A Real-Time Big-Data Control-Theoretical Framework for Cyber-Physical-Human Systems

Azwirman Gusrialdi, Ying Xu, Zhihua Qu, and Marwan A. Simaan

Abstract Cyber-physical-human systems naturally arise from interdependent infrastructure systems and smart connected communities. Such applications require ubiquitous information sensing and processing, intelligent machine-to-machine communication for a seamless coordination, as well as intelligent interactions between humans and machines. This chapter presents a control-theoretical framework to model heterogeneous physical dynamic systems, information and communication, as well as cooperative controls and/or distributed optimization of such interconnected systems. It is shown that efficient analytical and computational algorithms can be modularly designed and hierarchically implemented to operate and optimize cyber-physical-human systems, first to quantify individually the input-output relationship of nonlinear dynamic behaviors of every physical subsystems, then to coordinate locally both cyber-physical interactions of neighboring agents as well as physical-human interactions, and finally to dynamically model and optimize the overall networked system. The hierarchical structure makes the overall optimization and control problem scalable and solvable. Moreover, the three levels integrate individual designs and optimization, distributed cooperative optimization, and decision making through real-time, data-driven, model-based learning and control. Specifically, one of the contributions of the chapter is to demonstrate how the combination of dissipativity theory and cooperative control serves as a natural framework and promising tools to analyze, optimize, and control such large scale system. Application to digital grid is investigated as an illustrative example.

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1 Introduction

Cyber-physical-systems (CPSs) refer to the integrations of cyber core consisting of communication network, computation and physical processes (engineered systems) which are normally large scale and complex, as illustrated in Fig. 1. These two components are tightly coupled: embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa. In addition, CPSs will also interact with humans resulting in cyber-physical-human systems. Cyber-physical-human systems naturally arise from interdependent infrastructure systems and smart connected communities. Examples include smart grid [1], intelligent transportation systems [2], and smart city [3]. Such applications require ubiquitous information sensing and processing, intelligent machine-to-machine communication, a seamless coordination of physical systems, and intelligent interactions between humans and machines. While technological advances and the development of relatively inexpensive yet powerful communication, computation and sensing devices make the realization of such complex system become feasible, fundamental technical challenges centered on real-time big data processing, optimization and control of the spatially distributed complex systems remain to be solved. A major and fundamental challenge is to develop a control design theory that does not consider the physical and cyber components separately, but as two facets of the same system [4]. Another major challenge is the choice of control architecture which allows the designer to control the complex system efficiently and in real time. Traditional centralized control architecture, where all the data from ubiquitous sensors are gathered in a centralized processing center, which optimizes and computes the control input for the overall system is not appropriate to optimize and control such large scale interconnected system since it may suffer from explosion of data and and may also harm data privacy [5]. This calls for a scalable and modular system theoretic tools to analyze, optimize, and control the cyber-physical-human systems. In particular, distributed optimization and control algorithms are highly desirable for dealing with such complex systems due to its scalability and robustness against component faults and cyber-attacks [6].

The chapter presents a control-theoretical framework to model heterogeneous physical dynamic systems, information and communication, as well as cooperative controls and/or distributed optimization through which human operator or users can interact effectively with physical systems in a multi-agent setting to achieve various control and optimization objectives. It is shown that efficient computational algorithms can be applied hierarchically to operate and optimize cyber-physical-human systems, first individually to quantify the dynamic behavior of every agent, then locally to describe the local interactions of neighboring agents, and finally to the overall system. All the three control levels deal with real-time big data, and the hierarchical structure makes the overall optimization and control problem scalable and solvable. In particular, one of the contributions is to demonstrate how the concept of dissipativity theory and cooperative control serve as a natural framework and promising tools to analyze, optimize, and control such large scale systems in a scalable and modular manner. Application to digital power grid is investigated as an illustrative example.

The chapter is organized as follows. We begin with dynamic modeling of cyber-physical-human systems together with its optimization and control objectives in Section 2. A brief summary of the basic concepts of dissipativity theory and co-operative control as the main analytical and design tools are presented in Section 3. Section 4 provides an example of applying the dissipativity theory and cooperative control to design hierarchical control of power system. Modeling and analysis of human-machine interaction with focus on electricity market is presented in Section 5. The role of real-time big data and decision making in controlling cyber-physical-human systems is discussed in Section 6. Finally, we conclude in Section 7.

2 Dynamic modeling of cyber-physical systems and its optimization/control objectives

System modeling is an important step in designing control algorithms. Briefly speaking, a model is a mathematical representation of physical system which allows us to reason and predict how the system will behave. In this chapter, we are mainly interested in models of dynamical system describing the input/output behavior of systems. To this end, let us consider cyber-physical-human systems consisting of n heterogeneous physical systems whose individual dynamics can be modeled by differential equations in the form of

$$\dot{x}_i = f_i(x_i, u_i, r_i), \;\; y_i = h_i(x_i, r_i), \tag{1}$$

with $i = \{1, \cdots, n\}$. The model in (1) is known as state space models where variables $x_i \in \Re^{n_i}$ denotes the state which encodes what needs to be known about the past history, $u_i \in \Re^m$ is the control signals to be designed, and $y_i \in \Re^m$ denotes the output (measurement) signals of the i-th system. In addition, $r_i \in \Re^m$ in (1) is the operational decision as a result of the intelligent interaction between humans and the physical systems which may take place in a slower time-scale. In general, the physical systems may also be interconnected through a physical network whose characteristic could be described by the following algebraic equation

$$\kappa_i(y_1, \cdots, y_n, x_1, \cdots, x_n) = 0. \tag{2}$$

As an example, consider a power system where the individual physical system refers to the synchronous generator as shown in Fig. 1. For the sake of simplicity, the dynamics of synchronous generator is given by the following swing equation

$$M_i \ddot{\delta}_i = P_{m,i} - P_{e,i} - D_i \omega_0 \dot{\delta}_i, \tag{3}$$

where $M_i > 0$ denotes its inertia, $D_i > 0$ is its damping constant, $P_{m,i}$ denotes its mechanical power while $P_{e,i}$ is its active power output, and δ_i denotes its rotor an-

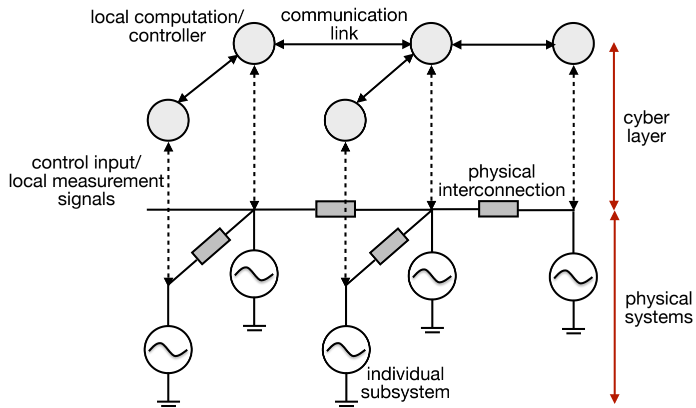

Fig. 1 An illustrative diagram of cyber-physical systems as exemplified by power system

gle measured with respect to a rotating frame with speed ω_0. The generators are physically interconnected with each other which can be characterized through the following nonlinear power flow equation

$$P_{e,i} = E_i^2 G_{ii} + \sum_{k \neq i} E_i E_k (G_{ik} \cos \delta_{ik} + B_{ik} \sin \delta_{ik}), \tag{4}$$

where $\delta_{ik} = \delta_i - \delta_k$, E_i is the voltage of the generator bus, and $Y_{ik} = G_{ik} + jB_{ik}$ is the transfer admittance between generators i and k. Defining respectively the states, input and output of the i-th generator as $x_i = [\delta_i - \delta_i^*, \omega_i]^T$, $u_i = P_{m,i}$ and $y_i = x_i$ with δ_i^* denotes the final angle, we can recast swing equation (3) together with power flow equation (4) with respect to their equilibrium in the form of (1) as [7]

$$\dot{x}_i = A_i(x_i)x_i + B_i(x_i)u_i + \sum_{k \in \mathcal{N}_i} H_{ik}(y_i, y_k)(y_k - y_i), \;\; y_i = C_i x_i \tag{5}$$

where $\mathcal{N}_i$ denotes the neighboring set of generator i, matrices A_i, B_i and coupling matrix H_{ik} are state/output-dependent. Note that generators with higher (e.g., 5th or 6th) order dynamics can also be represented by state-space model (5). In addition to the physical network, there is also a cyber-layer representing information/communication network for the system operator/local controller of physical systems to obtain/exchange measurements in order to monitor and control the overall system. The structure of communication network (information flow) in general is modeled using a graph as illustrated in Fig. 1. Let $\mathcal{N}_i^c$ denote the communication neighboring set of the i-th subsystem. In other words, subsystem $j \in \mathcal{N}_i^c$ if information on measurement y_j is available to the i-th subsystem. The communication network topology can also be represented by the following communication matrix

$$S^c = [S_{ij}^c] \in \Re^{n \times n}, \;\; S_{ii}^c = 1 \tag{6}$$

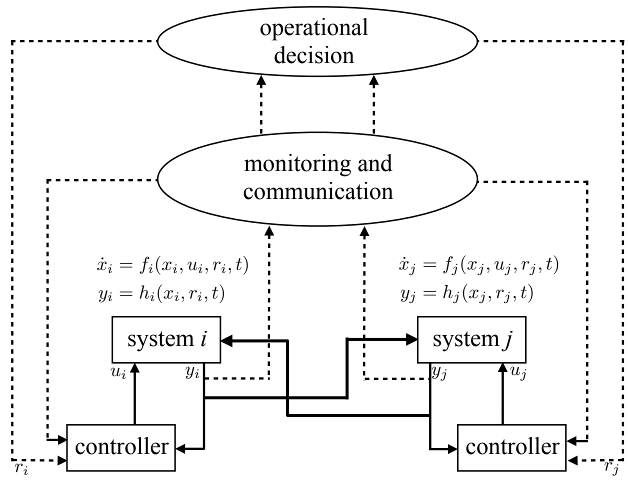

Fig. 2 Three-level data driven controls of cyber-physical-human systems. The dashed lines represent information flow between different levels

where $S^c_{ij} = 1$ if $j \in \mathcal{N}_i^c$ and $S^c_{ij} = 0$ otherwise.

Optimizing and controlling the above cyber-physical human systems calls for computationally efficient and scalable algorithms to deal with its large scale nature and complexity (in terms of heterogeneous individual nonlinear dynamics and their physical interconnections). To this end, we divide the control objective of cyber-physical-human systems into three levels as illustrated in Fig. 2. Specifically, the control input u_i in (1) is decomposed into the following hierarchical form

$$u_i = u_{s_i}(x_i) + \underbrace{u_{l_i}(y_i, y_j) + v_i}_{\overline{u_i}}, \tag{7}$$

each layer with the following control design objective:

1. the lowest level control u_{s_i} aims to stabilize each individual physical system
2. the mid-level control input u_{l_i} is to achieve a local coordination for a group of physical systems
3. the highest level control v_i aims at ensuring stability of the overall interconnected system.

For the example of power system whose dynamics is represented by (5), the goal of low-level (self-feedback) control u_{s_i} is to ensure (input-output) stability of the individual generator. The mid-level control u_{l_i} can be designed as a distributed optimization algorithm (by taking advantage of the communication network) to achieve a uniform voltage profile for a group of generators or minimize power loss. Finally, the high-level control v_i acts as a wide area control with the goal of ensuring stability and/or improving performance of the power system.

In what follows, we will present a control theoretic framework based on dissipativity theory and cooperative control for systematically optimizing and controlling cyber-physical-human systems and further demonstrate its effectiveness using the power system example described previously.

3 Main analytical and design tools: dissipativity theory and cooperative control

Dissipativity is an energy-like concept which describes input-output properties (e.g. stability) of a dynamical system. Input-output mapping becomes a useful way of quantifying input-output properties of the system when the dynamical model of the system is not available. Briefly speaking, dissipative system is a system that absorbs more energy from the external world than it supplies [8]. Passivity is a special class of dissipativity and is originated in circuit analysis. Passive systems are always decreasing in energy with respect to input energy. For example, an electrical circuit consisting of resistor, inductor and capacitor can dissipate energy by turning it into heat and also store energy, but it cannot supply more energy than what has been put into it. Another class of dissipative systems is what so-called passitivity-short systems. Compared to passive systems, passivity-short systems may increase or remain the same in energy from input to output during transience. One example is a generator that is not decreasing in energy at all times simply because it is producing some amount of energy. Dissipativity based approaches becomes attractive in analyzing and controlling CPS since its properties are preserved over system interconnections which makes the approach computationally scalable. For example, with individual output negative feedback, the passivity-short systems can be interconnected either in parallel or in series or in a positive feedback loop or a negative feedback loop while maintaining the same passivity-short property [9]. This compositional property makes dissipativity a powerful and promising tool to analyze and control large-scale system such as CPS [4].

The concept of dissipativity is captured by introducing two energy-like functions, namely, supply rate and storage functions. Depending on the choice of particular supply rate function, dissipativity can imply several important behaviors such as stability of dynamical systems and their interconnections. Consider system (1) with $r_i = 0$ and without physical interconnection. The i-th system with supply rate $\Phi_i(u_i(t), y_i(t))$ is said to be dissipative if there exists a nonnegative real storage function $V_i(x_i)$ such that the following inequality holds [10]

$$V_i(x_i(t)) - V_i(x_i(0)) \leq \int_0^t \Phi_i(u_i(\tau), y_i(\tau)) d\tau. \tag{8}$$

Choosing the supply rate function in a quadratic form, the i-th system is said to be input passivity-short with respect to a differentiable storage function $V_i(x_i)$ if the inequality

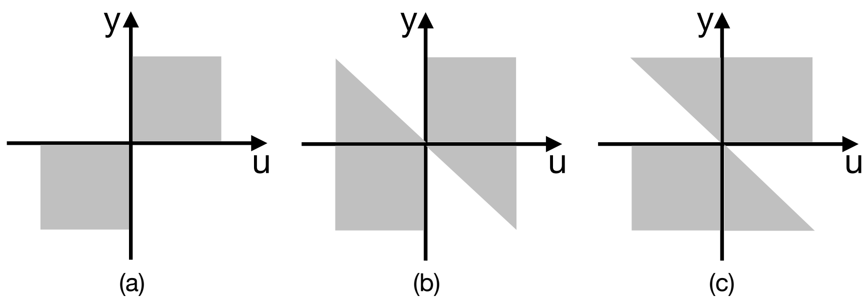

Fig. 3 Input-output diagram (shaded region) [7] of: (a) Passive; (b) Input passivity-short; (c) Output passivity-short

$$\dot{V}_i \leq u_i^T y_i + \frac{\varepsilon_{ii}}{2}\|u_i\|^2 - \frac{\rho_i}{2}\|y_i\|^2 \tag{9}$$

holds for some $\varepsilon_{ii} > 0, \rho_i \geq 0$ and it is said to be output passivity-short if (9) holds for some $\varepsilon_{ii} \leq 0, \rho < 0$. In addition, the system is said to be L_2 stable if inequality (9) holds for some $\rho_i > 0$ and a positive definite V_i resulting in

$$\|y_i\|_{L_2} \leq \left(\frac{2\varepsilon_{ii}}{\rho_i} + \frac{4}{\rho_i^2}\right)\|u_i\|_{L_2} + \text{constant}. \tag{10}$$

Finally, the system is passive if inequality (9) holds for some $\varepsilon_{ii} = 0$ (and $\rho_i = 0$). Fig. 3 illustrates a static input-output mapping of passivity and passivity-short systems. Note that passivity is quite restricted as it excludes most of linear dynamic systems such as nonminimum-phase systems and minimum-phase systems with relative degree 2 or higher. It is shown in [11] that most linear systems are passivity-short and that all linear Lyapunov-stable dynamic systems are either passivity-short or can be made passivity-short under an output-feedback control. The parameters ε_{ii} and ρ_i are important for analysis, control design, and stability of networked passivity-short systems and it is desirable to maximize the value of ρ_i and minimize ε_{ii}. In particular, ε_{ii} is also called *impact coefficient* and it quantifies the impact of individual passivity-short system on the network-level cooperative control as will be discussed later. Let us show now that a synchronous generator connected to infinite bus is passivity-short. Dynamics of the generator is given by the following swing equation

$$M_i\ddot{\delta}_i = b_i u_i - H_{ii}(\delta_i - \delta_i^*) - D_i\omega_0\dot{\delta}_i \tag{11}$$

and its output is defined as $y_i \triangleq \delta_i - \delta_i^*$. Taking the following positive definite storage function

$$V_i = \left(\frac{k_d}{2k\sqrt{kp}} + \frac{\sqrt{k_p}}{kk_d}\right)y_i^2 + \frac{1}{kk_d\sqrt{k_p}}\dot{y}_i^2 + \frac{1}{k\sqrt{k_p}}y_i\dot{y}_i$$

with $k = b_i/M_i$, $k_p = H_{ii}/M_i$, and $k_d = D_i\omega_0/M_i$ and computing its derivative yields

$$\dot{V}_i \leq u_i^T y_i + k\left(\frac{(1-\sqrt{k_p})^2}{2k_p\sqrt{k_p}} + \frac{1}{k_d^2\sqrt{k_p}}\right)u_i^2 - \frac{\sqrt{k_p}}{2k}y_i^2 \triangleq u_i^T y_i + \frac{\varepsilon_i}{2}\|u_i\|^2 - \frac{\rho_i}{2}\|y_i\|^2$$

which shows that the generator is passivity-short and L_2 stable. Furthermore, we can also obtain the physical meanings of ε_i and ρ_i. To this end, the transfer function of (11) can be written as

$$G(s) = \frac{k}{s^2 + k_d s + k_p}. \tag{12}$$

By writing $k_d = 2\xi\omega_n$, $k_p = \omega_n^2$, and $k \approx k_p$ where ω_n is the natural frequency and ξ denotes the damping ratio, it can be shown that

$$\varepsilon_i \approx \omega_n\left(1 - \frac{1}{\omega_n}\right)^2 + \frac{1}{2\xi^2\omega_n}, \;\; \rho_i \approx \frac{1}{\omega_n}.$$

Hence, we can see that the value of ε_i increases as ξ becomes smaller and the optimal value of ε_i is obtained for $\omega_n = 1$.

Cooperative control is another control design tool that has shown a great promise in optimizing and controlling large-scale system and has been successfully utilized to develop network-level control of a group of mobile robots [12, 13], power system [1], charging scheduling of electric vehicles [2], and complex network [14]. The goal of cooperative control is to achieve non-trivial concensus using only local information (and thus scalable) obtained via the communication network as illustrated in Fig. 1, that is for all individual systems i we have [15]

$$\lim_{t\to\infty}\|y_i(t) - y_j(t)\| = 0, \text{ or } \lim_{t\to\infty} y_i(t) = c. \tag{13}$$

Consider again physically decoupled CPS with individual dynamics (1). As shown in [16], the concept of passivity-short simplifies the design of cooperative control by modularizing the lower-level and network-level control designs. Specifically, a self-feedback control u_{s_i} is first designed so that individual system becomes passivity short. The cooperative control can then be designed by simply considering the following fictitious integrator dynamics

$$\dot{y}_i = u_{l_i} \tag{14}$$

where u_{l_i} is specified as

$$u_{l_i} = k_{y_i}\sum_{j\in\mathcal{N}_i^c} S_{ij}^c(y_j - y_i). \tag{15}$$

The closed-loop dynamics of (14) and (15) can be compactly written as

$$\dot{y} = -diag\{k_{y_1}, \cdots, k_{y_n}\}Ly, \tag{16}$$

with $y = [y_1, \cdots, y_n]^T$ and $L = diag\{S^c\mathbf{1}\} - S^c$. Consensus (13) is ensured if there is at least one node from which every other node can be reached and the gains $k_{y_i} > 0$ are chosen to be smaller than k^*. Moreover, if every node can be reached from any other nodes, k^* can then be computed according to [16]

$$k^* = \frac{\lambda_2(\Gamma L + L^T \Gamma)}{2(\max_i \varepsilon_{ii})\lambda_{\max}(L^T \Gamma L)}, \tag{17}$$

where $\lambda_2(\cdot), \lambda_{\max}(\cdot)$ denote the smallest non-zero and largest eigenvalues respectively, and matrix $\Gamma = diag\{\eta_1\}$ with $\eta_1^T L = 0$. It is worth to note that k^* in (17) can be computed in a distributed manner without requiring global information of L [17]. The communication topology embedded in matrix L can also be optimized to increase the convergence speed of (15), see e.g. [18–20]. As can be seen from (15) and (17), the design of cooperative control of networked passivity-short system does not require any explicit knowledge about the heterogenous physical systems other than their impact coefficients. Moreover, quantity $\max_i \varepsilon_{ii}$ in (17) can be viewed as the "worst" value of impact coefficients of all the passivity-short systems. Adding or removing subsystems into or from the networked systems result in different impact on the overall system operation. However, the performance of the overall system can still be guaranteed given that the control gains are appropriately upper-bounded to limit such impact. Hence, the operation of the networked system can be performed in a plug-and-play manner while its stability is guaranteed.

4 Hierarchical control design for cyber-physical-human systems

In this section, we utilize the concept of passivity-short and cooperative control presented in the previous section to design hierarchical control law (7) for power system whose dynamics is given by (5).

4.1 Low-level control design: ensuring input-output stability

Let us now consider the nominal subsystem in (5) by excluding its physical interconnections, i.e., assuming $H_{ik} = 0$ for all $i \neq k$. The first step is to design a self-feedback control u_{s_i} for individual physical system given by

$$u_{s_i} = -K_i x_i$$

such that: (i) the individual physical system is passivity-short and L_2 stable for input-output pair $\{\overline{u_i}, y_i\}$; (ii) its impact on the overall system, that is, the values ε_{ii} and $-\rho_i$ in (9) are minimized. To this end, taking the storage function $V = \frac{1}{2}x_i^T P_i x_i$ with P_i is a positive definite matrix, a self-feedback control can be designed by solving the following optimization problem

$$\begin{aligned} \underset{K_i,\varepsilon_{ii},\rho_i}{\text{minimize}} \quad & [\alpha_{ii}\varepsilon_{ii} - (1-\alpha_{ii}\rho_i)] \\ \text{subject to} \quad & P_i > 0, \\ & M_i(x_i) \le 0, \\ & \varepsilon_{ii}, \rho_i \ge 0, \end{aligned} \tag{18}$$

where $\alpha_{ii} \in (0,1)$ is a design parameter and matrix $M_i(x_i)$ is defined as

$$M_i(x_i) \triangleq (A_i(x_i) - B_iK_i)^T P_i + P_i(A_i(x_i) - B_iK_i) + \rho_i C_i^T C_i + \frac{1}{\varepsilon_{ii}}\|P_iB_i - C_i^T\|^2 < 0.$$

The second constraint in (18) guarantees that inequality (9) holds, i.e. the individual system is passivity-short and L_2 stable. Note that at any instant of time t, the state $x_i(t)$ becomes known from the Phasor Measurement Units (PMU) and so is matrix $A_i(x_i)$, and hence K_i can be designed adaptively by using available Lyapunov function $P_i > 0$.

After making the individual system passivity short and L_2 stable, next we consider the interconnected system to quantify the impact of nonlinear interconnections on subsystem (5) in a way parallel to that of $\varepsilon_{ii}\|\overline{u_i}\|^2$. Specifically, the goal is to minimize the transient impacts of the inter-area oscillations encoded in ε_{ij} by solving the following optimization problem

$$\begin{aligned} \underset{\varepsilon_{ij}}{\text{minimize}} \quad & \sum_{j\in\mathcal{N}_i} \alpha_{ij}\varepsilon_{ij} \\ \text{subject to} \quad & P_i > 0, \\ & M_i'(x_i, y_j) \le 0, \\ & \varepsilon_{ij}, \alpha_{ij} \ge 0, \\ & \sum_{j\in\mathcal{N}_i} \alpha_{ij} = 1, \end{aligned} \tag{19}$$

where

$$M_i' \triangleq M_i - \sum_{j\in\mathcal{N}_i} \left(P_iH_{ij}C_i + C_i^T H_{ij}^T P_i - \frac{1}{\varepsilon_{ij}P_iH_{ij}H_{ij}^T P_i} \right).$$

The second constraint in (19) guarantees that the following property holds

$$\dot{V}_i \le \overline{u_i}^T y_i + \frac{\varepsilon_{ii}}{2}\|\overline{u_i}\|^2 - \frac{\rho_i}{2}\|y_i\|^2 + \frac{1}{2}\sum_{j\in\mathcal{N}_i} \varepsilon_{ij}\|y_j\|^2$$

where the terms $\varepsilon_{ij}\|y_j\|^2$ quantify the impact of nonlinear interconnections on the subsystem. Standard techniques to solve Linear or Bilinear Matrix Inequality [21] can be readily used to compute the solutions to both optimization problems (18) and (19).

4.2 Mid-level control design: local coordination through cyber-physical interconnection

Next, we design local coordination (cooperative) control u_{l_i} in (7) to improve the voltage profile of the power system. As a scenario, we consider a distribution network divided into several clusters as illustrated in Fig. 5. The goal is for the distributed generators (DGs) to cooperatively control their reactive power injection such that the sum of quadratic voltage errors of the DGs in each cluster is minimized. The problem can be formulated as the following optimization problem

$$\min_{\vartheta_i} \sum_i f_i, \;\; f_i = \frac{1}{2}(1 - E_i)^2 \tag{20}$$

where the control variable are DGs reactive power fair utilization ratios ϑ_i defined as $\vartheta_i = Q_{e_i}/\overline{Q}_{e_i}$ with $\overline{Q}_{e_i}$ denotes the maximum reactive power available to the i-th DG. The reactive power and voltage are coupled through the following power flow equation

$$Q_{e_i} = -E_i^2 B_{ii} + \sum_{k \neq i} E_i E_k (G_{ik} \sin \delta_{ik} - B_{ik} \cos \delta_{ik}).$$

In addition, it is also desirable for the DGs in each cluster to contribute equally (i.e., the values ϑ_i reach a consensus for all DGs) in minimizing (20). To this end, the communication network is assumed to be bidirectional whose topology is similar to that of the distribution network as shown in Fig. 4. Cooperative control algorithm can then be designed to solve (20) as described in Section 3. Specifically, each DG adjusts its reactive power fair utilization ratio according to

$$\dot{\vartheta}_i = u_{l_i} = \sum_{j \in \mathcal{N}_i^c} (\vartheta_j - \vartheta_i) - \beta_i \frac{\partial f_i}{\partial \vartheta_i}, \tag{21}$$

where $\beta_i > 0$ [22]. The first term of update rule (21) is a consensus protocol which facilitates the equal contribution of DGs into the reactive power generation while the second term corresponds to a (sub)gradient algorithm which minimizes the objective function in (20). Note that a similar strategy can also be applied to distributed frequency control with DGs as presented in [1].

We evaluate the performance of the cooperative control (21) using IEEE 123-bus test system divided into six clusters as shown in Fig. 5. The objective is to regulate the bus voltages in cluster 4 with two photovoltaics installed at buses 76 and 83 respectively. The voltage regulation using cooperative control (21) is compared with the one using droop control where the droop control gain is manually tuned to achieve the best performance. Fig. 6 shows the simulation results under both droop control and cooperative control strategies. As can be observed from the figure, droop control strategy results in voltage violations, that is the voltage of the buses located far away from the substation exceed the voltage limit of 1.05 p.u. On the other hand, using cooperative control (21) the voltage level can be successfully driven close to unity and thus the over-voltage problem can be eliminated. In

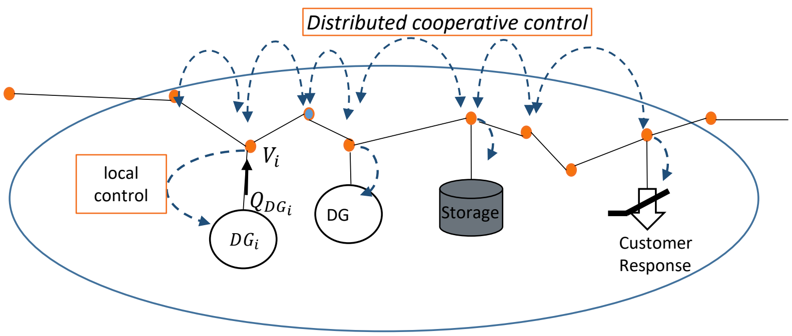

Fig. 4 Architecture of cooperative voltage control for distribution network as proposed in [22]

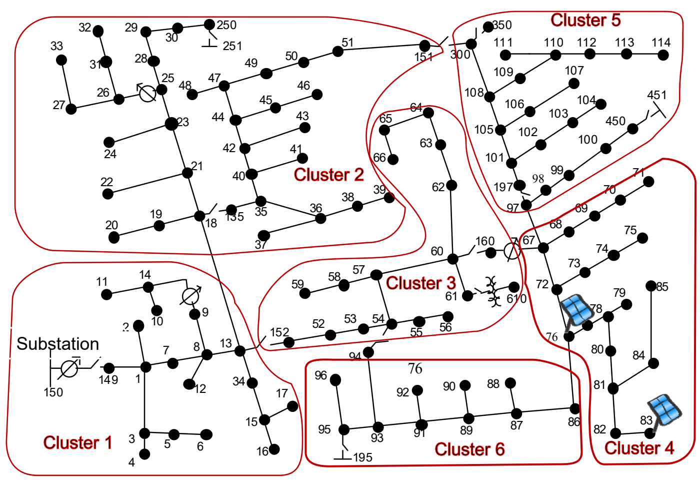

Fig. 5 A diagram of IEEE 123 bus system divided into six clusters

addition, the cooperative control strategy also yields an equal reactive power fair utilization ratio for the DGs as shown in Fig. 7.

4.3 High-level control design: wide-area coordination

The final step is to design network-level control v_i in (7) to ensure the overall system stability and hence to effectively damp out potential inter-area oscillations. As discussed in Section 3, the design of network-level control depends only on properties of individual subsystems, in particular their impact coefficient and L_2 parameter quantified by $\{\varepsilon_{ii}, \cdots, \varepsilon_{ij}, \cdots\}$ and ρ_i respectively. Similar to (15), the wide-area

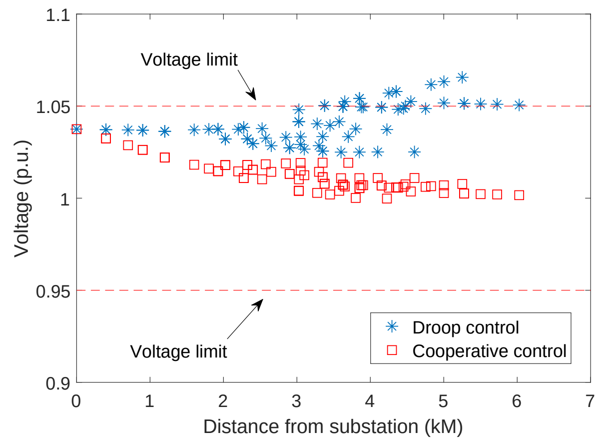

Fig. 6 Comparison of droop control and cooperative control strategies for regulating bus voltages in cluster 4

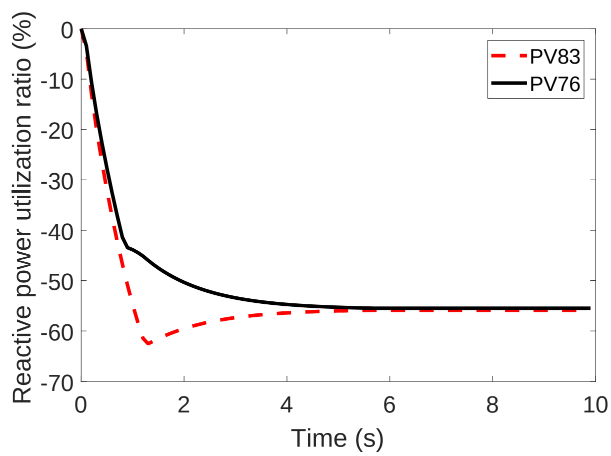

Fig. 7 Reactive power fair utilization ration for the DGs in cluster 4 under cooperative control (21)

control v_i is given by

$$v_i = k_{y_i}^w \sum_{j \in \mathcal{N}_i^w} S_{ij}^w (y_j - y_i) \tag{22}$$

where matrix $S^w = [S_{ij}^w]$ represents the communication network of wide-area control. By choosing control gain $k_{y_i}^w \approx k_w$ and considering storage function $V^w = \sum_i \frac{\gamma_i}{k_w} V_i$, it can be shown by following similar steps as in [16] that system (5) exponentially converges to the desired output consensus provided that control gain k_w satisfies

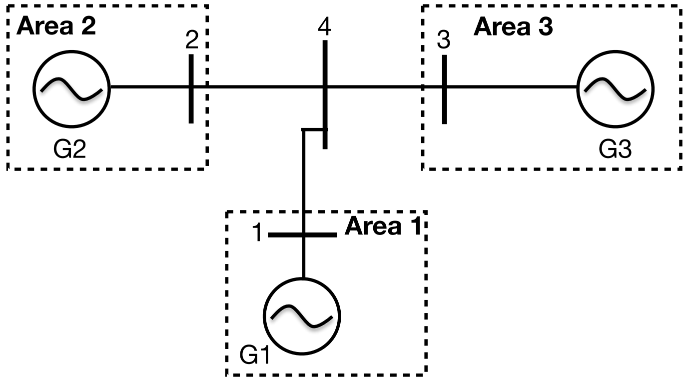

Fig. 8 A 3-area power system

$$-k_w L_w^T \Lambda L_w + (\Gamma_w L_w^T + L_w \Gamma_w) + \frac{\Phi}{k_w} \geq 0$$

where

$$L_w = diag\{S^w \mathbf{1}\} - S^w,\ \Lambda = diag\{\varepsilon_{ii}\},\ \Gamma_w = diag\{\gamma_i\},\ \Phi = diag\{\phi_i\},$$
$$\phi_i = \gamma_i \rho_i - \sum_j \gamma_j \varepsilon_{ji}.$$

The proposed wide-area control is evaluated using a 3-area power system as illustrated in Fig. 8. The simulation time is set to 60s where at $t = 0.0$s, a speed disturbance $\Delta = 0.01$ p.u. is added to the system. The wide-area control using cooperative control (22) is compared with the one using traditional control with typical design (constant gain). The simulation results of power angle for generator 3 for both control strategies are shown in Fig. 9. Even though the overall system is stable under both control strategies, it can be observed from the simulation results that by using the proposed cooperative control strategy, mitigation of the low frequency oscillation (i.e., inter-area oscillation) is considerably improved in comparison to the oscillation under traditional control with constant gain. Note that similar results can also be observed for the other two generators in the power system.

5 Analysis of human-machine interaction

Human interactions with the physical systems through the cyber components is a central aspect of cyber-physical-human systems. During the interactions, human may act as an operator such as in teleoperation [23] or semi-autonomous robot control systems [12] in general. On the other hand, human may also perform as players or agents in multi-agent systems as can be observed in electricity market [24].

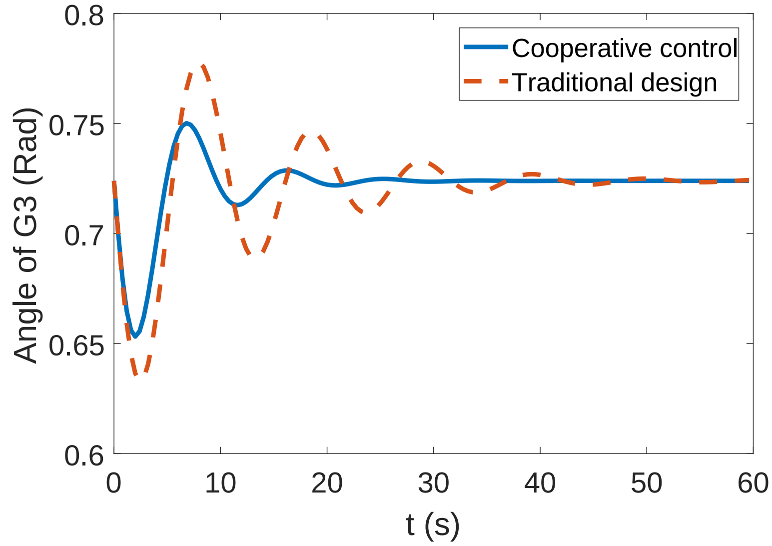

Fig. 9 Comparison of power angle for generator 3 under both cooperative wide-area control and traditional control strategies

Therefore, it is important to formally and rigorously analyze the human-machine interactions (i.e., human-in-the-loop control systems) in order to ensure the stability of the interconnected systems.

Dissipativity theory has been used to model the human decision making and action in human-machine interactions due to its effectiveness in dealing with the largely unknown human dynamics and its modular design. For example, dissipativity-based modeling is developed and validated in [23] to model human arm endpoint characteristics in a human-teleoperated system. In addition, human-machine interactions in semi-autonomous robotic swarm is modeled and analyzed in [12] using the concept of passivity-short systems. In particular, it is theoretically shown and experimentally validated that human-operator modeled in [25] can be assumed to be a passivity-short system.

5.1 Human-machine interaction in electricity market

We focus on human as players or agents in multi-agent systems. As an example, we consider an electricity market consisting of multiple areas. In the *i*-th area, there are set of consumers, generators and an independent system operator (ISO) engaged in electricity market trading. Specifically, the consumers and generators decide the

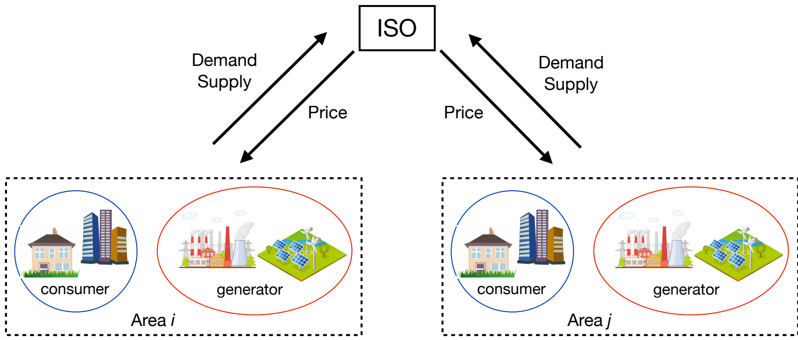

Fig. 10 Electricity market consisting of multiple areas

amount of demand and power supply and the ISO uses the information to update the electricity price in each area as illustrated in Fig. 10. The goal is to maximize the profit of each market participant while balancing the supply and demand. The problem can be formulated as the following social welfare maximization problem:

$$\begin{aligned} \underset{P_L, P_G}{\text{maximize}} \quad & W(P_L, P_G) \\ \text{subject to} \quad & P_L = P_G, \\ & \text{linear equality \& inequality constraints} \end{aligned} \tag{23}$$

where W is the social welfare function which depends on the utility function (i.e., financial satisfaction) of both the consumers and generators, P_L, P_G are stacks of total electricity demand and supply in each area respectively. Note that the solution to (23) may serve as the operational decision r_i in (1), see Fig. 2. The inequality constraints in (23) include upper and lower bounds on demand and supply. If the utility function of consumer and generator are strictly concave and convex functions respectively, then optimization (23) has a unique solution. The convergence analysis of market trading to the solution of (23) can be viewed as stability analysis of the interconnected system of consumers, generators, and ISO as illustrated in Fig. 11. In particular, dynamics of consumer demand, generator supply decisions and ISO price updating in Fig. 11 can be obtained by applying dual decomposition to the dual problem of (23) where its Lagrange multiplier represents the (electricity) price [26]. When the power demand curve representing input-output static mapping between (positive) price and demand in electricity market is given by Fig. 12a, it is shown in [24] that each block's dynamics in Fig. 11 is (strictly) passive and as a result the interconnected system is also passive and hence stable. This means that the market trading system will converge to the optimal solution of (23).

However, the price in electricity market is not always positive especially when the number of renewable energy sources feeding into the power grid increases. For example, when high and inflexible power generation simultaneously appears and followed by low electricity demand, power prices may fall below zero (i.e., neg-

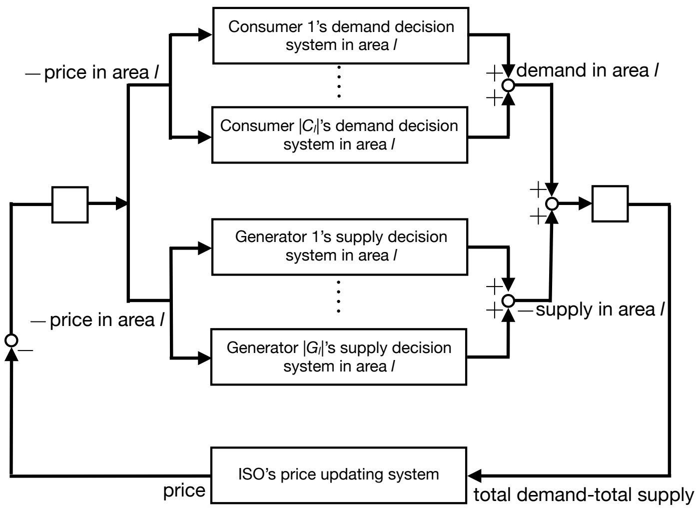

Fig. 11 Electricity market trading system in area l viewed as an interconnected system consisting of consumers, generators, and ISO

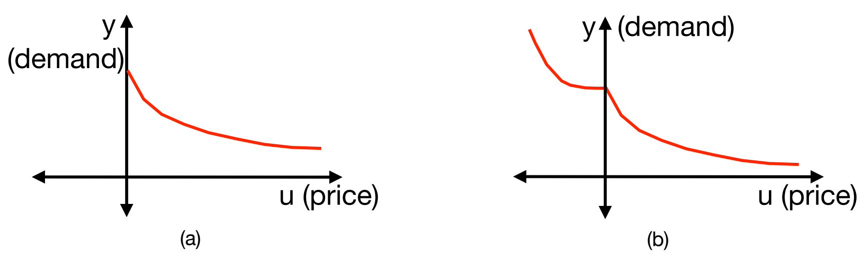

Fig. 12 Power demand curve with (a) normal (positive) price; (b) negative price

ative price) as can be often observed in Germany during public holidays such as Christmas. This means that power suppliers have to pay their customers to buy electric energy. The power demand curve when taking into account the negative price can be illustrated in Fig. 12b. Comparing the figure with input-output diagram in Fig. 3a, it is obvious that dynamics of consumer demand decision system in Fig. 11 is not passive. It is shown in [26] that under power demand curve given in Fig. 12b, dynamics of consumer demand and generator supply decision systems in Fig. 11 are passivity-short as can be observed by comparing Figs. 3c and 12b. As a result, stability of the electricity market, i.e., interconnected system can still be guaranteed.

The discussions above focus on consumer demand decision dynamics derived from the (static) optimization problem (23). Another important issue is the analysis of human decision making dynamics, that is how the human responds (in term of electricity demand) to the price change with main application to demand response (e.g., dynamic electricity pricing). There has been some efforts in dynamic modeling of price responsive demand in electricity market using real data. For example, empirical study in [27] using data acquired at ERCOT suggests that (i) demand response during normal and peak price periods may have qualitatively different behavior; and (ii) there is a demand response delay on a high price surge. From the empirical study, we can initially observe that the dynamics of price responsive demand is not a passive system due to the delay of the response. Further analysis is still required to investigate whether the dynamics exhibit passivity-short properties.

5.2 Transactive control

The above example on electricity (competitive) market is a special case of *transactive control*. Transactive control is a new type of framework to coordinate a large number of distributed generations/loads by combining concepts from microeconomic theory and control theory [28]. Transactive control extends the concept of demand response to both the demand and supply sides whose objective is to balance via incentives (pricing) the supply and demand autonomously, in real-time and a decentralized manner [29]. In comparison to demand response such as price responsive control and direct load control, transactive control preserves customer privacy and has more predictable and reliable aggregated load response. The potential of transactive control framework, in particular transactive energy system, has been demonstrated through several demonstration projects such as the Olympic Peninsula Demonstration [30] and AEP gridSMART demonstration [31]. Moreover, transactive control framework has been applied to manage distributed energy resources for different purposes such as congestion and voltage management [32, 33], providing spinning reserves [34], and residential energy management [35].

Broadly speaking, transactive control framework can be modeled using four key elements as proposed in [28]: payoff functions, control decisions, information, and solution concept. Consider a system consisting of $(n+1)$ agents, that is one coordinator (agent 0) and n distributed energy resources (DERs) where each DER can communicate with each other and also with the coordinator to perform local decision making. Local objective of both coordinator and DERs is represented by a payoff function U_i which depends on price μ_i and energy consumption p_i. Each DER aims at maximizing its own payoff function formulated as

$$\begin{aligned} \text{maximize} \quad & U_i(\mu_i, p_i; \theta_i) \\ \text{subject to} \quad & h_i(p_i; \theta_i) \le 0, \end{aligned}$$

where θ_i denotes private information of the agent such as preference and local constraints. Similarly, the coordinator aims to solve the following optimization problem

$$\begin{aligned} \text{maximize} \quad & U_0(\mu, p; \theta) \\ \text{subject to} \quad & g(p, \mu; \theta) \le 0; \;\; h_i(p_i; \theta_i) \le 0 \end{aligned}$$

where $p = [p_1, \cdots, p_n]^T, \mu = [\mu_1, \cdots, \mu_n]^T$ and $\theta = [\theta_1, \cdots, \theta_n]^T$. Note that the payoff function of coordinator depends on prices and consumption of all DERs. Moreover, the coordinator also has a global constraint such as power flow constraint in the whole network. Next, to optimize the payoff functions, control decision are defined for each agent denoted by $\pi_i \in \Pi_i$ where Π_i is the feasible control decision of agent i. For example, by taking $\pi_0 = \mu$ and $\pi_i = p_i$ the payoff functions become $U_i(\pi_i, \pi_0; \theta_i)$ and $U_0(\pi_0, \pi_1, \cdots, \pi_n; \theta)$ which yields a coupling between decisions of DERs and coordinator. Another important element in transactive control is information set available to each agent, denoted by Γ_i. Information set Γ_i consists of private information and information of control decision of each agent. Finally, information on control decisions provides a sequence of decision for the agents resulting in a multilevel decision problem. Within each layer, if the payoff function of each agent does not depend on decisions of other players then the solution is simply equal to the optimal solution to the standard optimization problem. On the other hand, if the payoff functions of each agent depends on the other agents, then we have a game problem whose solution corresponds to the game equilibrium. Two basic solution concepts to a game problem are Nash equilibrium (that is a collection of decisions from which no agent wants to deviate given that others stick to the equilibrium decision) and dominant strategy equilibrium (that is each agent will stick to the equilibrium strategy no matter what decisions other players make).

The four elements described above dictate the class of transactive problems (type of games) under consideration. For example, if the agent's payoff function is quasi-linear w.r.t. price and the coordinator's objective is to minimize the overall operational cost while satisfying some constraints, then we have a social maximization problem described in the previous subsection. On the other hand, if the payoff function is not quasi-linear and the coordinator's objective is different from maximizing the social welfare, we then have a Stackelberg game whose equilibrium computation is very challenging [36–39].

Research challenges in transactive control include investigating price-reponse bahavior of DERs and ensuring convergence of transaction control. For example, it is shown in [40] that a simple price strategy may stabilize the power system operation. Dissipativity theory provides a framework to systematically analyze this complex system as demonstrated in the previous subsection. Further research need to be performed to investigate the application of dissipativity theory for analyzing different transactive control problems.

6 Role of real-time big data and decision making

The hierarchical control/optimization architecture presented in the previous subsections relies on real-time big data. Rapid development of sensor, wireless transmission, network communication technologies, smart devices, and cloud computing makes it possible to collect large amounts of data in real-time. To illustrate further this point, let us take a smart grid as an example. The main data source in smart grid is the advanced metering infrastructure (AMI) which deploys a large number of smart meters at the end-user side and collects, e.g., customers's electricity consumption data every 15 mins [41, 42]. It is estimated that the amount of data collected by AMI will increase from 24 million a year to 220 million per day for a large utility company [42]. Moreover, the volume of data collected every 15 mins in a distribution network using 1 million devices will surge up to 2920 Tb [43]. In addition to AMI, PMUs are able to produce direct time-stamped voltage/current magnitudes and phase angle with sampling rate 30-60 samples per second, which is much faster than the data collection in Supervisory Control and Data Acquisition (SCADA) system [44]. As an illustration, the amount of data per day generated by100 PMUs with 20 measurements and at the sampling rate of 60Hz is equal to 100 GB [45]. Other sources of big data in smart grid include weather data, mobile data, thermal sensing data, energy database, electric vehicle data, transmission line sensor and dynamic pricing [42].

The increase of uncertainty (e.g., due to the high renewable energy penetration) and tight interconnection between and within the layers calls for real-time processing and decision making. To this end, big data can be utilized for developing novel real-time learning, optimization, and decision making (control) algorithms for cyber-physical-human systems as illustrated in the previous sections. For example, big data has many applications in the operation of smart grid [46]. A new algorithms using PMU data is proposed in [47] to accelerate the state estimation process. Moreover, a PMU based robust estimation method is presented in [48] to eliminate unwanted perturbed data and thus increases the robustness of state estimation algorithm. Big data can also be used for fault detection and classification in micro-grid leading to a much better performance compared to model-based approach [49]. AMI and other sensors provide opportunity to realize line impedance calibration (i.e., parameters) for distribution power system which was not possible previously [50]. Weather data can also be used for predicting the power generation of renewable energy sources such as wind turbines which further can be utilized for voltage control and demand response [51]. Furthermore, with the exponentially increasing number of PMUs deployed, and the resulting explosion in data volume, wide-area measurement systems (WAMS) technology as the key to guaranteeing stability, reliability, situational awareness, state estimation, and control of next-generation power systems is bound to transcend from centralized to a distributed architecture within the next few years. Motivated by this fact, a distributed optimization based learning algorithm is proposed in [52] for one of the most critical wide-area monitoring applications − namely, estimation of mode shapes for inter-area oscillation modes.

The exposure to external network such as internet comes at a price of data security and privacy [53, 54]. Cyber incidents or network intrusion may cause physical damage to the physical system due to the tight coupling between the physical system and the cyber layer. Unfortunately, traditional security solutions in the ICT (information and communications technology) domain are not sufficient to ensure security and resilience of the network since they do not take into account the physical attacks through direct interaction with the components in physical systems. For example, by placing a shunt around a meter the integrity of a meter can be violated without the need of breaking the cyber-security countermeasure. They may also introduce adverse effects on the operation of CPS. For example, while cryptography can enhance the confidentiality of data flows, it may result in unacceptable time latency and degrade the performance of time-critical functionalities in CPS. Moreover, coordinated network attacks by sophisticated adversaries undermine standard residual based detection schemes. It is discussed in [55, 56] that control theoretic framework together with recent advancement in cloud computing and network management (e.g., software defined networking) show promises in ensuring the resilient operation of CPS against (coordinated and intelligent) cyber-attacks.

7 Conclusion

The chapter presents a scalable and modular control-theoretical framework to model, analyze, optimize and control cyber-physical-human systems. It is shown that efficient computational algorithms can be applied hierarchically to operate and optimize cyber-physical-human systems, first individually to quantify the dynamic behavior of every agent, then locally to describe the local interactions of neighboring agents, and finally to the overall system. All the three control levels deal with real-time big data, and the hierarchical structure makes the overall optimization and control problem scalable and solvable. In particular, we present and highlight two main tools whose combination shows a great promise to optimize and control such tightly interconnected system. The first tool is the concept of dissipativity theory which is a useful way of quantifying input-output properties of dynamical systems and whose compositional property makes it a powerful tool to analyze and control CPS. The second tool is cooperative control which allows the designer to develop a scalable and robust optimization and control algorithms. Application to power system is investigated as an illustrative example.

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