Modeling of Future Cyber–Physical Energy Systems for Distributed Sensing and Control

Marija D. Ilić, Fellow, IEEE, Le Xie, Member, IEEE, Usman A. Khan, Student Member, IEEE, and José M. F. Moura, Fellow, IEEE

Abstract—This paper proposes modeling the rapidly evolving energy systems as cyber-based physical systems. It introduces a novel cyber-based dynamical model whose mathematical description depends on the cyber technologies supporting the physical system. This paper discusses how such a model can be used to ensure full observability through a cooperative information exchange among its components; this is achieved without requiring local observability of the system components. This paper also shows how this cyber–physical model is used to develop interactive protocols between the controllers embedded within the system layers and the network operator. Our approach leads to a synergistic framework for model-based sensing and control of future energy systems. The newly introduced cyber–physical model has network structure-preserving properties that are key to effective distributed decision making. The aggregate load modeling that we develop using data mining techniques and novel sensing technologies facilitates operations of complex electric power systems.

Index Terms—Communications and control of large energy systems, cyber–physical systems, distributed decision making, distributed sensing, energy and environment, future energy systems, infrastructures, load dynamics, load model identification, phasor measurement units (PMUs), sensors.

I. INTRODUCTION

This paper is concerned with the potential transformation of today’s electric power grids into enablers of future energy systems. The needs for modular integration into the existing electric power grid of many small distributed energy resources (DERs) and implementation of customer choice by the energy users are the basic drivers for such transformation. The future energy systems will have to exhibit adaptive performance such as flexibility, efficiency, sustainability, reliability, and security. Moreover, today’s hierarchical utility objectives are evolving into distributed multiple subobjectives. These are determined by the nonuniform needs of customers for differentiated quality of service (QoS) at the price they are willing to pay and by major societal pressures to utilize energy in efficient and sustainable ways during normal conditions and in reliable and secure ways during abnormal conditions [1]. Once more, the issue of energy is important, and there is much activity, including a strong desire to deploy large amounts of intermittent unconventional energy resources, wind power in particular, and to also empower customers to become responsive to system conditions. This integration of new resources will ultimately lead to significantly different architectures for future energy systems [2].

We stress in this paper that meeting the objectives of future energy systems can only be done through a systematic embedding of cyber technologies capable of monitoring, communicating, and controlling the evolving physical systems [3], [28]–[31]. The initial conditions in today’s electric power grids do not lend themselves easily to the effective embedding of cyber technologies. There exists a huge gap between the potential benefits to be brought about by deploying cyber technologies in today’s physical systems and the current operating and planning practices. However, it would defeat the purpose if we simply equip the power grid with the most advanced sensors and actuators and flood with data those responsible for operating the grid. What is needed, instead, is novel modeling methodologies for such cyber–physical systems. These methodologies should build on today’s supervisory control and data acquisition (SCADA) systems used for monitoring and controlling power grids and support future industry needs. It is essential to recognize the path dependence in evolving the system from today’s SCADA-supported system operations to the next-generation multilayered interactive sensing, communication, and control for meeting novel subobjectives. The tradeoffs among the subobjectives (reliability versus efficiency, for example) will be greatly affected by the type of cyber technology deployed and its costs. We introduce, in this paper, novel modeling, sensing, and control concepts that lend themselves to providing information about what is necessary to meet the subobjectives and to coordinate system-wide performance. The emphasis is on modeling which is required to design distributed sensing and decision making.

It is becoming increasingly clear that intelligent coordinated management of large-scale clean renewable resources and intelligent customers will require major changes to today’s operating and planning paradigms underlying the electric power.
grid. To understand the existing conditions, we point out that today’s operations and planning rests on static open-loop scheduling of resources for the assumed load patterns. There is very little automated feedback by a relatively small number of designated electric power plants for balancing power in response to frequency deviations caused by small unpredictable demand variations and other uncertainties during normal conditions. Moreover, the abnormal conditions are managed by operating and planning the system for the worst case scenario without relying on the response by the network end users. This leads to hard-to-predict situations and hard-to-involve end users during those situations. Moreover, it is important to recognize that today’s approach to abnormal operation is highly inefficient because of its needs of large stand-by reserves, in case an emergency occurs. The inefficiencies are cumulative over time and amount to major costs seen by the customers [4]. Perhaps, even more important is the fact that it is practically impossible to design a system for secure unconditional services during extreme conditions, such as intended attacks on its infrastructure. These practices must be changed in order to attempt to achieve sustainable energy and environment. In particular, it is essential to have load monitoring at least at the aggregate Extra High Voltage/High Voltage transmission level and to actively engage end users.

Important for this paper is the observation that, in sharp contrast to today’s lack of sufficiently granular online sensing and feedback by the customers, it is essential to empower and enable the end users with the right sensing and control technologies so that they adapt their utilization over broad ranges of energy availability. Customers today use energy without any feedback concerning its availability and price. In the future, the rebundling of electric and other forms of energy will, indeed, be dictated by the end users, and this information is essential for adaptive energy production, delivery, and utilization. Customers must become an integral active part of this process. In order to bring the customers’ function into focus, the first author has proposed a notion of just-in-time and just-in-place energy services [3].

While the recognition of the desired end state of future energy systems is emerging, it is also essential to revisit the modeling framework underlying the use of sensors and controllers in today’s electric power systems. This is a difficult task, and it will take real efforts by the community to move forward. Reasons are many and primarily related to the fact that the electric power systems were never designed for desired performance. They have, instead, evolved in response to specific customers’ needs. The availability of computing power has led to the development of algorithms for forecasting system load and dispatching ahead of time major generation resources plus stand-by reserve to balance the anticipated demand even when a single large piece of equipment fails. As part of assessing the worst case equipment scenario, complex nonlinear models were introduced to represent transient system response to large equipment outages. Much effort has gone toward simulations and analysis for so-called dynamic security assessment. Implanted in these simulation tools are some critical assumptions. These are real roadblocks to actively relying on customers’ response and on active participation of small DERs for stable balancing of supply and demand even during extreme operating conditions.

In contrast with today’s practices, a vision of so-called homeostatic control of electric power systems was proposed almost 20 years ago [5]; this vision was conceptual, and it evolved around the idea of all end users adjusting their consumption in real time in response to local frequency and voltage deviations. The system as a whole would consequently balance (self-regulate) in an entirely decentralized way. The process of moving such concepts into reality has proven to be very complex and, to a large extent, dependent on state policies in place. The idea of end users participating in automatic generation control and, more recently, in transmission congestion management has been actively revisited in recent times. All these ideas are an inherent part of designing protocols for future energy systems [6].

One hidden challenge is that models of the interconnected power system currently used for dynamic analysis are not capable of capturing the effects of end users’ feedback nor do they model very small scale DERs located close to them. In order to begin to overcome this problem, this paper describes a new framework for modeling actions of end users explicitly. The relevance of more accurate load modeling for small-scale power systems has been described in the past. This paper starts with the recognition that incorporating relevant load models for large-scale realistic power systems will require careful sensitivity analysis of dynamic interdependences of both transmission and distribution (T&D) systems, and further systematic load aggregation. The level of detail kept depends, to a large degree, on the tradeoffs between the following: 1) the type of flexibility, efficiency, reliability, and security desired; 2) candidate sensor technologies; 3) candidate communications technologies; and 4) the underlying cost-benefit analysis. One must also keep in mind the need for dynamic load aggregation over broad ranges of system conditions. The results of dynamic aggregation are boundaries of multilayers forming the basis for dynamic monitoring and decision systems in future energy services [7].

This paper is organized as follows. In Section II, a structure-preserving framework is introduced. Cyber–physical models of key components, power plants, and (groups of) loads are conceptualized. In Section III, a model of future interconnected energy system is presented by illustrating modeling of DERs as a generalization of today’s power plant modules in Section III-A and by formalizing a cyber–physical load model in Section III-B. These modules are combined by writing the network physical constraints in Section III-C. It is suggested that a less known state-space model introduced in [6] naturally lends itself to a structure-preserving model of the interconnected system in which the interactions between modules and network are explicit. Finally, an example of the modeling using a small system is given in Section III-D. The dependence of simulation results on the cyber support (load model, in this case) is demonstrated. In particular, it is shown that, at least in concept, unless loads are equipped with sufficient sensing and data mining, simulations may be so inaccurate that they may not predict system instabilities. Load data from two industry Web sites are used to demonstrate such potential problems. In Section IV, a cooperative sensing approach to ensuring system-wide observability of future energy systems is introduced. In Section V, a module-based interactive control is proposed. One possible protocol for interaction between the modules and the network is described. This protocol lends itself well.
to enhancing today’s SCADA for integrating wind power as new modules in the existing grid without losing system-wide performance. This protocol is illustrated on a small system with wind power. Finally, in Section VI, a brief synopsis of the proposed framework is presented.

II. STRUCTURE-PRESERVING MODELING APPROACH FOR FUTURE CYBER–PHYSICAL ENERGY SYSTEMS

In this paper, we recognize that, as today’s electric power system is utilized in ways for which it was not initially designed, notably for facilitating deployment of large-scale intermittent energy sources and price-responsive demand, it is becoming necessary to monitor and manage temporal variations throughout the system. In particular, it becomes necessary to provide a sufficiently flexible modeling approach capable of zooming into specific system components and zooming out to capture interactions between these components.

Dynamic models of today’s electric power grids must be generalized to represent the dynamics of newly deployed, often unconventional, DERs as well as the dynamics of loads, at least at the key load centers. In today’s models, the only near-real-time sensing and control takes place at the power plants, generally referred to as the generator–turbine–generator (G-T-G) sets. The G-T-G sets have, by and large, had synchronous machines as generators. Future models must be able to include modular representation of a variety of DERs as they get on the system. Coming up with sufficiently detailed and verifiable dynamic models is a major effort, and there is currently much work in this direction. While more complex, it is still possible to represent each DER as a G-T-G set, structurally similar to the models of power plants with synchronous generators. The complexity of the system model will increase as these DERs are added to the system. In this paper, we recognize the modular structure of the future energy system and allow for detailed representation of the different types of components (modules) to be added to the system.

Load modeling, sensing, and control are even more critical than modeling of DERs. Today’s loads are typically modeled as either constant power or constant impedance components. This is partly due to the inability to model a conglomerate of diverse loads from first principles, as it is possible to model a DER from first principles. As a consequence, in real-time operations, there is no fast online sensing of loads, although this is potentially useful for predicting fast instabilities and for controlling them. Today’s SCADA measures loads at the substations, and this information is used for static dispatch and/or state estimation without any assessment of temporal trends.

Although the need for such models has been recognized in the earlier literature, the progress has been slow mainly because it is very difficult to model load centers based on their physical characteristics; isolated experiments of this kind have been carried out, such as the early Commonwealth Edison experiment. There have been sporadic serious attempts for load modeling and their parameter identification in the past, notably the work by Galiana [8]. More recently, there has been research in the area of neural-network-based load modeling, primarily for slower load forecast purposes.

Here, we take a load modeling approach that directly depends on the type of sensors and communications among the sensors. To start with, load is viewed similarly to other components in the system, as a module with its internal characterization and interactions with the rest of the system. We show how to use cyber techniques to derive a model representing slower deviations in load consumption \( L_k \) as well as the model of fast load dynamics driven by the mismatch of power delivered to the load \( P_k \) and the power consumed \( L_k \). Such cyber-based load module is used to represent the load dynamics of interest at key locations. As a result, viewed from the electric power grid side, the loads at nodes have their own dynamics, much the same way as the cyber–physical models of the G-T-G sets. These dynamic modules are interconnected using a novel state-space approach to create the model of the system. The use of this novel state-space model enables one to recognize previously unexplored structural interdependencies. As a result, a truly intertwined cyber–physical system emerges in which the components connected to the nodes of the grid have closed-loop sensing, data mining, and actuation. This model lends itself to further development of network cyber in support of communications among the cyber–physical components for predictable performance of future energy systems. Design of the network cyber is not the subject of this paper.

The basic modeling approach taken includes the following.

1) Represent each (group of) component(s) as a specific cyber–physical module characterized by both physical and cyber input–output signals, internal dynamics, local sensing, and actuation.

2) Integrate the modular components according to the network constraints.

This approach allows for integrating even the unconventional energy sources, such as DERs, as well as for modeling the sensed and controlled loads. It fundamentally enables more active representation of the network end users than it is currently done. In particular, static SCADA-supported load estimation for scheduling purposes is complemented by the additional temporal sensing and control to monitor and stabilize fast system dynamics.

Once the model is derived, we utilize it for the following.

1) Conceptualizing cooperative sensing and communications to ensure system-wide observability. This is essential since no sensing scheme is capable of doing its job without having a system-wide observable model.

2) Conceptualizing module-based interactive control for ensuring system-wide controllability and stabilization. The tradeoff questions concerning the level of aggregation, number of controllers, and the resulting performance can be posed systematically using this module-based control approach (see also [9] and [10]).

Our modeling, sensing, and control approach is directly applicable to the immediate needs of the electric power industry for better situational awareness and preventing wide-spread blackouts, in particular. Our ongoing work is in the direction of posing sensing and communications objectives using the cyber–physical modeling framework to effectively utilize fast sensors, such as phasor measurement units (PMUs). These cyber technologies are beginning to be deployed, but more understanding of where the most effective locations are, number of PMUs, communication schemes between PMUs and with other less accurate and less fast sensors, and the SCADA system.
is needed. We believe that our framework naturally lends itself to answering these difficult challenges.

III. MODEL OF FUTURE CYBER–PHYSICAL ENERGY SYSTEMS

Consider a typical electric energy system that consists of G-T-G modules and load modules. These modules are interconnected via the electrical T&D network.\(^1\) Fig. 6 is a simplified electric energy system. The fundamental difference between the traditional electric utility systems and the future energy systems lies in enabling distributed subobjectives of the (groups of) module(s) to coexist within the interconnected system with the entire system’s objectives. For instance, given hard constraints on fuel resources, a future cyber-facilitated energy system needs to be sufficiently adaptive to sense, to adjust to the cost of energy, and to adjust its own subobjectives in an automated fashion by using both the sensed information at the distributed level and the information exchanged with the other components in order to manage available resources without destabilizing system-wide dynamics. Today’s electric utility system does not have the ability to reduce consumption adaptively; instead, blackouts may occur.

In the context of Fig. 6, each component \(i\) can be modeled as a single module represented by the following: 1) the internal physical states \(x_i\)’s and the interaction variables \(P_i\)’s between the module and the rest of the system, and 2) the internal cyber signals and the interaction cyber signals between the module and the rest of the system, and 2) the internal cyber signals and the interaction cyber signals between the module and the rest of the system. The conceptual cyber–physical representation of generation and load modules is shown in Figs. 1 and 2, respectively. In the next two sections, the cyber–physical representations for the G-T-G sets and the load modules are explained.

\(^1\)The T&D network can also be considered as system components, with their own dynamics, sensing, and actuation. However, for purposes of this paper, we model them as passive RLC devices, since their dynamics are assumed much faster than the dynamics of interest here. A detailed analysis of the transmission line dynamics, sensing, and actuation can be found in other literature.

A. Model of a G-T-G Cyber–Physical Module

Fig. 1 shows a cyber–physical representation of a G-T-G set in a power plant. The physical process is modeled as a closed-loop continuous-time dynamic model as follows:[11]:\(^2\)

\[
\begin{align*}
J_G \dot{\omega}_G + D_G \omega_G = P_T + c_T a - P_G \tag{1} \\
T_a \dot{P}_T = -P_T + K_T a \tag{2} \\
T_g \dot{a} = -r a - \omega_G + \omega_{G_{\text{ref}}} \tag{3}
\end{align*}
\]

where \(P_T\) and \(P_G\) are the mechanical and electrical powers of the turbine and the generator, respectively; \(c_T\) is the coefficient of the valve position, and \(J_G, D_G, T_u,\) and \(T_g\) stand for the moment of inertia of the generator, its damping coefficient, and the time constants of the turbine and generator, respectively. The state variables \(\omega_G\) and \(a\) correspond to the generator’s output frequency and the valve opening, respectively, and \(\omega_{G_{\text{ref}}}\) represents the set point value of the speed governor. Equation (1) shows the dynamics of the generator characterized by its local state variable \(\omega_G\) and actuated by the mechanical power of the turbine \(P_T\). The mechanical power is controlled by the speed governor, adjusting the valve position \(a\) in response to the locally sensed deviations of \(\omega_G\) from the desired reference signal \(\omega_{G_{\text{ref}}}\), as shown in (2) and (3). By denoting the G-T-G internal state variables as

\[
x_G = [\omega_G \ P_T \ a]^T \tag{4}
\]

and local input variable as \(u_G = \omega_{G_{\text{ref}}}\), (1)–(3) can be expressed in a standard state-space form

\[
\dot{x}_G = 
\begin{bmatrix}
0 & -1/T_u & K_T/T_u \\
-1/T_g & 0 & -r/T_g
\end{bmatrix} x_G \\
+ 
\begin{bmatrix}
0 \\
0 \\
1/T_L
\end{bmatrix} u_G + 
\begin{bmatrix}
-1/J_G \\
0 \\
0
\end{bmatrix} P_G 
= A_G x_G + B_G u_G + c_G P_G. \tag{5}
\]

\(^2\)All symbols corresponding to the state variables represent the deviations from a system operating point around which the linearized model is derived.
The matrix $A_G$ corresponds to the system matrix of the generator. It can be seen from (6) that the local dynamics $x_G$'s of each G-T-G set are physically coupled to the network only via the electrical power injected to the network $P_G$.3

B. Model of a Cyber–Physical Load Module

Here, we model load dynamics and provide an information theoretic load identification scheme. A typical energy system has millions of diverse loads, ranging from many components in residential households to medium-size industrial and commercial applications and very large size industrial and commercial utilities. Several of these loads are connected to the local electric power distribution grids and are not currently monitored by the EHV/HV SCADA that senses substation level loads and above. Today's SCADA senses and estimates minute-by-minute aggregate loads at substations.4 These are used by the control center operators of the EHV/HV transmission network to schedule generation to meet the load demand. All this is currently implemented in a static sense, i.e., the load is considered either a constant impedance or a constant power component. This has a major drawback since the temporal characteristics of the load demand variations are not modeled. Furthermore, since load estimation is done relatively slowly, the information cannot be used to ensure system-wide stability in response to fast load fluctuations and other fast disturbances.5

In this paper, we propose a dynamic load model that can capture essential temporal features of the load. This poses a challenge; since the substation loads are composed of many diverse components, it is practically impossible to model the substation and higher (zonal) loads from first principles. We characterize (groups of) load(s) as modules, much the same way as a G-T-G set is characterized. We represent such aggregate load module as shown in Fig. 2, where $L$ stands for the real energy consumed by the load, $P_L$ is the electrical energy delivered by the network to the load, and $J_L$ and $D_L$ are parameters of a postulated (nonphysical) load module whose local physical state variable is the frequency $\omega_L$ measured at the load location. This provides us a Newton-like cyber description of load dynamics that is driven by the instantaneous mismatch between net injection of power from load bus into the grid, $P_L$ (negative if this load bus is a net importer of real power), and the actual power consumed at the load, $L$ (positive if the load bus is a net importer of real power). Such physical load is then represented by its cyber model as follows:

$$J_L\omega_L + D_L\omega_L = -P_L - L$$

(7)

where $J_L$ and $D_L$ refer to the effective moment of inertia and the damping coefficient of the aggregate load. The values of $J_L$ and $D_L$ could be obtained using systematic model identification methods at each substation. We observe that, in principle, price-responsive loads and frequency-/voltage-controlled loads utilize external and/or internal cyber information for adjusting load consumed $L$. The load is sensed each $[k]$ seconds in order to represent temporal changes of the energy consumed by the aggregate load. We propose to use this information to obtain a time-varying linear load prediction model of the form

$$L_k = \sum_{j=1}^{p} \phi_{L,k-j} L_{k-j} + w_{L,k-1}$$

(8)

where $\Phi_L$ is computed using data mining algorithms described hereinafter and $w_L$ represents random noises.

By denoting the state variable vector relevant for the load dynamics as $x_L = [\omega_L, L_L]^T$, where $L_L = [L_k, L_{k-1}, \ldots, L_{k-p+1}]^T$, we may discretize (7) as:

$$x_{L,k} = \begin{bmatrix} \omega_{L,k} \\ L_k \end{bmatrix} = \begin{bmatrix} 1 - \Delta T \frac{J_L}{L} & -\Delta T \frac{D_L}{\Phi_L} \\ 0 & 1 \end{bmatrix} x_{L,k-1} + \begin{bmatrix} 0 \\ E_L^T \end{bmatrix} w_L$$

(9)

$$= A_L x_{L,k-1} + \begin{bmatrix} -\Delta T J_L \\ 0 \end{bmatrix} P_{L,k-1} + S_L w_L$$

(10)

where $\Delta T$ is the sampling period and $E_L = [1 \ 0 \ \cdots \ 0]$. The dimension of $A_L$ in (10) is $p \times p$, where $p$ is the order of the load predictor [see (8)]. The load $L_k$ at time $k$ is replaced by its estimate obtained by the cyber model of the load, as discussed in the following.

1) Sensor-Based Identification of $L_k$: Load demand modeling, in power systems, using information theoretic descriptions has been a topic of significant interest (see, for instance, [8] and [12]). The load demand can be viewed as a time series, and sophisticated time-series analysis techniques are available in the literature. We assume a linear time-series model of load demand that provides us with a simplistic, yet efficient, paradigm for identification. The goal is to express the future value of load demand as a linear combination of past values that are assumed to be available with appropriate measurements. To this end, linear regression can be employed for the purposes of prediction. Since we are only interested in one-step ahead prediction, seasonal dependences can be ignored, and an autoregressive (AR) model suffices for our purposes.

We assume that the power consumed by the $i$th aggregate load at time $k$, $L_{i,k}$, can be modeled as an AR process of order $p$. The AR expression for $L_{i,k}$ is given as

$$L_{i,k} = \sum_{j=1}^{p} \phi_{i,j} L_{i,k-j} + w_{i,L,k}$$

(11)

3Note that we denote a zero matrix or a zero vector as bold-faced 0, whose dimensions are apparent from the context. For a scalar zero, we use 0.
where \( \{\phi_j^i\}_{j=1}^{\infty} \) are the AR model coefficients and \( w_{i,L,k}^i \) is a zero-mean random variable at the \( i \)th aggregate. These random variables are further assumed to be uncorrelated across time \( k \). We can write (11) in state-space form, with

\[
L_k^i = \Phi_k^i L_{k-1}^i + w_{L,k}^i.
\]

Letting \( M \) be the total number of aggregated loads, then the total load dynamics under the AR process representation are given by

\[
\begin{bmatrix}
L_k^1 \\
L_k^2 \\
\vdots \\
L_k^M
\end{bmatrix} =
\begin{bmatrix}
\Phi_1^1 & 0 & \cdots & 0 \\
0 & \Phi_2^2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \Phi_M^M
\end{bmatrix}
\begin{bmatrix}
L_{k-1}^1 \\
L_{k-1}^2 \\
\vdots \\
L_{k-1}^M
\end{bmatrix} +
\begin{bmatrix}
w_{L,k}^1 \\
w_{L,k}^2 \\
\vdots \\
w_{L,k}^M
\end{bmatrix}
\]

which are predicted as

\[
\hat{L}_k = \Phi L_{k-1}.
\]

We assume that these past values of \( L_{k-1} \) are available through active sensing.

AR models are infinite impulse response filters [13], as can be seen from (11) since the load at time \( k \) is modeled as a linear combination of past load values. The model parameters \( \{\phi_j^i\}_{j=1}^{\infty} \) can be chosen from least squares or weighted least squares [14], [15]. The transfer function (Fourier transform of the impulse response) of (11) is shown in Fig. 3 for a \( p = 6 \) AR model. Fig. 3 shows the low-pass effect of the AR model fitting, where the lower frequencies are zoomed in (more weight on low frequencies), and higher frequencies are given negative (in decibels) weight. This essentially provides a smoothing of the load time series.

We tested the AR load modeling on the aggregated load from the New York (NY) power system in the month of August 2006. The load for 31 days in Aug. 2006, collected at 5-min intervals, is shown in Fig. 4, and the AR model prediction (zoomed in on the horizontal axis) is shown in Fig. 5. We fitted an AR model of order \( p = 2 \). We can also employ an AR moving average (ARMA) model for a different characterization of noise. ARMA identification techniques are, for example, in [17]. Holt-Winters filter [12] and ARMA models [15] are also implemented in the literature for load modeling, which also take into account the seasonal nature of the load data. Both Holt-Winters filters and ARIMA models work well when the prediction horizon is large (e.g., one day ahead). In our case, since we are only interested in the one-step ahead prediction, the AR models have comparable performance. This is also shown in [12].
C. Model of Modules Interconnected Via Transmission Network

When the modules get interconnected through a transmission network, the basic Kirchhoff’s laws govern the interactions between the modules. Namely, the electric power out of each module must instantaneously equal the sum of power flows into the transmission network. For transmission network topology characterized by its reduced incidence matrix \( M \), this implies that \[ \begin{bmatrix} P_G \\ P_L \end{bmatrix} = M \theta \] (16)

where \( \theta \) stands for the vector of power flows in transmission lines.\(^7\) In addition, the linearized power flows in lossless transmission lines are characterized by its reduced incidence matrix \( M \), which is diagonally dominant over a wide range of operating conditions.\(^8\) By using the diagonal dominance property of the power flow Jacobian matrix \( H \), conditions for localized response under system disturbances were defined for electric power networks in [18]. A discrete-time model for generator modules can be obtained by subtracting (18) for two consecutive samples \( [k - 1] \) and \( [k] \) and approximating \( \Delta \theta[k] \approx \omega[k - 1] \). Therefore, by combining with the discrete-time models of all modules, one can represent the discrete-time state-space model of the energy system as follows:

\[
\begin{bmatrix}
  x_{G,k} \\
  x_{L,k} \\
  P_{G,k} \\
  P_{L,k}
\end{bmatrix} =
\begin{bmatrix}
  I + A_G & 0 & C_G & 0 \\
  0 & A_L & 0 & C_L \\
  H_{GG}E_1 & H_{GL}E_2 & I & 0 \\
  H_{LG}E_1 & H_{LL}E_2 & 0 & I
\end{bmatrix}
\begin{bmatrix}
  x_{G,k-1} \\
  x_{L,k-1} \\
  P_{G,k-1} \\
  P_{L,k-1}
\end{bmatrix}
+ \begin{bmatrix}
  E_1 \\
  0 \\
  0 \\
  0
\end{bmatrix}
\begin{bmatrix}
  u_G \\
  w_L
\end{bmatrix}
\] (19)

where

\[
\begin{align*}
  x_G &= \begin{bmatrix} x_G^1 & \ldots & x_G^n \end{bmatrix}^T \\
  x_L &= \begin{bmatrix} x_L^1 & \ldots & x_L^n \end{bmatrix}^T \\
  P_G &= \begin{bmatrix} P_G^1 & \ldots & P_G^m \end{bmatrix}^T \\
  P_L &= \begin{bmatrix} P_L^1 & \ldots & P_L^n \end{bmatrix}^T \\
  A_G &= \text{blockdiag} (A_G^1, A_G^2, \ldots, A_G^n) \\
  A_L &= \text{blockdiag} (A_L^1, A_L^2, \ldots, A_L^n) \\
  C_G &= \text{blockdiag} (C_G^1, C_G^2, \ldots, C_G^n) \\
  C_L &= \text{blockdiag} (C_L^1, C_L^2, \ldots, C_L^n) \\
  u_G &= \text{diag} (u_G^1, u_G^2, \ldots, u_G^n) \\
  w_L &= \text{diag} (w_L^1, w_L^2, \ldots, w_L^n) \\
  E_1 &= \text{blockdiag} (e_1, e_1, e_1) \\
  E_2 &= \text{blockdiag} (e_2, e_2, \ldots, e_2) \\
  E_3 &= \text{blockdiag} (e_3, e_3, \ldots, e_3) \\
  e_1 &= \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \\
  e_2 &= \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \\
  e_3 &= \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}
\end{align*}
\]

The matrix

\[
H = \begin{bmatrix} H_{GG} & H_{GL} \\ H_{LG} & H_{LL} \end{bmatrix}
\]

represents the block partition of the steady-state power flow Jacobian matrix.

The model in (19) preserves the structure of the interconnected electric energy system and lends itself to distributed sensing and actuation.

D. Five-Node Example

In this section, we illustrate our approach with a toy example, a five-node system. A much larger system is illustrated elsewhere. The simple five-node system will lead to a 20-D system representation. Fig. 6 can be considered as a conceptual representation of two geographically interconnected power systems like New England and NY. Assume that all the transmission

---

7. The order of \( P_G \) is the total number of generators minus one, \((n_G - 1)\), since one generator, so-called slack, is used as the zero angle reference [11]. The order of the vector \( \theta \) is the total number of branches in the transmission network graph.

8. Under the assumption of real–reactive power decoupling and that voltage magnitudes at all buses are close to one per unit, the power flow Jacobian matrix \( H \) can be obtained from the negative of the susceptance matrix.
TABLE I
GENERATOR PARAMETERS FOR THE FIVE-BUS EXAMPLE

<table>
<thead>
<tr>
<th></th>
<th>D</th>
<th>J</th>
<th>e_T</th>
<th>K_L</th>
<th>T_u</th>
<th>T_g</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gen 1</td>
<td>2.0</td>
<td>1.26</td>
<td>0.15</td>
<td>0.95</td>
<td>0.20</td>
<td>0.25</td>
<td>0.50</td>
</tr>
<tr>
<td>Gen 2</td>
<td>1.8</td>
<td>1.15</td>
<td>0.13</td>
<td>0.92</td>
<td>0.18</td>
<td>0.23</td>
<td>0.48</td>
</tr>
<tr>
<td>Gen 3</td>
<td>1.8</td>
<td>1.15</td>
<td>0.13</td>
<td>0.92</td>
<td>0.18</td>
<td>0.23</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Then, by assigning appropriate parameter values to each generator and load module, one can start to simulate and analyze the dynamical behavior of an interconnected energy system while not losing the structure of the transmission network. Table I shows the parameters of generators in this example. This simulation is contrasted with the simulation done based on a model in which all the load buses are compressed (see, e.g., [19]). Based on the statistical study of the aggregated load behavior at both the NY and the New England systems, we represent the load dynamics in both systems by a second-order ARMA model. The complete state-space model of the system dynamics is now 20th order. In contrast, the traditional state-space model without considering load dynamics is 12th order.

Fig. 7 shows the trajectory of the power output from generator 1. The dashed line shows the power output without considering the load dynamics, which approaches a stable value after about 3 s. The solid line shows the power output trajectory under the new model, which includes the load module dynamics. As the load dynamics evolve, the system is no longer stable. Fig. 8 is zoomed in the plot of Fig. 7. This comparison shows the importance of modeling the load module dynamics in the system-wide dynamic study.

Furthermore, we study how the parameters of the load module dynamics impact the system-wide dynamical behavior. Fig. 9 and zoomed in Fig. 10 show the electrical power output from generator 1 under three different load moments of inertia: \( J_L = 0.2 \), 1.0, and 8.0. Fig. 11 and zoomed-in Fig. 12 show the frequency trajectory at load bus 4 under these three different load damping inertias. When the damping inertia is 0.2, the frequency trajectory blows up. In the other two cases, when the damping inertia is equal to 1.0 or 8.0, the frequency at load bus 4 is stable. This study shows the importance of accurately parameterizing load module dynamics.

IV. SYSTEM-WIDE OBSERVABILITY THROUGH COOPERATION OF SENSORS

In this section, we implement distributed observers using the cyber–physical model introduced in Section III by spatially...
by adding a zero-mean normal $\mathcal{N}(0, Q_G)$ noise, $u_{G,k}$, on the generator dynamics. The model becomes

$$x_{G,k+1} = \begin{pmatrix} \mathbf{I} + \Delta T & \mathbf{F}_{G} \omega_{L,k} + \Delta T \mathbf{K}_{G} P_{G,k} \\
0 & \mathbf{0}
\end{pmatrix} x_{G,k} + \begin{pmatrix} \mathbf{0} \\
\mathbf{0}
\end{pmatrix} + \mathbf{u}_{G,k}$$

(22)

where $x_{G,k} = [\omega_{G,k}^T P_{G,k}^T a_k^T]^T$ is the discretized version of (4). The load dynamics are taken from (9) after adding a $\mathcal{N}(0, Q_L)$ noise, $u_{L,k}$, and are given by

$$\omega_{L,k+1} = \begin{pmatrix} 1 - \Delta T \mathbf{J}_{L} \Delta \mathbf{L}_{k} - \Delta T \mathbf{J}_{L} \tilde{\mathbf{L}}_{k} + u_{L,k}
\end{pmatrix}$$

(23)

where $L_k$ in (9) is replaced by the cyber module and is estimated as in (15).

Combining (22) and (23), we now write the state-space description of a network of $Y$ nodes with $K$ generators and $M$ loads (such that $Y = K + M$). Let $\mathbf{P}_{G,k} = [P_{G,k}^1 \cdots P_{G,k}^K]^T$ be the vector of power supplied by the $K$ generators, let $\mathbf{P}_{L,k} = [P_{L,k}^1 \cdots P_{L,k}^M]^T$ be the vector of power delivered to the $M$ loads, let $\mathbf{\Omega}_{G,k} = [\omega_{G,k}^1 \cdots \omega_{G,k}^K]^T$, and let $\mathbf{\Omega}_{L,k} = [\omega_{L,k}^1 \cdots \omega_{L,k}^M]^T$. Then, $\mathbf{P}_{G,k}$ and $\mathbf{P}_{L,k}$ are related by

$$\begin{pmatrix} \mathbf{P}_{G,k+1} \\
\mathbf{P}_{L,k+1}
\end{pmatrix} = \begin{pmatrix} \mathbf{P}_{G,k} \\
\mathbf{P}_{L,k}
\end{pmatrix} + \Delta T \mathbf{H} \begin{pmatrix} \mathbf{\Omega}_{G,k+1} \\
\mathbf{\Omega}_{L,k+1}
\end{pmatrix}$$

(24)

where $\mathbf{H}$ is a $Y \times Y$ power flow Jacobian matrix, introduced in (18). Equation (22)–(24) complete the state-space description of the dynamics generated by a power system with $K$ steam-turbine generators and $M$ arbitrary loads and can be written concisely as an $n$-dimensional system

$$x_{k+1} = \mathbf{F} x_k + \mathbf{b} - \frac{1}{J_L} \tilde{\mathbf{L}}_k + \mathbf{u}_k$$

(25)

where $x_k = [x_{G,k}^T \cdots x_{G,k}^K \mathbf{\Omega}_{L,k}^T \mathbf{P}_{G,k}^T \mathbf{P}_{L,k}^T]^T$.

We now spatially decompose the power system model as a union of $N$ subsystems, where each subsystem $l$ measures a subset of the state variables (that are local to the subsystem) of the power system model in (25). The local observation vector for the $l$th subsystem is given by

$$y_k^{(l)} = \mathbf{C}_l x_k + \mathbf{w}_k^{(l)}$$

(28)

where $\mathbf{C}_l$ is the local observation matrix with the white observation noise vector $\mathbf{w}_k^{(l)} \sim \mathcal{N}(0, \mathbf{R}_l)$.

10We may stack the local observations to get the global observation vector

$$y_k = \mathbf{H} x_k + \mathbf{w}_k$$

(26)

$$y_k = \begin{pmatrix} y_k^{(1)} \\
\vdots \\
y_k^{(N)}
\end{pmatrix} \quad \mathbf{C} = \begin{pmatrix} \mathbf{C}_1 \\
\vdots \\
\mathbf{C}_N
\end{pmatrix} \quad \mathbf{w}_k = \begin{pmatrix} \mathbf{w}_k^{(1)} \\
\vdots \\
\mathbf{w}_k^{(N)}
\end{pmatrix}$$

(27)
At subsystem $l$, the dynamics after decomposing (25) can be written as an $n_l$-dimensional ($n_l \ll n$) local dynamical subsystem as follows:

$$\begin{align*}
x_{k+1}^{(l)} &= F^{(l)} x_k^{(l)} + \sum_{j \in \mathcal{K}(l)} F^{(l)} x_k^{(j)} + G^{(l)} \psi_k^{(l)} + u_k^{(l)} \\
y_k^{(l)} &= C^{(l)} x_k^{(l)} + w_k^{(l)}
\end{align*}$$

(29)

(30)

where $\mathcal{K}(l)$ contains the neighboring subsystems, $F^{(l)}$ defines the interaction between the subsystem $l$ and its $j$th neighbor, the vector $G^{(l)} \psi_k^{(l)}$ denotes the appropriate contribution of the input terms $b - (1/J_{lk}) \hat{L}_k$ to the local subsystem $l$, and $C^{(l)}$ is the local observation matrix pertinent to the local state variables $z_k^{(l)}$'s. Here, we note that the interactions from the neighboring subsystems $\sum_{j \in \mathcal{K}(l)} F^{(l)} x_k^{(j)}$ can only be treated as deterministic inputs if these states are available at the neighboring subsystems exactly. Since these states are unavailable, we use their estimates $\sum_{j \in \mathcal{K}(l)} F^{(l)} \hat{x}_k^{(j)}$ as the local interactions.

**Remark (R1):** We assume that the global state-space dynamical system (25), (26) is $(F, C)$ observable.

It is clear from (R1) that we do not require observability of the local subsystems and that each local subsystem may not be $(F^{(l)}, C^{(l)})$ observable. In such cases, independent local observers, implemented at the subsystems, result into unstable local error covariances

$$S_{k|k}^{(l)} = E \left[ (x_k^{(l)} - \hat{x}_{k|k}) (x_k^{(l)} - \hat{x}_{k|k})^T \right]$$

(31)

if they are not observable, i.e., the limit

$$\lim_{k \to \infty} \text{trace} \left( S_{k|k}^{(l)} \right)$$

(32)

may not exist, and furthermore, the sequence is unbounded.

**Remark (R2):** The coupling matrices of the entire dynamical system, $F^{(l) \cap} \forall l, j \neq j$, are sparse.

**Remark (R3):** The neighborhood $\mathcal{K} (\cdot)$ at each subsystem only contains close-by subsystems.

It is worth mentioning here that the sparsity (R2) and the locality (R3) are ensured because the cyber–physical models derived in Section III are structure preserving. These assumptions further guarantee local communications among the observers.

We now state the main result of this section.

**Result 1:** If the global system is observable, cooperation among the local (possibly unobservable) subsystems leads to observability of the local observers implemented at these subsystems.

Let the information matrix $Z_{k|k}$ be defined as

$$Z_{k|k} = S_{k|k}^{-1}.$$  

(33)

Let the local information matrix at subsystem $l$ be given by $Z_{k|k}^{(l)}$. We introduce the following assumption.

11Here, we mention that the local observers are implemented on the $n_l$-dimensional subsystems. Hence, the local observers are computationally much more efficient than the global observer that is implemented on the $n$-dimensional global model. The local observers further provide a scalable and robust estimation scheme.

**Remark (R4):** We assume that the local information matrices $\{Z_{k|k}^{(l)} \}_{l=1,...,N}$ preserve the $L$-band of the global information matrix $Z_{l|k}$, i.e., (with a slight abuse of notation)

$$\bigcup_{l=1}^{N} Z_{k|k}^{(l)} = Z_{l|k}$$

(34)

where $Z_{l|k} = L$-band$(Z_{k|k})$. The previous notation means that if we collect the information matrices for all of the local subsystems, the $L$-band of the global information matrix is preserved. It can be shown that (R4) requires the subsystems to be overlapping, i.e., the subsystems share some of the state variables (see [20]).

**Remark (R5):** By (34), it can be seen that the union of the local observers is an $L$-banded approximation of the global observer. This approximation leads to a Gauss–Markovian structure on the error process $\hat{x}_k - \hat{x}_{k|k}$ of the global observer. It can be shown [20] that the local observers are optimal under the $L$th-order Gauss–Markovian approximation on the error process.

It turns out [21] that, by cooperation among the local subsystems and under the assumptions (R1) and (R4), there is a choice of $L \geq L_{min}$ such that the trace of the local error covariances $\text{trace} (S_{k|k}^{(l)})$ can be bounded, i.e., the limit in (32) exists. The steady-state error for the collection of local observers implemented on the subsystems is thus bounded, and the bounded difference from the optimal (minimum) steady-state error

$$\text{trace} \left( \bigcup_{l=1}^{N} S_{k|k}^{(l)} \right) - \text{trace} (S_{k|k}) < M < \infty$$

(35)

($M \in \mathbb{R}_{\geq 0}$) can be characterized by the information loss incurred by approximating the global information matrices $Z_{k|k}$ and $Z_{k|k-1}$ to be $L$-banded information matrices $Z_{l|k}$ and $Z_{l|k-1}$. This cooperation is achieved by using the distributed iterate-collapse inversion (DICI) algorithm. The details on the DICI algorithm and the distributed observers can be found in [21] and [22].

Here, it is also necessary to comment on the random phenomena that are inherent in the communication required for cooperation. Broadly speaking, these random phenomena can be divided into the following: 1) communication noise; 2) random link failures or packet losses; and 3) imperfect knowledge of system parameters. Under these broad conditions, the convergence of cooperation algorithms in the context of distributed sensor localization is studied in [22]. We next provide an illustration of the distributed observers formulated on the five-bus system similar to the one presented in Section III-D.
A. Illustration

We consider a $Y = 5$ bus system with $K = 3$ generators and $M = 2$ loads (see Fig. 13). The large ovals represent the $N = 3$ subsystems. Each generator is considered to be a steam-turbine generator with the following parameters: inertia constant, $J = 1.26$, damping coefficient, $D = 2$, time constant of the turbine, $T_u = 0.2$, time constant of the generator, $T_G = 0.25$, coefficient of the valve position, $e_T = 0.15$, proportionality factor, $K_T = 0.95$, $r = 0.95$, and the sampling interval is $\Delta T = 0.01$ s. For the loads, we assume $J_L = 10$ and $D_L = 1$. The power flow Jacobian matrix $H$ represents the connectivity of the network; the nonzero pattern is given by

$$
H = \begin{bmatrix}
h_{11} & h_{12} & 0 & h_{14} & 0 \\
h_{12} & h_{22} & 0 & 0 & h_{25} \\
0 & 0 & h_{33} & 0 & h_{35} \\
h_{14} & h_{24} & 0 & h_{44} & 0 \\
0 & 0 & h_{35} & 0 & h_{55}
\end{bmatrix}
$$

The power consumed at the loads is modeled as an AR process of order $p = 2$. Load at bus 4 is taken from the NY-ISO from the month of August 2006, and load at bus 5 is taken for the New England ISO for the same month. For simplicity of illustration, we assume the load to be at the same timescale as the generation. The global observation model consists of the observations on the state variables

$$
\omega_G^1, \omega_G^2, \omega_G^3, P_G^1, P_G^2, P_G^3, P_L^1, P_L^2
$$

that is, the diagonal global observation matrix $C$ has nonzeros corresponding to the aforementioned states. The global model thus consists of the $K = 3$ steam-turbine generators with the aforementioned parameters, $M = 2$ loads (the power consumed for each of which is modeled using an AR(2) process), and the power flow equation with the $Y \times Y (5 \times 5)$ power flow Jacobian matrix $H$ given earlier. The resulting model is an $n = 16$-dimensional dynamical system that is $(F, C)$ observable with the aforementioned observations; the observability Grammian $\Theta_G$ has the largest singular value of 12.08 and smallest singular value of 0.0108 and thus has rank $n = 16$.

We now formulate subsystems on this network. Subsystem 1 has measurements corresponding to states $\omega_{G1}^1, \omega_{G2}^2, P_{G1}^1, P_{G2}^2$; subsystem 2 has measurements corresponding to states $\omega_{G1}^2, P_{G1}^2, P_{G2}^1, P_L^1$; and subsystem 3 has measurements corresponding to states $\omega_{G1}^3, P_{G1}^3, P_L^2$. It can be shown that each of the subsystems is unobservable with this set of measurements. Recall here that the global system is $(F, C)$ observable.

We now formulate subsystem dynamics. The $N = 3$ subsystems have the following state vectors:

$$
x^{(1)} = \begin{bmatrix} x_G^{(1)T} & x_G^{(2)T} & P_G^1 & P_G^2 & P_L^1 & \omega_L^1 & P_L^2 \end{bmatrix}^T
$$

$$
x^{(2)} = \begin{bmatrix} x_G^{(2)T} & P_G^2 & \omega_L^2 & P_L^2 \end{bmatrix}^T
$$

$$
x^{(3)} = \begin{bmatrix} x_G^{(3)T} & P_G^3 & \omega_L^3 & P_L^3 \end{bmatrix}^T
$$

The results are shown in Figs. 14–16. Fig. 14 shows the trace of the local error covariances at each subsystem when no cooperation is employed with $L = 5$-banded approximation (on the information matrices). Fig. 15 shows the trace of the local error covariances at each subsystem when the DICI algorithm is used to assimilate the local error
The sum of the squared errors over the error processes. This is achieved by using an assimilation filter (with no approximation).

With this illustration, we conclude that with the appropriate overlapping of the subsystems and using an assimilation procedure on the local error covariances, the unobservable subsystems can be made observable in the sense that the local error covariances remain stable. Local observers are implemented on the subsystems that guarantee a Gauss–Markovian structure on the error processes. This is achieved by using an assimilation procedure among the local error covariances that preserve the Gauss–Markovian structure. The sum of the squared errors (trace of the error covariance) thus remains bounded, and the aggregated performance over all of the subsystems is equivalent to the global observer with $L$-banded approximation on its information matrices.

V. Module-Based Distributed Control of Cyber–Physical Systems

In Section II, a structure-preserving model for future cyber–physical energy systems is presented. In the proposed model, each (group of) component(s) is defined as a module and is represented in terms of its local variables and the interconnection variables between the module and the network. Therefore, it is possible to specify the performance subobjectives of each module for a given range of variations in interaction variables and to ensure that the local subobjectives are met through distributed sensing and actuation. An interactive communication protocol between modules and the grid could be implemented for operating the system with prespecified linearized dynamical performance. Sufficient conditions on network properties are derived under which this interactive protocol between the module and the network. Therefore, it is practical to be deployed in the near future.

Step 1) At time step $t$, all the modules predict the range of real power generation (or demand) $[P_{\text{min}}, P_{\text{max}}]$ for the next time step interval, check its local control to guarantee that the local module dynamics are stabilized, and send it to the transmission operator (e.g., the independent system operator). Since this prediction is for the next time interval in the scale of a minute, it is reasonable to assume high confidence of prediction even for intermittent resources like wind generator module.

Step 2) The transmission operator runs the steady-state load flow and examines if Condition 3) of Theorem 1 is satisfied for the range of power injections from all the nodes. If this condition is passed, then go to Step 3). Otherwise, the transmission operator will communicate back to the modules with the information of what are the needed adjustments of power output range to guarantee that the load flow Jacobian matrix satisfies Condition 3) of Theorem 1.

Step 3) Once the modules receive the adjustment requirements from the transmission operator, distributed communication starts among the neighboring modules. They iteratively communicate and adjust their local controls to achieve an equilibrium under which no additional adjustment is needed to guarantee the

\[
x_k = \begin{bmatrix} x_{\text{mod},k} \\ x_{\text{int},k} \end{bmatrix} = \begin{bmatrix} A & C \\ H & O \end{bmatrix} \begin{bmatrix} x_{\text{mod},k-1} \\ x_{\text{int},k-1} \end{bmatrix} + Bu_{k-1}. \tag{40}
\]

1) All the eigenvalues of $A$ are inside the unit circle, i.e., $|\lambda(A)| < 1$, $i = 1, \ldots, n$.
2) Matrix $HC$ is symmetric, i.e., $(HC)^\top = HC$.
3) Matrix $HC$’s eigenvalues $\mu_j(\lambda(C))$ satisfy $0 > \mu_j > -(1/2)\lambda_2^2$, $j = 1, 2, \ldots, m$, where $\lambda_2 = \max \text{Re}(\lambda(A))$.

\textbf{Proof:} See [25] and [27].

Based on the sufficient condition for linearized dynamical stability, we propose an interactive communication protocol for future electric energy system operation with provable dynamical stability. The key features of the proposed protocol include the following: 1) iterative communication, in both centralized and distributed ways, and 2) quasi-static communication rate. Information (the range of real power injection at each node) could be exchanged at the rate of minutes, similar to the rate of the present SCADA system. This makes the proposed protocol practical to be deployed in the near future.

Let $G_i$ be the typical G-T-G module in the system. Let $WG_j$ be the proposed planned module $j$ to be integrated into the system (e.g., a new wind power plant). Let $L_k$ be the load module $k$ in the system. The cyber protocol for operation with guaranteed stability performance can be described as follows.

Cyber protocol of distributed system operation with guaranteed stability performance

\[\text{Step 1) } \text{At time step } t, \text{ all the modules predict the range of real power generation (or demand) } [P_{\text{min}}, P_{\text{max}}] \text{ for the next time step interval, check its local control to guarantee that the local module dynamics are stabilized, and send it to the transmission operator (e.g., the independent system operator). Since this prediction is for the next time interval in the scale of a minute, it is reasonable to assume high confidence of prediction even for intermittent resources like wind generator module.}\]

\[\text{Step 2) } \text{The transmission operator runs the steady-state load flow and examines if Condition 3) of Theorem 1 is satisfied for the range of power injections from all the nodes. If this condition is passed, then go to Step 3). Otherwise, the transmission operator will communicate back to the modules with the information of what are the needed adjustments of power output range to guarantee that the load flow Jacobian matrix satisfies Condition 3) of Theorem 1.}\]

\[\text{Step 3) } \text{Once the modules receive the adjustment requirements from the transmission operator, distributed communication starts among the neighboring modules. They iteratively communicate and adjust their local controls to achieve an equilibrium under which no additional adjustment is needed to guarantee the}\]

\[\text{system dynamic model is bounded-input–bounded-state stable if all the following three conditions are satisfied:}\]

\[x_k = \begin{bmatrix} x_{\text{mod},k} \\ x_{\text{int},k} \end{bmatrix} = \begin{bmatrix} A & C \\ H & O \end{bmatrix} \begin{bmatrix} x_{\text{mod},k-1} \\ x_{\text{int},k-1} \end{bmatrix} + Bu_{k-1}. \tag{40}\]

1) All the eigenvalues of $A$ are inside the unit circle, i.e., $|\lambda(A)| < 1$, $i = 1, \ldots, n$.
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Based on the sufficient condition for linearized dynamical stability, we propose an interactive communication protocol for future electric energy system operation with provable dynamical stability. The key features of the proposed protocol include the following: 1) iterative communication, in both centralized and distributed ways, and 2) quasi-static communication rate. Information (the range of real power injection at each node) could be exchanged at the rate of minutes, similar to the rate of the present SCADA system. This makes the proposed protocol practical to be deployed in the near future.

\[\text{Let } G_i \text{ be the typical G-T-G module } i \text{ in the system. Let } WG_j \text{ be the proposed planned module } j \text{ to be integrated into the system (e.g., a new wind power plant). Let } L_k \text{ be the load module } k \text{ in the system. The cyber protocol for operation with guaranteed stability performance can be described as follows.}\]

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\[\text{Step 3) } \text{Once the modules receive the adjustment requirements from the transmission operator, distributed communication starts among the neighboring modules. They iteratively communicate and adjust their local controls to achieve an equilibrium under which no additional adjustment is needed to guarantee the}\]
such as fuel cell and photovoltaic devices. Particular emphasis is on the aggregate load modeling enabled by novel sensing and data mining in order to facilitate EHV/HV operations. Exploring the structure of this model is beyond the objectives of this paper and is the subject for future work.

VI. CONCLUSION

In this paper, we have recognized that pressures facing future energy systems require qualitatively novel technological and organizational solutions. While new energy technologies are gradually making their inroads, much must be done toward developing cyber-supported frameworks for their systematic integration and online utilization. By a future energy system, we refer to a cyber–physical network interconnection of many diverse energy components, equipped with their own local intelligence. Future energy systems must manage tradeoffs among multiple objectives such as flexibility, efficiency, environmental sustainability, distributed QoS, and security according to the customers’ specifications and willingness to pay for such services. In such systems, the existing electric power network becomes the main coordinating enabler of utilizing various forms of energy converted into electric energy form, delivered via the electric power grid to the end users’ locations, and converted back to a mix of energy forms according to a well-defined customer choice.

This paper concerns basic modeling of such cyber-based physical energy systems. A novel cyber-based dynamic model is proposed in which a resulting mathematical model greatly depends on the cyber technologies supporting the physical system. It is shown how the inclusion of these models results in a cyber-based dynamic model that lends itself to distributed sensing and actuation within this complex system. Notably, the newly introduced models have network structure-preserving properties that are key to the effective distributed decision making. In addition, the proposed models can be extended to incorporate nonconventional energy-converting components such as fuel cell and photovoltaic devices. Particular emphasis is on the aggregate load modeling enabled by novel sensing and data mining in order to facilitate EHV/HV operations. Exploring the structure of this model is beyond the objectives of this paper and is the subject for future work.

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Le Xie (S’05–M’10) received the B.E. degree in electrical engineering from Tsinghua University, Beijing, China, the M.Sc. degree in engineering sciences from Harvard University, Cambridge, MA, in 2005, and the Ph.D. degree in electrical and computer engineering from Carnegie Mellon University, Pittsburgh, PA, in 2009.

Marija D. Ilic (M’80–SM’86–F’99) received the D.Sc. degree in systems science and mathematicks from Washington University in St. Louis, MO, in 1980.

She was an Assistant Professor with Cornell University, Ithaca, NY, and an Associate Professor with the University of Illinois at Urbana–Champaign. From 1987 to 2002, she was a Senior Research Scientist with the Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge. She is currently a Professor with Carnegie Mellon University, Pittsburgh, PA, and has a joint appointment in the Department of Electrical and Computer Engineering and the Department of Engineering and Public Policy. She is also the Honorary Chaired Professor for Control of Future Electricity Network Operations with Delft University of Technology, Delft, The Netherlands. She is a Distinguished Lecturer. She has 30 years of experience in teaching and research in the area of electrical power system modeling and control. Most recently, she became the Director of the Electric Energy Systems Group, Carnegie Mellon University (http://www.eesg.ece.cmu.edu), the group does extensive research on mathematical modeling, analysis, and decision-making algorithms for the future energy systems. She is leading the quest for transforming today’s electric power grid into an enabler of efficient, reliable, secure, and sustainable integration of many novel energy resources. Her main research interest is in the systems aspects of operations, planning, and economics of the electric power industry. She has authored several books in her field of interest.