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A Survey on Model-based Distributed Control and Filtering for Industrial Cyber-Physical Systems

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***Abstract*—Industrial cyber-physical systems (CPSs) are large-scale, geographically dispersed and life-critical systems, in which lots of sensors and actuators are embedded and networked together to facilitate real-time monitoring and closed-loop control. Their intrinsic features in geographic space and resources put forward to urgent requirements of reliability and scalability for designed filtering or control schemes. This paper presents a review of the state-of-the-art of distributed filtering and control of industrial CPSs described by differential dynamics models. Special attention is paid to sensor networks, manipulators and power systems. For real-time monitoring, some typical Kalman-based distributed algorithms are summarized and their performances on calculation burden, communication burden as well as scalability are discussed in depth. Then, the characteristics of non-Kalman cases are further disclosed in light of constructed filter structures. Furthermore, the latest development is surveyed for distributed cooperative control of mobile manipulators and distributed model predictive control in industrial automation systems. By resorting to droop characteristics, representative distributed control strategies classified by controller structures are systematically summarized for power systems with the requirements of power sharing, and voltage and frequency regulation. In addition, distributed security control of industrial CPSs is reviewed when cyber-attacks are taken into consideration. Finally, some challenges are raised to guide the future research.**

***Index Terms*—Industrial cyber-physical systems; distributed filtering; distributed control; power schedule; droop characteristics.**

I. Industrial Cyber-Physical Systems

A cyber-physical system (CPS), a fast-growing research area, is a highly integrated system of physical components involving sensors, actuators and various equipments, as well as cyber possessing ubiquitous computation and efficient communication. From the engineering point of view, CPSs are considered as the most promising industrial systems including transportation networks, energy systems, water/gas distribution networks, and unmanned factories. For example, multiple industrial robots with an inertial navigation device or various sensors are programmed for the movement along a programmed trajectory to cooperatively complete production tasks [1], [2]. The main advantage of these systems is that the tight coordination of cyber and physical elements provides greater autonomy, efficiency, functionality, reliability, and adaptability. Furthermore, industrial CPSs are regarded as a core ingredient in the so-called 4th industrial revolution [3], [4], and lots of efforts are made to establish their important position, such as, Industry 4.0 in Germany and Industrial Internet in the US.

Industrial CPSs are large-scale, geographically dispersed, federated, cooperative, and life-critical systems, in which lots of sensors and actuators are embedded and networked together to facilitate real-time monitoring and closed-loop control. In addition, the implementation of industrial CPSs largely depends on sensor networks and distributed control networks. In other words, these two networks are usually indispensable in a largely deployed CPS architecture [5]. Specifically, sensor networks are usually deployed in the interior or in the neighboring of plants to gather various critical information with the purpose of making correct perception of the physical plants. With the help of these information, actuators can have the opportunity to do real-time reaction to some changes of physical plants. As such, a closed loop is formed when integrating cyber and physical worlds through both communicating between sensors and actuators, and operating to plants via actuators [6]. In the past few years, many of commercial sensors and actuators equipped with some communication and data processing capabilities are made available benefiting from the hard work of research institutions and companies from around the world.

As is done for almost all of real-world engineering systems, the model-based performance analysis of an industrial CPS plays an important role in understanding and adjusting its dynamic behavior. Because of the limitation of geographic space and various resources in energy and communication aspects, there is an ever-increasing need to execute: 1) distributed control for satisfying reliability and scalability requirements while maintaining stability performance, and 2) distributed filtering for achieving scalability and disturbance attenuation capability while ensuring expected filtering accuracy. However, traditional tools developed in the central paradigm are not feasible to meet the demands of industrial CPSs due mainly to their inherent dynamic nature. Specifically, on the one hand, the complexity of industrial CPSs, in terms of its degree or intensity, could be great enhanced due to various network-induced phenomena and employed communication protocols [7], [8]. On the other hand, the varying topology, coming from connection failures or cyber-attacks [9], gives rise to an obstacle of the application of developed analysis approaches. As such, it is of both theoretical significance and practical

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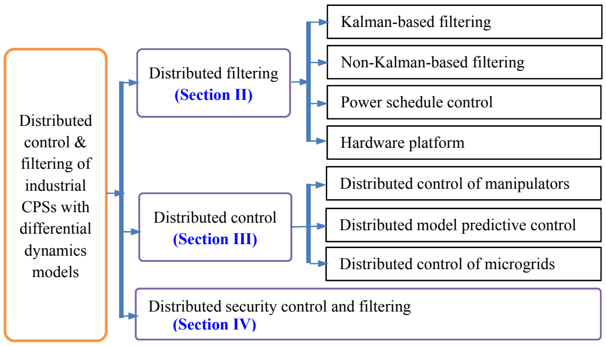

Fig. 1. The structure of this survey.

importance to develop an effective framework of performance analysis and synthesis under the distributed paradigm.

It is thus desirable to survey what results have been developed in the field of industrial CPSs modelled by differential dynamics equations, and further identify what challenges need to be dealt with. For this purpose, this paper intends to provide a review of the state-of-the-art of distributed control and filtering of industrial CPSs on sensor networks, manipulators and power systems, see Fig. 1 for the organization. Specifically, for real-time monitoring, we identify key techniques of Kalman-based filtering algorithms, review typical filter structures utilized in a non-Kalman framework, and provide a systematic performance analysis from three aspects: calculation burden, communication burden, and scalability. For distributed closed-loop control, we first survey the latest advances on distributed control of manipulators in industrial automation systems, and then summarize typical distributed control strategies in microgrids via droop characteristics with the requirements of power sharing and voltage and frequency regulation. Furthermore, we summary recent developments on distributed security control of industrial CPSs when a cyber-attack is a concern. Finally, we raise some challenging issues to guide the future research.

II. Distributed Filtering for Industrial Cyber-Physical Systems

As an indispensable part, sensor networks are usually seamlessly integrated into industrial CPSs to facilitate the real-time sensing, monitoring and control. Sensor nodes in reality are sparsely deployed in a predetermined field along with subsystems or distributed actuators. Benefiting from embedded algorithms, i.e. distributed filtering algorithms, these sensor nodes can effectively process the collected information in function and meanwhile exchange necessary data via a communication topology. As such, distributed filtering based on sensor networks fills in the gap between the wealth of distributed information and the understanding of physical behavior [10]. Therefore, it receives considerable research interest in the past few years and some typical filtering algorithms are proposed in the literature. It is worth noting that, in comparison with the centre filtering or fusion, a critical challenge here is how to ensure the consensus or global performance of all estimates while guaranteeing the effectiveness of filtering algorithms. Various consensus strategies are proposed with intent to deal with such a challenge. Up to date, two fashionable schemes realizing both consensus and effectiveness of filtering are, respectively, the iterative computation via captured information and the design of distributed filtering structures via distributed information fusion. In this section, the latest development is systematically surveyed and some typical applications in industrial CPSs are further summarized.

A. Kalman-based Distributed Filtering

In order to clearly present the filtering structure and discover the corresponding performance, let us introduce the following simple dynamics process

$$\begin{cases} x_{k+1} = A_k x_k + w_k \\ y_{i,k} = C_{i,k} x_k + v_{i,k} \end{cases}$$

for $i \in \{1, 2, \cdots, N\}$, where $x_k \in \mathbb{R}^n$ is the process state, and $y_{i,k} \in \mathbb{R}^m$ is the measurement on sensor i. The disturbances $w_k \in \mathbb{R}^n$ and $v_{i,k} \in \mathbb{R}^m$ are mutually independent white Gaussian random variables with zero mean values and bounded covariance $Q > 0$ and $R_i > 0$.

Define that the *local* and *modified* updates are, respectively, $\hat{x}^o_{i,k}$ and $\hat{x}_{i,k}$, and the one-step prediction is $\hat{x}^-_{i,k}$. It is well-known that the local Kalman filtering on the ith sensor can be expressed as

$$\begin{cases} \hat{x}^-_{i,k} = A_k \hat{x}_{i,k-1} \\ \hat{x}^o_{i,k} = \hat{x}^-_{i,k} + K_{i,k}(y_{i,k} - C_{i,k}\hat{x}^-_{i,k}) \\ P^-_{i,k} = A_k P_{i,k-1} A_k^T + Q, \\ K_{i,k} = P^-_{i,k} C^T_{i,k}(C_{i,k} P^-_{i,k} C^T_{i,k} + R_i)^{-1} \end{cases} \quad (1)$$

where $P^-_{i,k}$ and $P_{i,k}$ are the prediction and estimation error covariances, and $K_{i,k}$ is the optimal filter gain under the given performance index.

In this survey paper, the topology of sensor networks is described by a triple $\mathscr{G} = (\mathscr{V}, \mathscr{E}, \mathscr{S})$. In this triple, $\mathscr{V} = \{1, 2, \cdots, N\}$, $\mathscr{E}$ and $\mathscr{S} = [\alpha_{ij}]_{N\times N}$ with nonnegative adjacency element α_{ij} stand for the sets of nodes, edges and adjacency matrix, respectively. The set of neighbors of node i is denoted by $N_i = \{j : (i, j) \in \mathscr{E}\}$ and Θ_i stands for the number of neighbors. In addition, the induced weighted matrix of this graph is denoted as $\mathscr{A} = [\alpha_{ij}]_{N\times N} = \mathscr{S} + \mathrm{diag}_{i,N}\{\sum_{j=1}^{N} \alpha_{ij}\}$. Additionally, the shorthand $\mathrm{diag}_{i,n}\{M_i\}$ used in this paper denotes a block diagonal matrix with diagonal blocks being matrices M_1, M_2, $\cdots$ M_n.

With the help of adopted consensus mechanisms and filter structures, Kalman-based distributed filtering algorithms can be roughly divided into the following six cases.

1) **Algorithm 1: Kalman-consensus filtering**

Inspired by the result in [11], a two-stage Kalman-consensus filtering algorithm is developed in [12]. This kind of algorithm described by (2) is composed of a classical local Kalman filter (1) and a consensus update of information matrices and vectors

$$\begin{cases} \Omega_{i,k}(l+1) = \sum_{j\in N_i} \pi_{ij}\Omega_{j,k}(l) \\ q_{i,k}(l+1) = \sum_{j\in N_i} \pi_{ij} q_{j,k}(l) \\ P_{i,k} = (\Omega_{i,k}(L))^{-1}, \quad \hat{x}_{i,k} = P_{i,k} q_{i,k}(L) \end{cases} \quad (2)$$

with $\Omega_{i,k}(0) = (P^-_{i,k} - K_{i,k}C_{i,k}P^-_{i,k})^{-1}$ and $q_{i,k}(0) = \Omega_{i,k}(0)x^o_{i,k}$, where π_{ij} is the consensus weight, and L is the

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Algorithm 1

1: *Prediction updates*
  Calculate $\hat{x}_{i,k}^{-}$, $\hat{x}_{i,k}^{o}$, $P_{i,k}^{-}$ and $K_{i,k}$ via (1);
2: *Consensus calculation*
3: Initialize $\Omega_{i,k}(0)$, $q_{i,k}(0)$ and the step length L;
4: Repeat each step until $l = L - 1$:
5: *Communications*
  Broadcast $\Omega_{i,k}(l)$ to all neighbors;
  Receive $\Omega_{j,k}(l)$ from all neighbors $j \in N_i$;
6: *Iteration updates*
  Calculate $q_{i,k}(l+1)$ via (2);
  Calculate matrix $\Omega_{i,k}(l+1)$ via (2);
7: *Estimation updates*
  Return estimate $\hat{x}_{i,k} = P_{i,k} q_{i,k}(L)$;
  Return covariance $P_{i,k} = (\Omega_{i,k}(L))^{-1}$.

Algorithm 2

1: *Prediction updates*
  Calculate $\hat{x}_{i,k}^{-}$, $P_{i,k}^{-}$ and $K_{i,k}$ via (1);
2: *Diffusion calculation*
3: *Communications*
  Broadcast $y_{i,k}$ to all neighbors;
  Receive $y_{j,k}$ from all neighbors $j \in N_i$;
4: *Calculations*
  Calculate matrices $\Omega_{i,k}$ and $P_{i,k}$ via (3);
  Calculate vectors $q_{i,k}$ and $\hat{\varphi}_{i,k}$ via (3);
5: *Communications*
  Broadcast $\hat{\varphi}_{i,k}$ to all neighbors;
  Receive $\hat{\varphi}_{j,k}$ from all neighbors $j \in N_i$;
6: *Estimation updates*
  Return $\hat{x}_{i,k} = \sum_{j \in N_i} \pi_{ij} \hat{\varphi}_{j,k}$.

selected step length of consensus calculation. Its pseudocode is provided in Algorithm 1.

Note that, even if the local sensor was undetectable, a sufficient condition is proposed in [13] to expose the uniform boundedness under the assumption of weightedly uniform detectability, which includes uniform detectability as a special case. Such an algorithm is further extended to two more general cases: 1) the one is under the unscented Kalman filtering framework, and 2) the other is under the cubature Kalman filtering (CKF) framework. For the first case, the boundedness condition of consensus-based algorithm is derived in [14] with the help of a series of assumptions on system parameters. For the second one, an improved version, named as variational Bayesian consensus CKF, is proposed in [15], where the variational Bayesian approximation is utilized to estimate the covariance of measurement noises. Furthermore, a hybrid Kalman algorithm via CKF is designed in [16] by blending the consensus strategies on both measurements and information matrices. Finally, when the random link failure is a concern, in [17], a renewed weighted matrix is introduced in consensus steps to implement distributed filtering and the effect on boundedness from the statistics information of random link failures is thoroughly investigated.

2) **Algorithm 2: Diffusion Kalman filtering**

The diffusion Kalman filtering is developed in [18] by replacing consensus strategies [12] with diffusion strategies [19] after the measurement update of the Kalman filter. The purpose of diffusion step $\hat{x}_{i,k} = \sum_{j \in N_i} \pi_{ij} \hat{\varphi}_{j,k}$ (see its information version (3) and Algorithm 2 for the corresponding pseudocode) is to approximate the global filtering performance via local node interactions

$$\begin{cases} \Omega_{i,k} = \sum\limits_{j \in N_i} C_{i,k}^T R_j^{-1} C_{j,k}, \quad P_{i,k}^{-1} = (P_{i,k}^{-})^{-1} + \Omega_{i,k} \\ \hat{x}_{i,k} = \sum\limits_{j \in N_i} \pi_{ij} \hat{\varphi}_{j,k}, \quad q_{i,k} = \sum\limits_{j \in N_i} C_{i,k}^T R_j^{-1} y_{j,k} \\ \hat{\varphi}_{i,k} = \hat{x}_{i,k}^{-} + P_{i,k}(q_{i,k} - \Omega_{i,k} \hat{x}_{i,k}^{-}) \end{cases} \tag{3}$$

In comparison with Algorithm 1, this strategy is independent of the consensus iteration between two consecutive Kalman filter updates and thus improves the fusion efficiency of new measurement information [20]. Based on this seminal research, diffusion Kalman filtering receives great attention [21] and the diffusion weights π_{ij} are further optimized through the well-known covariance intersection approach. Especially, when the uniform observability condition is satisfied under global measurements, an improved algorithm developed in [20] can guarantee the boundedness of estimation error covariances of each sensor under a certain connectivity condition of time-varying topologies.

3) **Algorithm 3: Kalman-based filtering I**

Based on the consensus-based Kalman filter designed in [11], a version relying on neighbors' estimate is proposed in [22] and the corresponding filter structure is constructed as follows

$$\begin{cases} q_{i,k} = \sum_{j \in N_i} (\hat{x}_{j,k-1} - \hat{x}_{i,k-1}) \\ \hat{x}_{i,k} = \hat{x}_{i,k}^{-} + F_{i,k} A_k q_{i,k} + K_{i,k}(y_{i,k} - C_{i,k} \hat{x}_{i,k}^{-}) \end{cases} \tag{4}$$

where $q_{i,k}$ describes the consensus error of estimated states, and the consensus gain $F_{i,k}$ is exploited to guarantee the stability. Additionally, the formulas on $K_{i,k}$, $P_{i,k}$ and cross-covariance $P_{ij,k}$ can be obtained by using the same method in [22] and hence omitted in this survey paper for the convenience of presentation. For the convenience of application, the pseudocode is provided in Algorithm 3. Obviously, the accumulative error of neighbors' estimate is utilized to achieve the consensus by replacing raw measurements and covariance information. In comparison with the local Kalman filter, the introduced accumulative error leads to the coupling of filtering error dynamics, and thereby the cross-covariance needs to be handled when discussing the stability of developed filtering algorithm. Nowadays, a suboptimal algorithm ignoring cross-covariance is developed in [23] to deal with the filtering issue with event-triggered communication protocols.

4) **Algorithm 4: Kalman-based filtering II**

Combing with the advantage of consensus schemes in Algorithm 2 and Algorithm 3, a filtering algorithm is designed in [24] only via the weighted sum of neighbors' innovation

$$\begin{cases} q_{i,k} = \sum_{j \in N_i} \alpha_{ij} (y_{j,k} - C_{j,k} \hat{x}_{i,k}^{-}) \\ \hat{x}_{i,k} = \hat{x}_{i,k}^{-} + K_{i,k}^{1} q_{i,k} + K_{i,k}^{2}(y_{i,k} - C_{i,k} \hat{x}_{i,k}^{-}) \end{cases} \tag{5}$$

where matrices $K_{i,k}^{1}$ and $K_{i,k}^{2}$ are two gains, and the corresponding pseudocode can be find in Algorithm 4.

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Algorithm 3

1: *Prediction updates*
 Calculate $\hat{x}^-_{i,k}$ via (1);
2: *Consensus error calculation*
3: *Communications*
 Broadcast $\hat{x}_{i,k-1}$ and $P^-_{ij,k}$ to all neighbors;
 Receive $\hat{x}_{j,k-1}$ and $P^-_{ji,k}$ from all neighbors;
4: *Gain calculations via similar formulas in [22]*
 Select $F_{i,k}$ via a similar formula (18);
 Calculate $K_{i,k}$ and $P_{ij,k}$ via a similar formula (13);
 Calculate $P^-_{ij,k+1} = A_k P_{ij,k} A^T_k + Q$;
5: *Error calculations*
 Calculate $q_{i,k}$ via (4) in this paper;
6: *Estimation updates*
 Return $\hat{x}_{i,k}$ via (4).

Algorithm 4

1: *Prediction updates*
 Calculate $\hat{x}^-_{i,k}$ via (1);
2: *Consensus error calculation*
3: *Communications*
 Broadcast $y_{i,k}$ and $C_{i,k}$ to all neighbors;
 Receive $y_{j,k}$ and $C_{j,k}$ from all neighbors;
4: *Gain calculations via similar formulas in [24]*
 Calculate $P^-_{i,k}$ via a similar formula (11);
 Calculate $K^1_{i,k}$ and $K^2_{i,k}$ via similar formula (12);
5: *Error calculations*
 Calculate $q_{i,k}$ via (5);
6: *Estimation updates*
 Return $\hat{x}_{i,k}$ via (5).

Specially, the distributed recursive filtering issue is investigated in [24] for systems in the presence of time-delays, uniform quantization as well as deception attacks. By resorting to the gradient-based method, the desired gains $K^1_{i,k}$ and $K^2_{i,k}$ are analytically designed so as to minimize the trace of an upper bound of filtering error covariance (FEC). Additionally, in light of the mathematical induction combined with eigenvalue analysis, the challenge from double gains is skilfully overcome in filtering performance analysis, and a sufficient condition is derived to ensure the asymptotic boundedness of a sequence of error covariances. What particularly worth mentioning is that this algorithm possesses the high scalability with both low calculation and communication burden by sacrificing the consensus performance.

5) **Algorithm 5: Kalman-based filtering III**

In the above algorithm, all innovations are summed together with given weights and then employed to update the prediction. Such an algorithm cannot adequately identify the effect on filtering performance from different neighbors' information, especially, for the case with heterogeneous sensors. As such, a more general structure is designed in [25], and removing gain uncertainties leads to the following simplified version

$$\hat{x}_{i,k} = \hat{x}^-_{i,k} + \sum\nolimits_{j\in N_i\cup\{i\}} \alpha_{ij} K^{ij}_k (y_{j,k} - C_{i,k}\hat{x}^-_{i,k}) \tag{6}$$

where the formula K^{ij}_k, dependent on global error covariance $P_{i,k}$, can be derived along the same line in [25], [26] and hence omitted in this survey paper for the simplicity of presentation. Obviously, in comparison with algorithms 3 and 4, the gain K^{ij}_k provides more design freedom although the calculation burden is increased. The pseudocode is provided in Algorithm 5.

Algorithm 5

1: Initialize the weighted matrix $\mathscr{A}$ for all nodes;
2: *Prediction updates*
 Calculate $\hat{x}^-_{i,k}$ via (1);
3: *Calculations*
4: *Communications*
 Broadcast $y_{i,k}$ to all neighbors;
 Receive $y_{j,k}$ from all neighbors $j \in N_i$;
5: *Gain calculations via similar formulas in [26] (needing a computation center)*;
 Calculate upper bounds of $P^-_{i,k}$ and $P_{i,k}$ for all nodes via similar formulas (14a) and (14b);
 Calculate gains K^{ij}_k via a similar formula (18);
6: *Communications*
 Receive K^{ij}_k from the computation center;
7: *Estimation updates*
 Return $\hat{x}_{i,k}$ via (6).

6) **Algorithm 6: "Consensus+innovation" filtering**

By resorting to the pseudo-observation, a distributed estimator of pseudo-state $G_k x_k$, a linear transformation of target states, is embedded into the fusion process based on transformed measurements, which results in the following algorithm

$$\begin{cases} z_{i,k} = C^T_{i,k} R^{-1}_i y_{i,k}, \quad q_{i,k} = \sum\nolimits_{j\in N_i} L^{ij}_k (\hat{y}^-_{j,k} - \hat{y}^-_{i,k}) \\ \hat{y}_{i,k} = \hat{y}^-_{i,k} + q_{i,k} + L^{ii}_k (z_{i,k} - (\tilde{C}_{i,k}\hat{y}^-_{i,k} - \hat{C}_{i,k}\hat{x}^-_{i,k}) \\ \hat{x}_{i,k} = \hat{x}^-_{i,k} + K_{i,k}(\hat{y}_{i,k} - G_k \hat{x}^-_{i,k}) \\ \hat{y}^-_{i,k+1} = \tilde{A}_{i,k}\hat{y}_{i,k} + \hat{A}_{i,k}\hat{x}_{i,k}, \quad \hat{x}^-_{i,k+1} = A_{i,k}\hat{x}_{i,k} \end{cases} \tag{7}$$

where $q_{i,k}$ describes the weighted consensus error of predicted pseudo-states. In above algorithm, some critical matrices are defined as $G_k = \sum^N_{i=1} C^T_{i,k} R^{-1}_i C_{i,k}$, $\tilde{A}_k = G_k A_k G^\dagger_k$, $\hat{A}_k = G_k A_k (I - G^\dagger_k G_k)$, $\tilde{C}_{i,k} = C^T_{i,k} R^{-1}_i C_{i,k} G^\dagger_k$ and $\hat{C}_{i,k} = C^T_{i,k} R^{-1}_i C_{i,k}(I - G^\dagger_k G_k)$, where $\dagger$ stands for the Moore-Penrose pseudo-inverse. The formula L^{ij}_k and $K_{i,k}$ can be found in [27], and the corresponding pseudocode is provided in Algorithm 6. In comparison with distributed information Kalman filter developed in [28], the algorithm for the time-invariant case can converge to a bound only requiring global detectability and network connectivity.

Generally speaking, the calculation complexity and communication burden are two important indexes for above discussed filtering algorithms. For Kalman-based algorithms, the calculation complexity at each instance is mainly dependent on the number of consensus steps, the inversion operation with $O(n^3)$ for an $n \times n$ square matrix, and the multiplication operation with $O(nsm)$ for an $n \times s$ matrix multiplying an $s \times m$ matrix. Meanwhile, the communication burden relies on the number of transmitted data. Assuming that $x_k \in \mathcal{R}^n$, one

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Algorithm 6

1: *Prediction updates*
   Calculate $\hat{x}_{i,k}^-$ and $\hat{y}_{i,k}^-$ via (7);
2: *Consensus error calculation*
3: *Communications*
   Broadcast $\hat{y}_{i,k}^-$ to all neighbors;
   Receive $\hat{y}_{i,k}^-$ from the computation center;
4: *Gain calculations via Algorithm 2 in [27]*
   Calculate matrices G_k, $\tilde{A}_k$, $\hat{A}_k$, $\tilde{C}_{i,k}$ and $\hat{C}_{i,k}$;
   Calculate $K_{i,k}$ and L_k^{ij} via Algorithm 2 in [27];
5: *Error calculations*
   Calculate $q_{i,k}$ via (7);
6: *Estimation updates*
   Make the pseudo-observation $z_{i,k}$ via (7);
   Return $\hat{x}_{i,k}$ and $\hat{y}_{i,k}$ via (7).

needs to implement 3 times of matrix inversion operation, 12 times of matrix multiplication operation, and the transmission of $\Theta_i n(n+2)(L+1)$ data for Algorithm 1, and $2\Theta_i + 2$, $4\Theta_i + 6$, and $2\Theta_i n$ for Algorithm 2. As such, Algorithm 1 possesses a low calculation complexity and Algorithm 2 has a low communication burden. In summary, by analyzing the iterative process, one can get that: 1) Algorithm 1 needs to carry out the L-step consensus calculation at each instant, Algorithm 3 depends on the cross-covariance of filtering errors, and Algorithm 4 has to execute complex calculation to obtain the filter gains; 2) Algorithm 3 and Algorithm 4 need to exchange cross-covariances and global error covariances, respectively; and 3) Algorithm 5 is highly dependent on global error covariances, which reduces its scalability, see TABLE I for more details. Finally, recalling Algorithm 1 and Algorithm 2, the selection of weight π_{ij} shows a considerable impact on filtering performance, and thereby the optimized weight design receives the persistent investigation, see [13], [14] and the references therein.

TABLE I
PERFORMANCE OF KALMAN-BASED ALGORITHMS.

	Algorithm	High	Middle	Low
Calculation burden	I			√
	II		√	
	III	√		
	IV		√	
	V	√		
	VI	√		
Communication burden	I		√	
	II		√	
	III	√		
	IV			√
	V	√		
	VI			√
Scalability	I	√		
	II	√		
	III		√	
	IV	√		
	V			√
	VI		√	

In the past few years, Algorithm 1 with $L = 1$ is employed in [29] to implement the dynamic state estimation for real-time monitoring of power systems. It should be pointed out that distributed estimators using local data effectively overcome the challenges from both communication latency and communication burden existing in a central case. Under the variational inference framework, a simplified version of Algorithm 2 is developed in [30] for distributed hybrid power state estimation, where an auto-encoder technique is adopted to reduce the data dimensionality in mixed measurements subject to phase errors. Algorithm 3 is employed to estimate the operating condition of renewable microgrids with reliable channels in [31] and with packet losses in [32], and the conditions of corresponding convergence related on the Laplacian matrix are also analyzed simultaneously. For large-scale power networks, the merit of Algorithm 4 is clearly shown in [33] and the estimated state is utilized to compensate the information loss in distributed control due to the multi-rate nature of systems. Finally, according to a weighted least-squares cost, a "consensus+innovation" based algorithm is proposed in [34] to estimate the vector of bus angles, and converges almost surely to the centralized least squares estimator when the assumption of connectivity is satisfied.

B. Non-Kalman-based Distributed Filtering

In parallel with the evolution of Kalman-based filtering algorithms, the finite-horizon distributed filtering of various time-varying systems receives an ever-increasing interest. Different from the consensus or diffusion strategies adopted in Kalman-based filtering algorithms, the improvement of filtering performance mainly relies on the distributed fusion of neighbors's information, which is realized via designed filter structures where the filter gains act as the role of fusion weights. Denote the innovation and the consensus error as $\gamma_{i,k} = y_{i,k} - C\hat{x}_{i,k}$ and $\delta_{ij,k} = \hat{x}_{j,k} - \hat{x}_{i,k}$, and gains of sensor i as $K_{i,k}$, $L_{i,k}$, $K_{ij,k}$ and $L_{ij,k}$ for different scenarios. Taking the available information into account, some typically distributed filter structures are summarized in TABLE II. Obviously, Structure I is a typical Luenberger observer, and Structures II and IV can be regarded as its variant via replacing neighboring innovation by consensus errors. Furthermore, Structure III with most design parameters is usually employed to deal with the filtering issue of complex plants with unknown time-delays, uncertainties, as well as weak nonlinearities.

TABLE II
DISTRIBUTED FILTER STRUCTURES.

	Filter structure
I	$\hat{x}_{i,k+1} = A_k\hat{x}_{i,k} + \sum_{j\in N_i\cup\{i\}} \alpha_{ij}K_{ij,k}\gamma_{j,k}$
II	$\hat{x}_{i,k+1} = A_k\hat{x}_{i,k} + \sum_{j\in N_i\cup\{i\}} \alpha_{ij}(K_{i,k}\gamma_{j,k} + L_{i,k}\delta_{ij,k})$
III	$\hat{x}_{i,k+1} = \sum_{j\in N_i\cup\{i\}} \alpha_{ij}(K_{ij,k}\hat{x}_{j,k} + L_{ij,k}y_{j,k})$
IV	$\hat{x}_{i,k+1} = A_k\hat{x}_{i,k} + K_{i,k}\gamma_{i,k} + L_{i,k}\sum_{j\in N_i} \delta_{ij,k}$

From a technical point of view, there are three representative approaches to designing desired gains, namely, the backward recursive Riccati difference equation (BRDE), the recursive linear matrix inequality (LMI), and the set-membership approach. With the help of Moore-Penrose pseudo inverse, the BRDE approach is firstly developed in [35] by blending the finite-horizon H_∞ performance and the nominal H_2 cost, and further adopted to deal with some fashionable topics with

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various communication protocols, see [36] and the references therein. Furthermore, the recursive LMI tool is employed to handle the distributed filtering issue in [37], under which the conception of finite-horizon H_∞-consensus is creatively defined to quantify bounded consensus regarding to filtering errors. In addition to these two approaches, the set-membership approach serves as another effective tool for handling filtering issues of time-varying systems. Different from popular point-estimation ones, such an approach provides a reliable interval involving true values and therefore satisfies various hard-constraints from practical engineering. Here, we refer the readers to [38]–[40] for some most cutting-edge researches on this topic. It is worth pointing out that, in almost all literature considering randomly occurring network-induced phenomena, the augmentation of filtering errors is usually inevitable, which leads to the obtained design condition dependent on the global topology information. This typical characteristic extremely limits the application in large-scale sensor networks. In other words, in order to execute the filtering task online, the network scale is commonly required to be small and the topology information is usually open. Additionally, their calculation complexity is dependent on the number of dimensions of linear matrix inequalities and the number of decision variables. As such, Algorithm III owns the highest calculation complexity. Furthermore, Algorithms II-IV all need to transmit $2(\Theta_i+1)n$ data and thus have the same communication burden. The concrete performance is summarized in TABLE III.

TABLE III
PERFORMANCE OF NON-KALMAN-BASED ALGORITHMS.

	Structures	High	Middle	Low
Communication burden	I			√
	II		√	
	III		√	
	IV		√	
Scalability	I			√
	II			√
	III			√
	IV			√

When the research concern is extended into infinite-horizon, various distributed filtering schemes based on stability or H_∞ performance analysis were developed in recent years, see [41], [42] and the references therein. For instance, the distributed H_∞ filtering of polynomial nonlinear stochastic systems is investigated in [41] by constructing a polynomial Lyapunov function candidate, and the filter gains are designed in terms of the solution of parameter-dependent LMIs. For sensor networks with a randomly varying topology described by Markovian, some sufficient conditions are derived in [42] to satisfy the predetermined H_∞ level evaluating relative disagreement of estimated states both in the mean-square sense and with probability 1. Furthermore, some interesting results can be found in [43] for the case with event-triggered communication, in [44] for the case with sampled-data, and in [45] for the case subject to time-delays. Compared with the finite-horizon case, the filter parameters can be obtained off-line and therefore their scalability can be improved to some extent. Note that, due to the unavoidable impact from various network-induced phenomena, the obtained design condition applying to networked systems also relies on the augmented filtering error dynamics and their disadvantages in performance analysis are similar to that in finite-horizon cases. Additionally, the conservatism from time-delays can be reduced possibly via various tools of time-delayed analysis adopted in [46]. Generally speaking, the application of these tools maybe sacrifice the computing performance partly.

Finally, let us briefly review the state-of-the-art of distributed filtering in the frameworks of Bayesian filtering and particle filtering. Under the probability perspective, it is interesting to utilize the well-known Bayesian interpretation to disclose 1) what kind of posterior probability distribution of unknown states is reasonable in the formalization of distributed Kalman filtering and 2) how it is compared to the optimal posterior distribution of states conditioned on all present and past network data [47]. Usually, the locally available measurements $Y_{i,k}=\{y_{j,k}, j\in N_i\cup\{i\}\}$ together with mutual independence assumptions are first used to update the desired posterior PDF $\tilde{p}_i(x_k|Y_{i,k})$, and then the obtained PDFs are assimilated into a PDF $p_i(x_k|Y_{i,k})\propto\prod_{j\in N_i\cup\{i\}}[\tilde{p}_j(x_k|Y_{j,k})]^{\alpha_j}$ [48] via optimizing average KL divergence [49] or Logarithmic opinion [50] where $\sum\alpha_j=1$. Recently, various alternative schemes are developed to overcome the deficiency of above fusion approach in communication and computation. For instance, in the framework of consensus, alternating direction methods of multipliers combined with variational Bayesian algorithms are proposed to carry out the fusion in [51], [52] for systems with non-gaussian noises or gaussian noises with unknown covariance. Additionally, discussing the Cramér-Rao lower bound can realize the efficient sensor selection [53], and adopting the structure of information filter can obtain a compact form of filtering algorithm [52].

It should be pointed out that the calculation of PDFs results in a great challenge of the implementation of distributed Bayesian filters. As an alternative scheme, their approximation can be performed via Monte Carlo simulation and importance sampling, which is the main conception of particle filtering (PF). In the distributed fashion, each sensor runs a localized PF existing many literature and then disseminates and fuses local information by resorting to various distributed schemes, such as consensus, gossip as well as diffusion [54]. Recently, the consensus-based algorithms are receiving a considerable research attention due to no requirement of both routing protocols and global knowledge. According to the types of quantities, the developed algorithms can be roughly divided into three categories [55]: algorithms focusing on calculation of particle weights [54], algorithms focusing on calculation of posterior parameters [56], and ones focusing on calculation of likelihood parameters [57]. Note that distributed PFs usually outperform standard Kalman filtering when the underlying plant and/or measurements models are nonlinear and/or non-Gaussian [58].

C. Power Schedule Control of Sensor Networks

In parallel with distributed filtering, significant efforts are devoted to the energy consumption minimization issues of sensor networks with the purpose of extending the lifespan via MAC protocols or sensor scheduling. Sensor scheduling in

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general refers to reducing the communication rate or energy consumption intentionally in order to achieve a desirable tradeoff between the filtering quality and the limited resource utilization [59], [60]. In other words, a suitable scheduling strategy of sensors should be adopted to effectively decrease the negative impact that FEC is usually enlarged along with the reduced communication energy or communication rate. In the framework of Kalman filtering, various strategies are developed recently and can be roughly categorized as: i) the FEC optimization under given scheduling constraints [61], [62], ii) the FEC optimization under given constraints on average energy usage [63], [64], iii) the optimization of energy usage under given FEC constraints [65], and iv) the combination optimization between FEC and energy usage [66], [67].

For the purpose of analysis, a set of determinate or random binary variables are usually employed to indicate scheduled sensors, and the evolution of FEC is highly dependent on these binary variables. For issues with predetermined scheduling limitation, the sum of binary variables is subject to a given constraint describing the number of authorized sensors [62] or senors with the high transmission power [61]. For finite-horizon scheduling, the characteristic of optimal policy is to schedule all transmission in a certain part of the horizon [61] or the limited number of transmission as uniformly as possible [68]. For an infinite horizon case, a metric of averaged FEC is generally adopted and some interesting algorithms, such as greedy algorithms and convex optimization approaches [62], [69], are developed to find optimal policies themselves or corresponding parameters therein (e.g. the ideal scheduling probability) in the limit case. Furthermore, the optimal policy can be approximated closely by a periodic scheduling with finite length [70]. On the other hand, considering the constraint on energy usage, a Markov decision process is utilized to reveal the structure of optimal scheduling policies and the derived sufficient and necessary condition of filtering stability depends on the high-energy packet reception ratio in [63] or the channel recovery rate in [64]. Unfortunately, it is indispensable for the feedback information from the remote estimator.

D. Hardware Platform

Sensor network platforms are likewise undergoing a revolution along with improving processors and memories to enhance the capabilities of local processing and computing, and various platforms with different CPU and OS are designed to satisfy the commercial application, see [71] for more details. For example, as one of the most popular micro sensor platforms, the Mica platform, which is designed by UC Berkeley, is with an Atmel Atmega processor running the TinyOS operating system, see Fig. 2 for its node [72]. In [73], three typical platforms of sensor networks, i.e. Particle, μNode and Sindrion, are systematically designed by using a service-oriented approach and the first two ones are confirmed by a BP petrochemical plant in UK, where PIC18f6720 and MSP430 microcontrollers are, respectively, integrated into sensor nodes, see Fig. 3 [73] for more details. In [74], a DKF algorithm is implemented in the Tmote Sky sensor network together with a small ultrasound

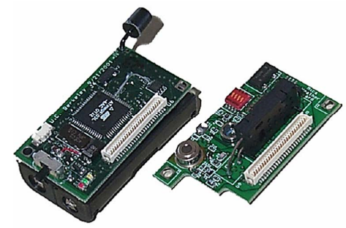

Fig. 2. Mica node.

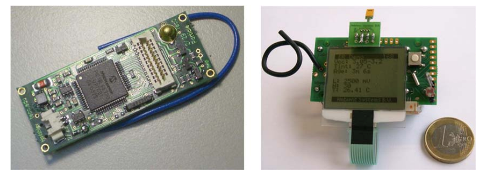

Fig. 3. Sensor node: Particle and μNode.

receiver in order to realize the localization, where the desired weights are optimized off line to yield a small estimation error covariance in stationarity. Recently, various hardware used for sensor networks and robot platforms are thoroughly surveyed and the scope of services with different facilities are also discussed in [75]. Finally, the sequential discrete KF algorithm is performed in FPGA to obtain the real-time state estimate of active distribution networks [76].

III. Distributed Control for Industrial Cyber-Physical Systems

Distributed control is one of attractive technologies in industrial CPSs, and widely implemented in various industrial manipulator systems as well as power grids.

A. Distributed Cooperative Control of Manipulators

Benefiting from higher degrees of freedom, the cooperation control of mobile manipulator systems is considered as an important technique to enhance efficiency and flexibility of industrial automation systems [77]. The kinematics and dynamics of manipulators can be modelled by an Euler-Lagrange (EL) equation [78] providing an ideal foundation of performance analysis and synthesis. Therefore, it becomes one of the emerging research topics in industrial CPSs, and some preliminary results can be found in the literature, see [79]–[82] to name a few. For instance, in [82], the distributed optimal tracking control with omnidirectional vision sensors is transformed into an optimal regulation issue of an integrated system, and an algorithm is developed accordingly to approximate the solution of corresponding Hamilton-Jacobi-Isaac equations.

1) **Distributed control based on CQP**

For redundant manipulators, the purpose of the inverse-kinematics issue, one of the most fundamental issues, is to generate an ideal trajectory in the joint space according to the desired trajectories of manipulator's end-effector being provided in the Cartesian space [83]. Note that the number of equations in such a problem is less than the number of decision variables, which proposes extra design freedom and thus increases the applicability. In other words, this property

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offers more design selections with the concern of certain optimum criteria (e.g. minimum joint velocity $\|\dot{q}\|$, tracking error $\|\dot{r}_d - \dot{q}\|$) and extra constraints from practical engineering requirements (e.g. joint limits and collision avoidance) [84]. In addition, solving the ideal trajectory can be easily reformulated as a constrained quadratic program (CQP) issue:

$$\min_{\dot{q}} f(\dot{q}, \dot{r}_d - \dot{q}) \quad \text{s.t.} \quad \dot{q} \in \Omega, \text{ and/or } g(J(q)) = 0$$

where f is a convex function, and $g(J(q))$ stands for the Jacobian equality constraint. According to derived Karash-Kuhn-Tucker conditions, the optimal solution can be obtained via constructed recurrent neural networks (NNs) [85], [86]. When the local communication among neighbor manipulators is taken into consideration, the addressed issue has to be enslaved to a set of auxiliary constraints only dependent on the neighbor information [83], [87], [88]. For instance, considering the limited communication bandwidth, communication range as well as electromagnetic interferences, a distributed scheme via a noise-tolerant zeroing NN is developed in [83] to solve a CQP problem constructed by a Lagrange-multiplier method. Theoretical analysis reveals that the proposed scheme without noises can make position errors exponentially convergent.

2) **Distributed control based on NNs**

Different from solving a CQP issue, NNs or adaptive NNs can be utilized to approximate the nonlinear kinematics function of manipulators involving various complex cases, such as modeling uncertainties, input deadzones, output constraints, as well as torque disturbances [89], [90]. The main idea is that an ideal controller is first derived via a constructed Lyapunov candidate and then its unknown part is approximated via NNs [91], [92]. For instance,$W\sigma(q,\dot{q}) = C(q,\dot{q})\dot{q} + G(q)$ where W is the neural network weight, σ means the adopted activation function, $C(q,\dot{q})\dot{q}$ denotes the Centripetal and Coriolis torques, and $G(q)$ stands for the gravitational force. For distributed cooperative control, the developed control scheme makes manipulators realize position and velocity synchronization while guaranteeing a formation. In addition, the designed controller has to embed an error term relying on both received information and communication topology to compensate the drift from predetermined ideal trajectory and, at the same time, a decomposition in the null space is employed to handle the challenges from nonintegrable and independent constraints in [85], [93]. Under this conception, a vector can be artificially introduced to construct a dynamic equation of motion in reduced feasible-space [77], [85]. For instance, by resorting to a decoupled dynamics, the distributed control of both the end-effector motion and the mobile base motion is investigated in [77] to achieve different missions of mobile manipulators with a jointly connected topology. A master-slave framework based on NNs is adopted to handle the teleoperation subject to geometrically unknown constraints in [93] and both communication delays and input uncertainties in [85]. However, various network-induced phenomena, switching topologies as well as communication protocols have still not been fully taken into account due mainly to the difficulties of controller construction.

3) **Distributed control based on MASs**

The cooperative control of multiple manipulators is adopted to realize the position and velocity synchronization while guaranteeing a formation or the joint trajectory for a primary task. In the past few years, multiple mobile manipulators are widely utilized in material transportation in modern factories, space exploration and dangerous fields for dismantling bombs, and moving nuclear infected objects [94]. Formation control of vehicles or distributed cooperative control of various industrial mobile manipulators can be transformed into the consensus issues of MASs, each agent in which is described by an operational space model [77], [95]

$$\tilde{M}_i(q_i)\ddot{\theta}_i + \tilde{C}_i(q,\dot{q})\dot{\theta}_i + \tilde{G}(q_i) = \tilde{B}(q_i)\tau_i$$

where τ_i is the input torque vector, and other parameter matrices are dependent on both the EL equation of ith manipulators and the nonlinear mapping function between the joint trajectory and the Cartesian coordinate. Recently, there are a rich body of results on consensus control of MASs with various networked-induced phenomena, switching network topologies, or sampling, see [96], [97] and the references therein. Furthermore, considering limited communication and energy resources, event-triggered consensus protocol receives considerable research attention and some interesting reviews on this topic are published in [98]. Specifically, the recent advance is systematically surveyed in [99] according to different sampling mechanisms, especially event-triggered sampling with various thresholds. Based on the merit of event-triggered mechanism, the applications of consensus analysis in power sharing of microgrids and formation control of multirobot systems are summarized in [98]. It is worth noting that the fashionable results for linear multi-agent systems cannot be effectively utilized to solve the specific challenges coming from the inherent nonlinearity of networked EL systems, not to mention that from various network-induced phenomena and communication protocols.

B. Distributed Model Predictive Control in industrial CPSs

Benefiting from the merit of satisfaction of certain constraints, distributed model predictive control (DMPC) is receiving considerable research interest. Specifically, in the framework of DMPC, the transient performance can be effectively adjusted according to current and predicted information obtained by the solution of an optimization problem with some physical constraints. In this paper, the latest developments are roughly introduced according to the following three cases.

1) **The case with coupled constraints**

In many practical engineering, lots of distributed systems, such as power systems and cooperative robot systems, are governed by a group of uncoupled system dynamics but a possibly coupled constraint on global system states and control inputs [100]. This global constraint can be described by $\sum_{i=1}^{m} g_i(x_i, u_i) \leq \mathbf{1}$, where m is the number of subsystems, see [101] for more details. Recently, it is disclosed that the optimality of the overall system is dependent on a dual problem of the Lagrangian function. Under this dual problem, dual variables associated with the above constraint can be regarded as consensus variables and therefore the solution of DMPC can be transformed into a distributed consensus optimization problem, which can be dealt with decomposition methods [102], alternating direction multiplier methods [103], dual accelerated gradient methods [104] and other optimization-based approaches. Among others, serial DMPC schemes [101], in which one subsystem is optimized at a time slot while holding all others constant. In other words, local optimization problems are solved sequentially in each subsystem, where neighboring interaction and/or solutions have to be take into consideration. Unfortunately, the optimality applying this kind of methods is unclear although it offers greater flexibility in communication and computation.

DMPC with probabilistic coupled constraints also becomes a concern [105], [106], and the corresponding form is $\mathbb{P}\big\{\sum_{i=1}^{m} g_i(x^i,u^i)\le b\big\}\ge p$ where b is a known threshold and p is the permitted probability. In contrast to deterministic forms, addressed issues allow constraint violations with the occurring probability below a prespecified threshold. For this topic, the stochastic tube approach embedded in serial DMPC schemes is utilized to ensure the probabilistic constraint while satisfying the recursive feasibility and closed-loop stability, see [105] and the references therein.

2) **The case with coupled dynamics**

As is well known, the resultant feature of interconnection leads to significant difficulties for the application of model predictive control (MPC) in large-scale systems with coupled dynamics. The impact from neighboring states and/or control is generally handled by regarding them as a bounded mutual disturbance when performing the prediction of system behavior by resorting to both a nominal model of each subsystem and local interactions. Specifically, each subsystem transmits firstly its future reference trajectory to its neighbors while guaranteeing that the actual trajectory lies within a certain bound [107]. Some standard MPC tools are then employed to solve the addressed local optimization problem with various communication constraints. This route gives rise to some interesting tube DMPC approaches, see [108] for more details.

It is worth pointing out that most existing approaches can satisfy the primary concern on feasibility and stability, but expose two critical drawbacks: the conservatism induced by the boundedness of the mutual disturbance and the deficiency in global performance due to the local optimization. In order to overcome the conservatism drawback, some improved DMPC schemes are developed in recent years, such as DMPC with sharing contract sets [109], DMPC with terminal sets reconfigured on-line [110], and DMPC with switched cost functions [111]. At the same time, some prediction schemes are proposed to compensate the missing variables caused by event-triggered protocols and multi-rate mechanism in [112], [113]. Furthermore, to improve the global performance, some iterative coordination-based algorithms are proposed to solve a centralized optimization problem in a distributed fashion [114].

3) **The case with coupled cost functions**

The essential difference from above two cases is that the connection among subsystems is realized by means of coupled cost functions [103], [115]

$$J_i = J(x_i, u_i, \{x_j, u_j\}), \quad j\in\mathcal{N}_j.$$

For instance, a dual-mode MPC strategy, which satisfies the feasibility and the stability for overall system, is developed in [116] to increase the robustness against the external disturbances. Note that the above result is dependent on a necessary assumption that a state-feedback control law of uncoupling subsystems is predetermined such that there is a constraint admissible invariant set, which plays an important role to guarantee the stabilization of closed-loop systems and the feasibility of developed DMPC schemes [115].

C. Distributed Control of Microgrids via Droop Characteristic

Microgrids, a kind of typical industrial CPSs, are usually an aggregation of distributed generators (such as renewable energy sources and conventional generators), energy storage systems, and other equipments. Their upcoming, large-scale interconnection with the national primary grid requires urgent research attention to focus on highly reliable distributed regulation technologies. Especially, at the forefront of the field, a hierarchical control scheme, including the primary control and the secondary control, is conventionally adopted for this operation. The purpose of primary control, a decentralized control approach realized through a droop mechanism, is to stabilize microgrids and handle proportional load sharing among inverters. This control forces the bus voltages and frequency to deviate from their nominal values and could lead to poor reactive power sharing in presence of unequal bus voltages. To overcome these shortcomings, secondary control under a distributed architecture is necessary to update the set points of the local primary control [117], [118].

1) **Conventional distributed control based on droop characteristics**

Under the well-known d-q (direct-quadrature) reference frame, the large-signal nonlinear dynamical model of microgrids with voltage source converters [119], [120] can be described in a compact form

$$\begin{cases} \dot{x}_i = f_i(x_i) + g_i(x_i)u_i + h_i(x_i)D_i \\ y_i^1 = v_{odi}, \;\; y_i^2 = w_i = -d_i^p P_i + u_{2,i} \end{cases} \tag{8}$$

where y_i^1 and y_i^2 are outputs, x_i is the state vector usually selected as

$$x_i = [\ \theta_i \quad P_i \quad Q_i \quad i_{Ldi} \quad i_{Lqi} \quad v_{odi} \quad v_{oqi} \quad i_{odi} \quad i_{oqi}\ ]^T$$

and other parameters can be found in [121]. Here, i_{Ldi}, i_{Lqi}, v_{odi}, v_{oqi}, i_{odi} and i_{oqi} are the quadratic and direct components of converter current i_{Li}, LC filter voltage v_{di}, and output connector current i_{oi}. Furthermore, a more general 13th-order nonlinear model can be found in [122]. According to the partial feedback linearizing scheme, an auxiliary controller based on consensus errors constructed in [119] is as follows

$$\begin{aligned} u_{i,\mathrm{aux}} = & -\kappa_i\Big(\sum_{j\in N_i}\alpha_{ij}(v_{odj}-v_{odi}) \\ & + p_i(v_{odi}-v_{\mathrm{ref}}) + \sum_{j\in N_i}\alpha_{ij}(d_j^q Q_j - d_i^q Q_i)\Big) \end{aligned} \tag{9}$$

for voltage control, where there exists at least one pinning gain $p_i > 0$ for voltage source converter i. In addition, taking proportional real power sharing into account, one has [123]

$$\begin{aligned} u_{i,\mathrm{aux}} = & -\kappa_i\Big(\sum_{j\in N_i}\alpha_{ij}(\omega_j-\omega_i) \\ & + p_i(\omega_i-\omega_{\mathrm{ref}}) + \sum_{j\in N_i}\alpha_{ij}(d_j^p P_j - d_i^p P_i)\Big) \end{aligned} \tag{10}$$

for frequency control. It should be pointed out that the regulating error of active power allocation $\sum_{j\in N_i}\alpha_{ij}(d_j^p P_j - d_i^p P_i)$ is embedded in the control strategy with intent to maintain the equal cost increment achieved in the primary control [123].

By utilizing iterative learning approaches, a robust distributed secondary control is presented in [124] to achieve both active power sharing accuracy and voltage/frequency restoration of microgrids with uncertain communication links. Furthermore, an improved controller by combining tracking performance and regulator synchronization is developed in [123] for islanded microgrids with a sparse communication network, and in [125] for inverter-based AC microgrids with additive channel noises. A consensus based distributed controller is designed in [120] to provide more robustness to unmodelled dynamics, unknown disturbances, and uncertainties while restoring the desired voltage magnitude and frequency within finite time. Generally speaking, the controller gain usually depends on the eigenvalues of a Laplacian matrix, which are essentially global information. In contrast to these existing distributed methods, a fully distributed adaptive controller designed in [119] only utilizes the dynamics model of DG units and neighbors' information and therefore eliminates the need of a central computing and communication unit. Furthermore, both single and multiple pinning schemes are discussed in [126] and it is disclosed that the selection of a pinning set depends on both the degree of algebraic connectivity and the distance of leaders. However, the problems on the selection of pinning nodes and the design of pinning strength are not solved effectively, especially for the cases with network-induced phenomena and communication protocols.

2) **Distributed control based on averaging conception**

With the help of the standard frequency/active-power (f/P) and voltage/reactive-power (V/Q) properties, one has the following conventional controller structure with the conception of distributed averaging [127], [128] to adjust the inverter frequency ω_i and the amplitude E_i of output voltage

$$\omega_i = \omega^* - d_i^p P_i - u_i^\omega, \quad E_i = E^* - d_i^q Q_i - u_i^E \tag{11}$$

where ω^* and E^* are the nominal network frequency and the nominal voltage of microsource i. A feasible distributed secondary control [128] is

$$\begin{cases} \kappa_i^\omega \dot{u}_i^\omega = -(\omega_i - \omega^*) - \sum\limits_{j\in N_i}\alpha_{ij}\big(u_i^\omega - u_j^\omega\big) \\ \kappa_i^E \dot{u}_i^E = -\beta_i(E_i - E^*) - \sum\limits_{j\in N_i}\alpha_{ij}\Big(\dfrac{Q_i}{Q_i^*} - \dfrac{Q_j}{Q_j^*}\Big) \end{cases} \tag{12}$$

where β_i, κ_i^ω and κ_i^E are positive gains, Q_i^* is the reactive power rating of distributed generation (DG) i, and α_{ij} is the ijth element of microgrid's Laplacian matrix.

Different from structure (10), the diffusive averaging term $\sum_{j\in N_i}\alpha_{ij}\big(u_i^\omega - u_j^\omega\big)$ is introduced into the above controller to maintain active power sharing. This kind of controllers is also named as distributed-averaging proportional-integral ones. An early version developed in [129] relies on both average voltage and average frequency of DG units and therefore there exists a forced assumption on the communication among all DGs. Fortunately, such a shortcoming is overcome via the above controller. As stated in [128], the designed distributed control removing the need of a central supervisory satisfies a tunable trade-off between reactive power sharing and voltage regulation. In addition, in light of Lyapunov stability theory, some sufficient conditions are derived to evaluate the system stability and robustness to incomplete communication links.

3) **Distributed control based on angle droop characteristics**

Similar to the above droop control scheme, one has the following angle droop control model for a microgrid [130], [131] with purely inductive lines

$$d_i^p \dot{\theta}_i = \Delta P_i^* - \sum\nolimits_{j=1}^{N} l_{ij}\sin(\theta_i - \theta_j) - u_i \tag{13}$$

where $d_i^p > 0$, θ_i, u_i and l_{ij} denote, respectively, the droop coefficient, the bus phase angle, the control input determined by a secondary control loop, and the magnitude of pure imaginary admittance of the interconnecting line between inverters i and j. ΔP_i^* represents the inverter power mismatch between the nominal injection setpoint of inverters and the load demand of buses. To eliminate this angle deviation, a typical distributed secondary controller is

$$\kappa \dot{u}_i = d_i^p \dot{\theta}_i - \sum\nolimits_{j=1}^{N}\alpha_{ij}\Big(\frac{u_i}{d_i^p} - \frac{u_j}{d_j^p}\Big)$$

where $\kappa > 0$ is the coefficient, and α_{ij} is of the same with one in (12). This distributed controller is employed in [132] to offer the best combination of flexibility and performance by using communication among generation units. Especially, when $\theta_i \simeq \theta_j$, the above control model can be simplified as (12).

Lately, stability and convergence properties receive considerable research efforts, see, e.g. [131], [133]. Specially, a necessary and sufficient condition is derived in [131] to disclose the existence and uniqueness of locally exponentially stable equilibrium. In addition, frequency regulation without assuming time-scale separation can be ensured and ultimate boundedness can also be satisfied under a condition on power mismatch [130]. In particular, a simplified distributed controller is designed in [133] to steer the microgrid with security constraints to a desired steady state. The designed controller is also robust for loss of communication links and failures of distributed energy resources.

4) **Distributed control based on state-space models**

In addition, by regarding each control area as a single-machine single-load system or using the droop characteristics of power sharing, a state-space model of power systems can be described by

$$\dot{x}_i = A_{ii}x_i + \sum\nolimits_{j=1, j\neq i}^{N} A_{ij}x_j + Bu_i + \Gamma_i n_{di} \tag{14}$$

where state vector x_i can be selected as $x_i = [\ \Delta\omega_i \ \ \Delta P_{ti} \ \ \Delta P_{gi} \ \ \Delta P_{tie}^i\ ]^T$ for multi-area power systems [134], [135] augmenting the deviation of frequency ω_i, generator mechanical power P_{ti}, turbine valve position P_{gi} and the net tie-line power flow ΔP_{tie}^i, or selected as $x_i = [\ V_i \ \ I_{ti} \ \ \phi_V \ \ \phi_I \ \ \varphi_V \ \ \varphi_I\ ]^T$ for DC microgrids [33], [136], [137] reflecting the load voltage at point of common coupling, the filter current, the dynamics of primary control (the third and fourth states), and the dynamics of secondary voltage controllers (the last two states). Additionally, n_{di} stands for a load disturbance, and A_{ij} represents the coupled

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matrix of interconnected areas. The adopted distributed control is with the form [134], [135]

$$u_i = K_i x_i + \sum\nolimits_{j=1, j\neq i}^{N} K_{ij} x_j$$

or the form based on consensus control [136]

$$u_i = K_i \sum\nolimits_{j=1, j\neq i}^{N} \alpha_{ij} (\hat{x}_j - \hat{x}_i)$$

where $\hat{x}_i$ is the estimated state, and K_i and K_{ij} are two controller gains to be designed. Furthermore, one can obtain a model similar to (14) by using small signal analysis under the d-q (direct-quadrature) reference frame, see [138] and the references therein.

For large-scale power systems with limited bandwidth constraints, a delay-dependent stability criterion is proposed in [135] for systems subject to communication delays, and the relationship between delay margins and control gains is exposed in detail. Furthermore, the impact on the closed-loop system performance from both time delays and varying communication topologies is examined in [134] via multi-agent technologies, and the dynamic performance under event-triggered scheme is also analysed via simulations. In order to reduce the communication burden, event-triggered protocols dependent on dynamic consensus algorithms are designed in [136], [137] to achieve both voltage regulation and proportional current (or load) sharing. With the help of constructed consensus estimators combined with Lyapunov stability theory, the desired event-triggering conditions are obtained, and the convergence and stability of proposed dynamic consensus algorithm are discussed. In comparison with the condition in [136], the setup of adaptive strategy in [137] results in a requirement of global GPS signal.

IV. Distributed Security Control and Filtering of Industrial CPSs

There is no doubt that the increased interaction between physical realms and cyber will result in unavoidable security vulnerabilities. In real-word CPSs, typical cyber-attacks include DoS attacks, replay attacks, deception attacks, and so forth. Any successful attacks against industrial CPSs may cause the serious impact on the human society and national economy [139]. As such, the security of industrial CPSs to defend against these attacks is an urgent research concern [140]–[142]. It is worth mentioning that, compared with relatively mature techniques under traditional distributed frameworks, distributed control and filtering with security perspective still remain at an infant stage. Recently, from the perspective of defenders, the effect on state estimation from attacks was investigated, see [143], [144] and the references therein. Usually, the security can be enhanced by effectively utilizing the identification information of cyber-attacks or necessary attack information (i.e. attack intensity or attack frequency).

In light of Kalman filtering theory with generalized cumulative sum algorithms, a distributed state estimator is designed in [145] to attempt to realize a quick attack mitigation and system recovery. In comparison with the existing results based on least square approaches, the proposed scheme can not only successfully recognize bad data but also identify structured false data injection attacks. Besides, according to the well-known gradient descent, a recursive algorithm is designed in [24] to handle a distributed filtering issue over sensor networks subject to deception attacks and a sufficient condition is derived to check the stability of proposed algorithm. A distributed filter owning the capabilities of attack detection and state estimation is designed and tested via the wide-area monitoring of a power network in [146], where a hybrid Bernoulli random set is introduced to describe the joint information on the attack presence or no. Different from distributed filtering algorithms in the mean square sense [147], the paradigm of Kullback-Leibler fusion is utilized to handle the challenge from probability density function. It should be pointed out that the obtained algorithm only has limited robustness to attacks arising from the assumption on attack intensity.

In the context of industrial CPS security, the performance indexes mainly include security, stability as well as resilience where the trade-off between security and stability receives growing attention in the literature [9]. Similar to the distributed filtering of industrial CPSs discussed above, it is also urgent to mitigate the threat from various cyber-attacks via designed control strategies. In view of the core of critical infrastructures, the resulting successful attack on industrial CPSs is generally more serious in contrast to attacks on traditional networked control systems. In addition, according to system recovery, two schemes of attack-resilient cooperative control for industrial CPSs consisting of distributed agents are investigated in [148] via the identification and isolation of the misbehaving cyber elements, and the cascade protection design of lossless systems, respectively. For operator-vehicle networks remotely maneuvered by an operator, a distributed resilient algorithm is developed in [149] to steer vehicles to the desired formation against attackers. The designed control algorithm can be effectively performed under a distributed form by resorting to the introduction of an auxiliary receding-horizon control. A cooperative resilient control strategy is introduced in [148] to regulate the active power from a cluster of DGs at a certain ratio of their maximal available power. Such a strategy combined with a proper observation networks can effectively monitor the behaviors of all neighbors and isolate the misbehaving DGs coming from non-colluding cyber-attacks. Additionally, a resilient distributed algorithm is proposed in [150] to solve DC optimal power flow issue against data integrity attacks. In these two papers, the consensus conception is utilized to estimate the utilization ratios of DGs in [148] by introducing a virtual power plant, and estimate the bus power imbalance in [150] by adopting the primal-dual decomposition method. It should be pointed out that almost all results on security in the framework of control theory are based on an assumption that system dynamics need to be simple, which leads to a gap between theoretical results and practical engineering applications.

V. Conclusions and Challenging Issues

A survey on distributed control and filtering has been provided for industrial CPSs described by differential dynamics models. For real-time monitoring, some typical Kalman-based distributed algorithms and various filter structures have been systematically summarized and their performances have been also discussed in detail. For distributed closed-loop systems, the development of distributed control strategies has been well addressed, especially for mobile manipulator systems and power systems with the requirements of power sharing, and voltage and frequency regulation. However, there are still various limitations from communication links, bandwidth, computational burden, scalability as well as special engineering requirements, which potentially offer some scope for improving existing results or methodologies. In what follows, we pay more attention to these limitations and propose some important and yet challenging research topics, which sheds insightful light on the further research.

- For practical CPSs, resource constraints or practical function, such as communication bandwidth, limited energy or plug-and-play, usually need to be taken into consideration. Under these constraints, it is no longer effective for the study of distributed control and filtering via established methods dependent on the eigen-structure of the coupling matrix. In other words, most of existing research results are based on some specific assumptions on topology structures and therefore there is a unavoidable stumbling block for practical applications. A feasible idea is to find a suitable condition of connectivity for randomly varying topologies or a condition on dwell-time for general switching topologies to guarantee the stability of addressed systems.
- When occurring above resource constraints, existing distributed filtering schemes cannot simultaneously satisfy the requirements of computation burden, communication burden and scalability so far. The main reason could come from the calculation of cross-covariances, the utilization of augmentation approaches, or consensus iteration. In addition, in light of its reliability in describing filtering accuracy, the filtering performance in probability sense is more suitable for practical engineering with various random phenomena. Unfortunately, it has been largely omitted due probably to the difficulty in mathematic analysis.
- According to the characteristic of line impedance, Q/V and P/f droop control schemes are usually utilized in a microgrid with inductive lines, and Q/F and P/V ones are for the case with resistive lines. When considering a microgrid subject to complex line impedance or inaccurate P or Q regulation, the existing strategies for above two cases cannot guarantee a reliable control performance. The main reason could arise from the challenges of coupled P and Q equations. Hence, it is of significance to develop some novel distributed control strategies for more general power systems, which deserves deep investigation.
- It is noteworthy that multiple pinning control has been regraded as an effective scheme in distributed secondary control of microgrids. However, to the best of the authors' knowledge, the problems on the selection of pinning nodes and the design of pinning strength are not solved effectively, especially for the cases with network-induced phenomena and communication protocols. Note that such a control issue presents the intermittent feature due to the data sparsity induced by above cases, and thereby it is a meaningful attempt to carry out the performance analysis in the framework of intermittent control.
- Due to the vulnerability, cyber-attacks can be regarded as one of the major threats of CPSs. Up to date, some interesting results have been developed to detect whether the discussed system is subject to attacks. Unfortunately, the detected results cannot be effectively utilized to improve the performance of control or filtering. In other words, it is considerable to integrate the attack detection into the designed distributed filtering and control strategies against various cyber-attacks. In light of its good statistical characteristic, the χ^2 detector combined with an indicator function could be one of the best options.
- Further research topics also include to deepen practical engineering applications of the developed theory, such as approximate dynamic control of mobile cooperative manipulator systems, distributed energy management of smart grids, supervisory control and data acquisition of power systems, industrial process control of metallurgy and petrochemistry areas, and so forth.

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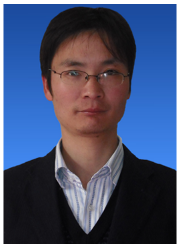

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