, 2017.

[75] D. Liu, Z. Wang, Y. Liu, F. E. Alsaadi and F. E. Alsaadi, Recursive state estimation for stochastic complex networks under Round-Robin communication protocol: Handling packet disorders, *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 3, pp. 2455–2468, 2021.

[76] L. Liu, L. Ma, J. Guo, J. Zhang and Y. Bo, Distributed set-membership filtering for time-varying systems: A coding-decoding-based approach, *Automatica*, vol. 129, art. no. 109684, 2021.

[77] L. Liu, L. Ma, J. Zhang and Y. Bo, Distributed non-fragile set-membership filtering for nonlinear systems under fading channels and bias injection attacks, *International Journal of Systems Science*, vol. 52, no. 6, pp. 1192–1205, 2021.

[78] Q. Liu, Z. Wang, J. Zhang and D. H. Zhou, Necessary and sufficient conditions for fault diagnosability of linear open- and closed-loop stochastic systems under sensor and actuator faults, *IEEE Transactions on Automatic Control*, in press, doi:10.1109/TAC.2021.3108587.

[79] S. Liu, Z. Wang, L. Wang and G. Wei, On quantized H_∞ filtering for multi-rate systems under stochastic communication protocols: The finite-horizon case, *Information Sciences*, vol. 459, pp. 211–223, 2018.

[80] S. Liu, Z. Wang, G. Wei and M. Li, Distributed set-membership filtering for multirate systems under the Round-Robin scheduling over sensor networks, *IEEE Transactions on Cybernetics*, vol. 50, no. 5, pp. 1910–1920, 2020.

[81] W.-Q. Liu, X.-M. Wang and Z.-L. Deng, Robust centralized and weighted measurement fusion Kalman estimators for uncertain multisensor systems with linearly correlated white noises, *Information Fusion*, vol. 35, pp. 11–25, 2017.

[82] Y. Liu, B. Shen and H. Shu, Finite-time resilient H_∞ state estimation for discrete-time delayed neural networks under dynamic event-triggered mechanism, *Neural Networks*, vol. 121, pp. 356–365, 2020.

[83] R. López-Negrete and L. T. Biegler, A moving horizon estimator for processes with multi-rate measurements: A nonlinear programming sensitivity approach, *Journal of Process Control*, vol. 22, no. 4, pp. 677–688, 2012.

[84] M. S. Mahmoud and M. F. Emzir, State estimation with asynchronous multi-rate multi-smart sensors, *Information Sciences*, vol. 196, pp. 15–27, 2012.

[85] J. Mao, D. Ding, Y. Song, Y. Liu and F. E. Alsaadi, Event-based recursive filtering for time-delayed stochastic nonlinear systems with missing measurements, *Signal Process*, vol. 134, pp. 158–165, 2017.

[86] J. Mao, Y. Sun, X. Yi, H. Liu and D. Ding, Recursive filtering of networked nonlinear systems: A survey, *International Journal of Systems Science*, vol. 52, no. 6, pp. 1110–1128, 2021.

[87] D. G. Meyer, A new class of shift-varying operators, their shift-invariant equivalents, and multirate digital systems, *IEEE Transactions on Automatic Control*, vol. 35, no. 4, pp. 429–433, 1990.

[88] M. Moarref and L. Rodrigues, Observer design for linear models of multi-rate asynchronous aerospace systems, *Aerospace Systems*, vol. 3, pp. 127–137, 2020.

[89] M. Mosalanejad and M. M. Arefi, UKF-based soft sensor design for joint estimation of chemical processes with multi-sensor information fusion and infrequent measurements, *IET Science Measurement & Technology*, vol. 12, no. 6, pp. 755–763, 2018.

[90] Y. Niu, L. Sheng, M. Gao and D. Zhou, Dynamic event-triggered state estimation for continuous-time polynomial nonlinear systems with external disturbances, *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 3962–3970, 2020.

[91] L. Orihuela, S. Roshany-Yamchi, R. A. García and P. Millán, Distributed set-membership observers for interconnected multi-rate systems, *Automatica*, vol. 85, pp. 221–226, 2017.

[92] F. Peng and S. Sun, Distributed fusion estimation for multisensor multirate systems with stochastic observation multiplicative noises, *Mathematical Problems in Engineering*, vol. 2014, art. no. 373270, 2014.

[93] W. Qian, Y. Li, Y. Chen and W. Liu, L_2-L_∞ filtering for stochastic delayed systems with randomly occurring nonlinearities and sensor saturation, *International Journal of Systems Science*, vol. 51, no. 13, pp. 2360–2377, 2020.

[94] W. Qian, Y. Li, Y. Zhao and Y. Chen, New optimal method for L_2-L_∞ state estimation of delayed neural networks, *Neurocomputing*, vol. 415, pp. 258–265, 2020.

[95] B. Qu, N. Li, Y. Liu and F. E. Alsaadi, Estimation for power quality disturbances with multiplicative noises and correlated noises: A recursive estimation approach, *International Journal of Systems Science*, vol. 51, no. 7, pp. 1200–1217, 2020.

[96] B. Qu, B. Shen, Y. Shen and Q. Li, Dynamic state estimation for islanded microgrids with multiple fading measurements, *Neurocomputing*, vol. 406, pp. 196–203, 2020.

[97] B. Qu, Z. Wang and B. Shen, Fusion estimation for a class of multi-rate power systems with randomly occurring SCADA measurement delays, *Automatica*, vol. 125, art. no. 109408, 2021.

[98] Y. Salehi and B. Huang, Offline and online parameter learning for switching multirate processes with varying delays and integrated measurements, *IEEE Transactions on Industrial Electronics*, in press, doi:10.1109/TIE.2021.3095807.

[99] J. Salt, J. Alcaina, Á. Cuenca and A. Baños, Multirate control strategies for avoiding sample losses. Application to UGV path tracking, *ISA Transactions*, vol. 101, pp. 130–146, 2020.

[100] S. Safari, F. Shabani and D. Simon, Multirate multisensor data fusion for linear systems using Kalman filters and a neural network, *Aerospace Science and Technology*, vol. 39, pp. 465–471, 2014.

[101] M. Sathishkumar, R. Sakthivel, C. Wang, B. Kaviarasan and S. M. Anthoni, Non-fragile filtering for singular Markovian jump systems with missing measurements, *Signal Processing*, vol. 142, pp. 125–136, 2018.

[102] Y. Shen, Z. Wang, B. Shen and F. E. Alsaadi, Nonfragile H_∞ filtering for discrete multirate time-delayed systems over sensor networks characterized by Gilbert-Elliott models, *International Journal of Robust and Nonlinear Control*, vol. 30, no. 8, pp. 3194–3214, 2020.

[103] Y. Shen, Z. Wang, B. Shen and H. Dong, Outlier-resistant recursive filtering for multi-sensor multi-rate networked systems under weighted Try-Once-Discard protocol, *IEEE Transactions on Cybernetics*, in press, doi:10.1109/TCYB.2020.3021194.

[104] Y. Shen, Z. Wang, B. Shen and Q.-L. Han, Recursive state estimation for networked multi-rate multi-sensor systems with distributed time-delays under the Round-Robin protocol, *IEEE Transactions on Cybernetics*, in press, doi:10.1109/TCYB.2020.3021350.

[105] J. Sheng, T. Chen and S. L. Shah, Optimal filtering for multirate systems, *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 52, no. 4, pp. 228–232, 2005.

[106] R. G. Shenoy, D. Burnside and T. W. Parks, Linear periodic systems and multirate filter design, *IEEE Transactions on Signal Processing*, vol. 42, no. 9, pp. 2242–2256, 1994.

[107] Y. Shi, E. Tian, S. Shen and X. Zhao, Adaptive memory-event-triggered H_∞ control for network-based T-S fuzzy systems with asynchronous premise constraints, *IET Control Theory & Applications*, vol. 15, no. 4, pp. 534–544, 2021.

[108] A. Smyth and M. Wu, Multi-rate Kalman filtering for the data fusion of displacement and acceleration response measurements in dynamic system monitoring, *Mechanical Systems and Signal Processing*, vol. 21, no. 2, pp. 706–723, 2007.

[109] H. Song, L. Yu and W.-A. Zhang, Multi-sensor-based H_∞ estimation in heterogeneous sensor networks with stochastic competitive transmission and random sensor failures, *IET Control Theory & Applications*, vol. 8, no. 3, pp. 202–210, 2014.

[110] J. Song, D. Ding, H. Liu and X. Wang, Non-fragile distributed state estimation over sensor networks subject to DoS attacks: The almost sure stability, *International Journal of Systems Science*, vol. 51, no. 6, pp. 1119–1132, 2020.

[111] Q. Song, Y. Chen, Z. Zhao, Y. Liu and F. E. Alsaadi, Robust stability of fractional-order quaternion-valued neural networks with neutral delays and parameter uncertainties, *Neurocomputing*, vol. 420, pp. 70–81, 2021.

[112] W. Song, J. Wang, S. Zhao and J. Shan, Event-triggered cooperative unscented Kalman filtering and its application in multi-UAV systems, *Automatica*, vol. 105, pp. 264–273, 2019.

[113] S. Sun, Distributed optimal linear fusion estimators, *Information Fusion*, vol. 63, pp. 56–73, 2020.

[114] S. Sun, H. Lin, J. Ma and X. Li, Multi-sensor distributed fusion estimation with applications in networked systems: A review paper, *Information Fusion*, vol. 38, pp. 122–134, 2017.

[115] J. Suo, N. Li and Q. Li, Event-triggered H_∞ state estimation for discrete-time delayed switched stochastic neural networks with persistent dwell-time switching regularities and sensor saturations, *Neurocomputing*, vol. 455, pp. 297–307, 2021.

[116] H. Tan, B. Shen, Y. Liu, A. Alsaedi and B. Ahmad, Event-triggered multi-rate fusion estimation for uncertain system with stochastic nonlinearities and colored measurement noises, *Information Fusion*, vol. 36, pp. 313–320, 2017.

[117] H. Tan, B. Shen, K. Peng and H. Liu, Robust recursive filtering for uncertain stochastic systems with amplify-and-forward relays, *International Journal of Systems Science*, vol. 51, no. 7, pp. 1188–1199, 2020.

[118] X. Tian, G. Wei, L. Wang and J. Zhou, Wireless-sensor-network-based target localization: A semidefinite relaxation approach with adaptive threshold correction, *Neurocomputing*, vol. 405, pp. 229–238, 2020.

[119] J. Wang, Y. Alipouri and B. Huang, Dual neural extended Kalman filtering approach for multirate sensor data fusion, *IEEE Transactions on Instrumentation and Measurement*, vol. 70, art. no. 6502109, 2021.

[120] L. Wang, Z. Wang, G. Wei and F. E. Alsaadi, Variance-constrained H_∞ state estimation for time-varying multi-rate systems with redundant channels: The finite-horizon case, *Information Sciences*, vol. 501, pp. 222–235, 2019.

[121] G. Wei, W. Li, D. Ding and Y. Liu, Stability analysis of covariance intersection-based Kalman consensus filtering for time-varying systems, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 50, no. 11, pp. 4611–4622, 2020.

[122] G. Wei, L. Liu, L. Wang and D. Ding, Event-triggered control for discrete-time systems with unknown nonlinearities: An interval observer-based approach, *International Journal of Systems Science*, vol. 51, no. 6, pp. 1019–1031, 2020.

[123] S. Wen, T. Huang, X. Yu, M. Z. Q. Chen and Z. Zeng, Aperiodic sampled-data sliding-mode control of fuzzy systems with communication delays via the event-triggered method, *IEEE Transactions on Fuzzy Systems*, vol. 24, no. 5, pp. 1048–1057, 2016.

[124] T. Wen, L. Zou, J. Liang and C. Roberts, Recursive filtering for communication-based train control systems with packet dropouts, *Neurocomputing*, vol. 275, pp. 948–957, 2018.

[125] Q. Wu, Q. Song, Z. Zhao, Y. Liu and F. E. Alsaadi, Stabilization of T-S fuzzy fractional rectangular descriptor time-delay system, *International Journal of Systems Science*, vol. 52, no. 11, pp. 2268–2282, 2021.

[126] N. Xu, Y. Chen, A. Xue and Q. Yu, A new approach to stability analysis of switched systems composed of two subsystems with average dwell time switching, *International Journal of Systems Science*, vol. 51, no. 10, pp. 1862–1872, 2020.

[127] W. Xu, D. W. C. Ho, J. Zhong and B. Chen, Event/self-triggered control for leader-following consensus over unreliable network with DoS attacks, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 30, no. 10, pp. 3137–3149, 2019.

[128] W. Xu, S. Yang and J. Cao, Fully distributed self-triggered control for second-order consensus of multiagent systems, *IEEE Transactions on Systems, Man and Cybernetics: Systems*, vol. 51, no. 6, pp. 3541–3551, 2021.

[129] L. P. Yan, B. S. Liu and D. H. Zhou, The modeling and estimation of asynchronous multirate multisensor dynamic systems, *Aerospace Science and Technology*, vol. 10, no. 1, pp. 63–71, 2006.

[130] L. P. Yan, B. S. Liu and D. H. Zhou, Asynchronous multirate multisensor information fusion algorithm, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 43, no. 3, pp. 1135–1146, 2007.

[131] L. P. Yan, B. Xiao, Y. Q. Xia and M. Y. Fu, State estimation for asynchronous multirate multisensor nonlinear dynamic systems with missing measurements, *International Journal of Adaptive Control and Signal Processing*, vol. 26, no. 6, pp. 516–529, 2012.

[132] L. P. Yan, D. H. Zhou, M. Y. Fu and Y. Q. Xia, State estimation for asynchronous multirate multisensor dynamic systems with missing measurements, *IET Signal Processing*, vol. 4, no. 6, pp. 728–739, 2010.

[133] C. Yang, Z. Yang and Z. Deng, Robust weighted state fusion Kalman estimators for networked systems with mixed uncertainties, *Information Fusion*, vol. 45, pp. 246–265, 2019.

[134] X. Yin and J. Liu, Event-triggered state estimation of linear systems using moving horizon estimation, *IEEE Transactions on Control Systems Technology*, vol. 29, no. 2, pp. 901–909, 2020.

[135] B. Yu, Y. Shi and H. N. Huang, l_2-l_∞ filtering for multirate systems based on lifted models, *Circuits Systems and Signal Processing*, vol. 27, no. 5, pp. 699–711, 2008.

[136] Y. Yuan, Y. Wang and L. Guo, Sliding-mode-observer-based time-varying formation tracking for multi-spacecrafts subjected to switching topologies and time-delays, *IEEE Transactions on Automatic Control*, vol. 66, no. 8, pp. 3848–3855, 2021.

[137] J. Zhang, Q. Zhang, X. He, G. Sun and D. Zhou, Compound-fault diagnosis of rotating machinery: A fused imbalance learning method, *IEEE Transactions on Control Systems Technology*, vol. 29, no. 4, pp. 1462–1474, 2021.

[138] P. Zhang, Y. Yuan and L. Guo, Fault-tolerant optimal control for discrete-time nonlinear system subjected to input saturation: A dynamic event-triggered approach, *IEEE Transactions on Cybernetics*, vol. 51, no. 6, pp. 2956–2968, 2021.

[139] W.-A. Zhang, B. Chen and M. Z. Q. Chen, Hierarchical fusion estimation for clustered asynchronous sensor networks, *IEEE Transactions on Automatic Control*, vol. 61, no. 10, pp. 3064–3069, 2016.

[140] W.-A. Zhang, G. Feng and L. Yu, Multi-rate distributed fusion estimation for sensor networks with packet losses, *Automatica*, vol. 48, no. 9, pp. 2016–2028, 2012.

[141] X.-M. Zhang, Q.-L. Han, X. Ge, D. Ding, L. Ding, D. Yue and C. Peng, Networked control systems: A survey of trends and techniques, *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 1, pp. 1–17, 2020.

[142] X.-M. Zhang, Q.-L. Han and X. Yu, Survey on recent advances in networked control systems, *IEEE Transactions on Industrial Informatics*, vol. 12, no. 5, pp. 1740–1752, 2016.

[143] Y. Zhang, Z. Wang and F. E. Alsaadi, Detection of intermittent faults for nonuniformly sampled multi-rate systems with dynamic quantisation and missing measurements, *International Journal of Control*, vol. 93, no. 4, pp. 898–909, 2020.

[144] Y. Zhang, Z. Wang and L. Ma, Variance-constrained state estimation for networked multi-rate systems with measurement quantization and probabilistic sensor failures, *International Journal of Robust and Nonlinear Control*, vol. 26, no. 16, pp. 3507–3523, 2016.

[145] Y. Zhang, Z. Wang, L. Zou and H. Fang, Event-based finite-time filtering for multirate systems with fading measurements, *IEEE Transactions on Aerospace and Electronic Systems*, vol. 53, no. 3, pp. 1431–1441, 2017.

[146] Y. Zhang, Z. Wang, L. Zou and Z. Liu, Fault detection filter design for networked multi-rate systems with fading measurements and randomly

occurring faults, *IET Control Theory & Applications*, vol. 10, no. 5, pp. 573–581, 2016.
[147] Z. Zhang, Y. Niu, Z. Cao and J. Song, Security sliding mode control of interval type-2 fuzzy systems subject to cyber attacks: The stochastic communication protocol case, *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 2, pp. 240–251, 2020.
[148] Z. Zhang, Y. Niu and H.-K. Lam, Sliding-mode control of T-S fuzzy systems under weighted Try-Once-Discard protocol, *IEEE Transactions on Cybernetics*, vol. 50, no. 12, pp. 4972–4982, 2020.
[149] Z. Zhang, S.-F. Su and Y. Niu, Dynamic event-triggered control for interval type-2 fuzzy systems under fading channel, *IEEE Transactions on Cybernetics*, in press, doi:10.1109/TCYB.2020.2996296.
[150] Y. Zhao, X. He, J. Zhang, H. Ji, D. Zhou and M. G. Pecht, Detection of intermittent faults based on an optimally weighted moving average T^2 control chart with stationary observations, *Automatica*, vol. 123, art. no. 109298, 2021.
[151] Z. Zhao, Z. Wang, L. Zou and J. Guo, Set-membership filtering for time-varying complex networks with uniform quantisations over randomly delayed redundant channels, *International Journal of Systems Science*, vol. 51, no. 16, pp. 3364–3377, 2020.
[152] X. Zheng, H. Zhang, Z. Wang and H. Yan, Almost surely state estimation for multi-rate networked systems under random and malicious packet losses, *Journal of the Franklin Institute*, vol. 356, no. 17, pp. 10593–10607, 2019.
[153] Y. Zheng, W. Zhou, W. Yang, L. Liu, Y. Liu and Y. Zhang, Multivariate/minor fault diagnosis with severity level based on Bayesian decision theory and multidimensional RBC, *Journal of Process Control*, vol. 101, pp. 68–77, 2021.
[154] X. Zhou, Y. Chen, Q. Wang, K. Zhang and A. Xue, Event-triggered finite-time H_∞ control of networked state-saturated switched systems, *International Journal of Systems Science*, vol. 51, no. 10, pp. 1744–1758, 2020.
[155] K. Zhu, J. Hu, Y. Liu, N. D. Alotaibi and F. E. Alsaadi, On ℓ_2-ℓ_∞ output-feedback control scheduled by stochastic communication protocol for Two-dimensional switched systems, *International Journal of Systems Science*, in press, doi: 10.1080/00207721.2021.1914768.
[156] M. Zhu, Y. Chen, Y. Kong, C. Chen and J. Bai, Distributed filtering for Markov jump systems with randomly occurring one-sided lipschitz nonlinearities under Round-Robin scheduling, *Neurocomputing*, vol. 417, pp. 396–405, 2020.
[157] L. Zou, Z. Wang, H. Dong and Q.-L. Han, Moving horizon estimation with multirate measurements and correlated noises, *International Journal of Robust and Nonlinear Control*, vol. 30, no. 17, pp. 7429–7445, 2020.