State Estimation and Branch Current Learning Using Independent Local Kalman Filter With Virtual Disturbance Model

Junqi Liu, *Graduate Student Member, IEEE*, Andrea Benigni, *Graduate Student Member, IEEE*, Dragan Obradovic, Sandra Hirche, *Member, IEEE*, and Antonello Monti, *Senior Member, IEEE*

***Abstract*—This paper presents a generalized approach to the design of independent local Kalman filters (KFs) without communication to be used for state estimation in distributed generation-based power systems. The design procedure is based on an improved model of the virtual disturbance concept proposed in a previous work. The local KFs are then synthesized based only on local models of the power network and on the characteristics of the associated virtual disturbance. The proposed solution is applied to an interconnected power network. By choosing appropriate models for the virtual disturbance, the local KFs can be suited for both dc and ac distribution systems. It is shown for both cases that the local KF can infer the local states of the network, including the aggregated branch currents coming from the other buses. Simulation results show improved results with respect to the previous proposed modeling approach even when the subsystems present widely different dynamics. The herein presented approach is well suited for the agent-based decentralized control of microgrids.**

***Index Terms*—Decentralized state estimation, distributed power generation, Kalman filters (KFs), noise shaping, power systems, smart grids.**

I. Introduction

A RELIABLE monitoring and control process is a critical issue for a safe and efficient power system operation. For such purpose, it is necessary to know system states that are, however, typically not directly available or not easily measurable. In such process, state estimation serves as the key tool to provide the system status to support decision making for control actions [1], [2].

In modern power grids with wide dispersion of distributed power generation units and power electronic converters, the overall system presents increasing complexity. Traditional state estimation, as part of a centralized control system and based on static or quasi-static system models, becomes inadequate to manage such large-scale complex systems.

The Kalman filter (KF) is widely used to estimate and track the states of a system based on the process model and the process measurements. Dynamic state estimation for power systems based on a centralized KF is discussed in [1] and [4]. A KF in the presence of unknown disturbance or inputs has been proposed for centralized control schemes with disturbance rejection in [5], [6], and [16].

Recently, the distributed and decentralized KF (DKF) has attracted a lot of attention due to its distribution of computational loads and operational robustness. Prominent recent applications for DKFs are in the area of data fusion in sensor networks [6], [8], [9] and state estimation for electric power systems [11], [12].

The synthesis procedure for the proposed independent local KFs consists of first building the full system model and then decomposing it into local subsystems. The approaches proposed in the preceding papers still need communication to accomplish the state estimation process. However, this communication requires synchronization between the local estimators, which increases the complexity of the system. In addition, the network-induced parasitic effects, such as time delay and packet loss, reduce the estimator performance. Thus, avoiding communication channels as much as possible is desirable for performing the state estimation.

In [14], we proposed the independent local KF approach without communication synthesized using local models of the power network associated with a virtual disturbance model. This virtual disturbance model is used to represent the interconnections of the local systems: in this case, the unknown branch current injections to bus that also represent the dynamics of the rest of the power network. By choosing appropriate models for the virtual disturbance, the local KFs are designed for both dc and ac cases. It is shown for both cases that the local KFs can estimate the local states and the aggregated branch current injections independently without any information exchange between them. The independent local KF implementation as an estimation of local dynamics and aggregated states of the rest of the network can be used for control purposes, such as shown in [13].

In this paper, we follow the same principle as in [14] and extend it to the formalization, giving guidelines for a systematic design of the proposed independent local KFs with the modified virtual disturbance model. We consider now the virtual random

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J. Liu, A. Benigni, and A. Monti are with the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University, 52074 Aachen, Germany (e-mail: amonti@eonerc.rwth-aachen.de; jliu@eonerc.rwth-aachen.de; abenigni@eonerc.rwth-aachen.de).

D. Obradovic is with the Corporate Technology, Siemens AG, 81739 Munich, Germany (e-mail: dragan.obradovic@siemens.com).

S. Hirche is with the Institute of Automatic Control Engineering, Technische Universität München, 80290 Munich, Germany (e-mail: hirche@tum.de).

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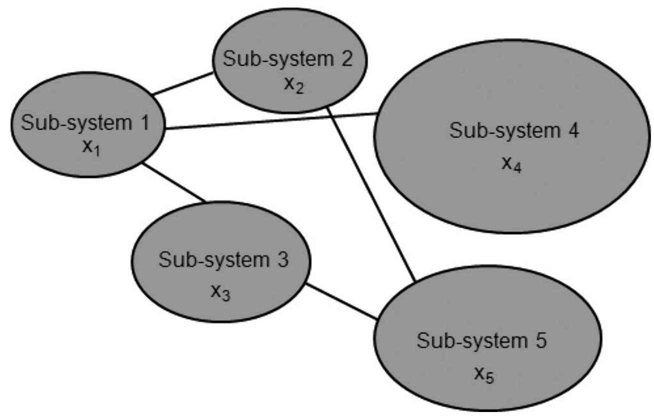


Fig. 1. Partitioned power system.

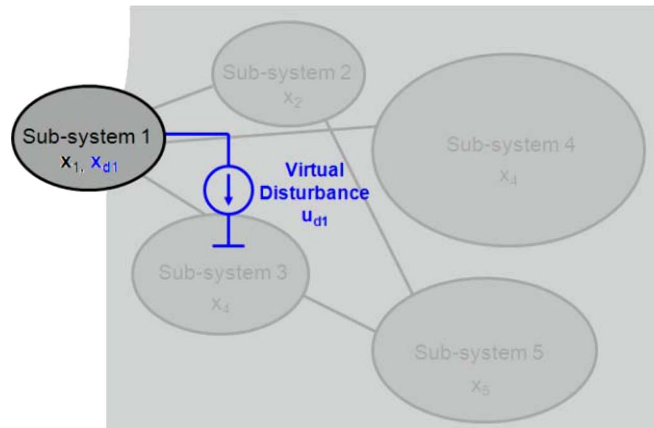


Fig. 2. Subsystem and virtual disturbance source.

disturbance that is modeled as a nonwhite noise inserted into each subsystem. This nonwhite noise is generated by shaping a white noise signal by a linear filter. Thus, the dynamic model of the virtual disturbance is determined by the state model of the linear filter driven by the white noise. The linear filter and thus the dynamic model of the virtual disturbance are designed based on the characteristics of the assumed random behavior of the virtual disturbance. By choosing appropriate parameters for the virtual disturbance model, improvements in the estimation performance are shown in the simulation. On the other hand, while in [14] all the subsystems are assumed to have nearly the same dynamics, we also investigate the interconnected system with fast and slow dynamics of the subsystems. The simulation results also show good performance of the estimators in this case.

This paper is organized as follows: In Section II, the overall approach is illustrated, whereas in Section III, the guidelines for the design of linear filter and thus the virtual disturbance model are provided. The system model with its state space representation is introduced in Section IV. Next, the local KF with a virtual disturbance model is proposed and analyzed in Section V. Finally, the proposed approach is evaluated in Section IV. The same topology of [14] is proposed but now we analyze how the local filters behave when the different subsystems have different dynamics.

II. Approach of Independent Local KF With Virtual Disturbance

In general, considering a power system such as shown in Fig. 1, different subsystems with local state variables $\mathbf{x}_i$ can be identified, and they are dynamically and nonhomogenously interconnected. In the conventional way, the state estimator is designed based on the complete knowledge about the system, and state estimation of the individual local state variables has to take into account the dynamic interactions with the others.

Without considering any particular topology of the different subsystems and their interconnections, we assume that, from the view point of each subsystem, the rest of the network is represented by an equivalent virtual source with unknown dynamics, as illustrated in Fig. 2. It could also be interpreted as that the interconnections between one subsystem and all the others are lumped into the virtual source. Following this concept, the local state estimation of each sub system only depends on its local state variable and the virtual source. In addition, we consider the virtual source as a disturbance with unknown dynamic inserted into the subsystem that can also randomly change and denote it as virtual disturbance source for the rest of this paper.

Since we consider the equivalent virtual source as an unknown disturbance for the subsystem, a proper augmented local KF can be implemented, where the state vector is composed of the real local state variable of the subsystem and by the states that represent the dynamics of the virtual disturbance, i.e.,

$$\mathbf{x}_{i,\text{ext}} = \begin{bmatrix} \mathbf{x}_i \\ \mathbf{x}_{di} \end{bmatrix}$$

where $\mathbf{x}_i$ is the local state of the subsystem, and $\mathbf{x}_{di}$ is the state of the virtual disturbance model.

Accordingly, the local KF is to be designed based on the augmented state space representation and measurement equation of the subsystem that are shown in generic form as

$$\frac{d}{dt}\mathbf{x}_{i,\text{ext}} = \mathbf{A}_{i,\text{ext}}\mathbf{x}_{i,\text{ext}} + \mathbf{B}_{i,\text{ext}}\mathbf{u}_i \tag{1}$$

$$y_i = \mathbf{C}_{i,\text{ext}}\mathbf{x}_{i,\text{ext}} + \mathbf{D}_{i,\text{ext}}\mathbf{u}_i + v_i. \tag{2}$$

The matrices $\mathbf{A}_{i,\text{ext}}$, $\mathbf{B}_{i,\text{ext}}$, $\mathbf{C}_{i,\text{ext}}$, and $\mathbf{D}_{i,\text{ext}}$ consists of the local state matrices of the subsystem and the virtual disturbance model. The derivation of the augmented state space model is explained more in detail with an example power network in Sections IV and V.

The local augmented KF is thus given by

$$\frac{d}{dt}\hat{\mathbf{x}}_{i,\text{ext}} = \mathbf{A}_{i,\text{ext}}\hat{\mathbf{x}}_{i,\text{ext}} + \mathbf{B}_{i,\text{ext}}u_i + \mathbf{K}_{i,\text{ext}}(y_i - \mathbf{C}_{i,\text{ext}}\hat{\mathbf{x}}_{i,\text{ext}}) \tag{3}$$

where $\hat{\mathbf{x}}_{i,\text{ext}}$ is the estimation of $\mathbf{x}_{i,\text{ext}}$, and $\mathbf{K}_{i,\text{ext}}$ is the Kalman gain computed using the standard algebraic Riccati equation [15].

In contrast to the synthesis procedure for the conventional decentralized state estimation, in which the full system model is first built and then decomposed, the proposed local KFs associated with each generation unit only needs local information about the network and are independent of each other.

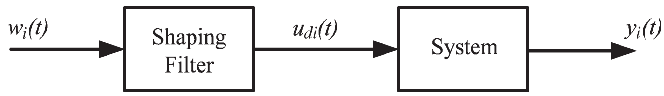


Fig. 3. Virtual disturbance generation as nonwhite noise using shaping filter.

It should be underlined that the state estimation based on the proposed algorithm has the advantage that each observer is completely independent from the other observers of the system. It also means that no communication and no synchronization are needed.

III. Design Guidelines

A. Virtual Disturbance as Nonwhite Noise

As introduced in the preceding section, the virtual disturbance is considered as an unknown input to the subsystem. To include the virtual disturbance into the augmented state estimation, a dynamic model for the virtual disturbance is needed.

Generally, in control and estimation theory, an unknown input is usually treated as a stochastic process with wide-sense representation [10]. In this sense, the virtual disturbance could be considered as a nonwhite noise input to each subsystem. On the other hand, as discussed in [16], any reasonable nonwhite noise process can be generated as the output of a linear filter, so-called shaping filter, driven by white noise input with a unit spectral density. The response of the original system to the nonwhite noise, in our case the virtual disturbance, is then equivalent to the response of the series combination of the original system and the shaping filter to the white noise input [16]. This concept is illustrated in Fig. 3, where $w_i(t)$ is the white noise input, and $u_{di}(t)$ is the generated virtual disturbance.

Therefore, the linear shaping filter determines the dynamic model of the generated virtual disturbance. In general, a state model for the linear filter can be formulated as [16]

$$\frac{d}{dt}\mathbf{x}_{di} = \mathbf{A}_{di}\mathbf{x}_{di} + \mathbf{B}_{di}w_i$$
$$u_{di} = \mathbf{C}_{di}\mathbf{x}_{di}. \tag{4}$$

The transfer function of the linear filter is therefore

$$G(s) = \frac{U_{di}(s)}{W_i(s)} = \mathbf{C}_{di}(s\mathbf{I} - \mathbf{A}_{di})^{-1}\mathbf{B}_{di} \tag{5}$$

where $U_{di}(s)$ and $W_i(s)$ are the spectral representations of the virtual disturbance and the white noise, respectively.

In the following, we introduce two different dynamic models of the virtual disturbance for state estimation in dc and ac power networks.

B. Disturbance for DC Power Network

In a dc power network, the currents flowing in the branches, which also represent the interactions between the subsystems in Fig. 1, are constant signals in steady state. Therefore, the virtual disturbance source, in which all the dynamic interactions are lumped in, is modeled as a randomly stepwise changing source that can be considered a nonwhite noise.

A randomly stepwise changing signal, in our case the virtual disturbance u_{di}, can be modeled driven by white noise w_i with zero mean and unit spectral density according to

$$\frac{d}{dt}u_{di} = -a_{di}u_{di} + b_{di}w_i. \tag{6}$$

This model is the first-order form of the linear shaping filter model in (4) for nonwhite noise generation with $x_{di} = u_{di}$ and $\boldsymbol{C}_{di} = 1$. The transfer function of the shaping filter is thus obtained by

$$G(s) = \frac{U_{di}(s)}{W_i(s)} = \frac{b_{di}}{s + a_{di}}. \tag{7}$$

As shown in [16], the shaping filter output u_{di} has the variance σ_{di}^2 and the correlation time τ_{di} given by

$$\sigma_{di}^2 = \frac{b_{di}^2}{2a_{di}}; \tau_{di} = \frac{1}{a_{di}} \tag{8}$$

and thus the filter is specified by the parameters a_{di} and b_{di} obtained by

$$a_{di} = \frac{1}{\tau_{di}} \quad b_{di} = \sqrt{2\sigma_{di}^2 a_{di}}. \tag{9}$$

C. Disturbance Model for AC Power Network

Since in ac power networks the dynamic interactions between the subsystems have a sinusoidal waveform, the disturbance model for the dc case in (6) is no longer appropriate. In addition, we assume here that the changes in the interconnections are only related to the amplitude and phase of the sinusoidal wave.

For a sinusoidal disturbance with known frequency f but unknown amplitude and phase, the modified model similar to that in [6] is considered, i.e.,

$$\frac{d}{dt}\begin{bmatrix} x_{d1} \\ x_{d2} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -(2\pi f)^2 & 0 \end{bmatrix}\begin{bmatrix} x_{d1} \\ x_{d2} \end{bmatrix} + \begin{bmatrix} b_{di} \\ 0 \end{bmatrix} w_i;$$
$$u_{di} = [1 \quad 0] \cdot \begin{bmatrix} x_{d1} \\ x_{d2} \end{bmatrix}. \tag{10}$$

The term w_i is again the white noise with zero mean and unit spectral density. In this case, the model of the virtual disturbance corresponds to a shaping filter of the second-order filter with the transfer function given by

$$G(s) = \frac{U_{di}(s)}{W_i(s)} = \frac{b_{di}}{s^2 + (2\pi f)^2}. \tag{11}$$

It is noted that, for dc network, the virtual disturbance model is designed by the two parameters a_{di} and b_{di}, whereas according to the model for the ac network, the design parameter is only b_{di}.

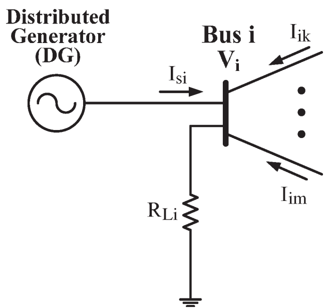


Fig. 4. Generic power network bus model.

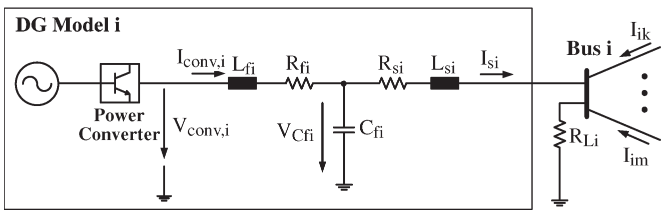


Fig. 5. DG model.

IV. System Model and Case Study

In the following, we investigate the approach introduced in the last two sections with an example power network and show the design process in detail. We start considering a generic power network bus i connected to a distributed generator, a load, and network branches $k \ldots m$ with branch currents $I_{ik} \ldots I_{im}$, as illustrated in Fig. 4. For the sake of simplicity, we consider a constant resistance R_{Li} as the load in this paper. In the case of time-varying loads, the value of the loads could be obtained by historical data combined with a separate estimation step.

In general, renewable distributed generation (DG) units cannot directly be connected to the power system due to the irregularity of the generated power. It is widely recognized in the literature the important role of using power electronics to interface the DG units to the power network, as discussed in [17]. Without loss of generality, we represent distributed generation units as power converters interfaced to the power network with an LCL filter, as shown in Fig. 5.

Considering the output voltage $V_{\text{conv},i}$ of the power converter as input to the model, the state space representation of the DG model i connected to bus i is given by

$$\frac{d}{dt}\mathbf{x}_i = \mathbf{A}_i\mathbf{x}_i + \mathbf{B}_i V_{\text{conv},i} + \mathbf{F}_i \sum_{j=k,j\neq i}^{m} I_{ij} \tag{12}$$

with

$$\mathbf{x}_i = \begin{bmatrix} I_{\text{conv},i} \\ V_{Cf,i} \\ I_{si} \end{bmatrix} \qquad \mathbf{A}_i = \begin{bmatrix} -\frac{R_{fi}}{L_{fi}} & -\frac{1}{L_{fi}} & 0 \\ \frac{1}{C_{fi}} & 0 & \frac{1}{C_{fi}} \\ 0 & \frac{1}{L_{si}} & \frac{R_{si}+R_{Li}}{L_{si}} \end{bmatrix}$$
$$\mathbf{B}_i = \begin{bmatrix} \frac{1}{L_{fi}} & 0 & 0 \end{bmatrix}^T \qquad \mathbf{F}_i = [0 \quad 0 - \tfrac{R_{Li}}{L_{si}}]^T. \tag{13}$$

The state vector $\mathbf{x}_i$ is comprised of the output current of the power converter $I_{\text{conv},i}$, the voltage V_{Cfi} over the capacitor C_{fi}, and the output current I_{si} of the DG model injected into the bus i. The parameters R_{fi}, L_{fi}, C_{fi}, R_{si}, and L_{si} are the components of the LCL filter shown in Fig. 5. The term $\mathbf{F}_i \sum_{j=k,j\neq i}^{m} I_{ij}$ represents the sum of the branch currents flowing from other neighbor buses $k, \ldots, m$ into bus i and also represents the interconnection between the different actors in the power network.

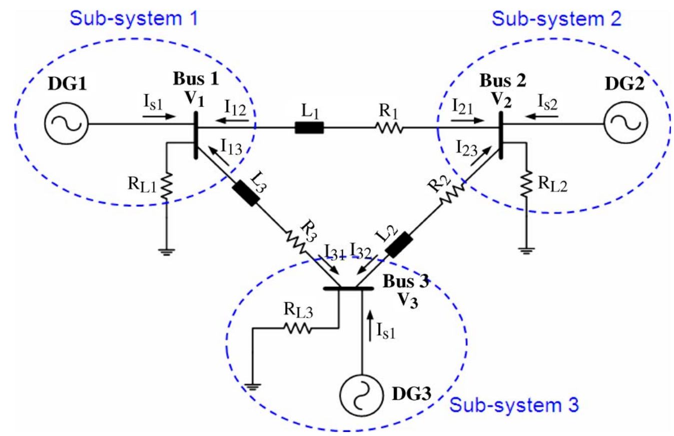


Fig. 6. Power network for case study.

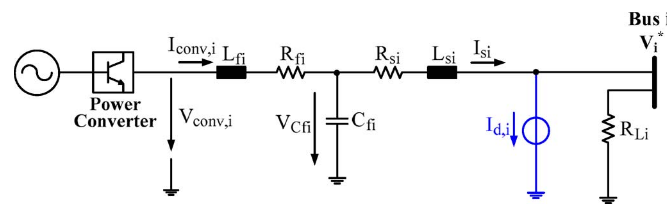


Fig. 7. Model for the local KF.

The bus voltage V_i over the load is related to the injected current I_{si} from the DG model and the injected currents $I_{ik}, \ldots, I_{im}$ from the branches connected to the bus. The voltage V_i is thus defined as

$$V_i = \mathbf{C}_i\mathbf{x}_i + R_{Li} \sum_{j=k,j\neq i}^{m} I_{ij} \tag{14}$$

with

$$\mathbf{C}_i = [0 \quad 0 \quad R_{Li}]. \tag{15}$$

For the case study, we consider an interconnected power network in Fig. 6 with three subsystems consisting of the model in Figs. 4 and 5. Due to limited space, the network model is not derived in this paper. In this case study, the parameter m in (12) and (14) is equal to 3.

V. Proposed Local KF

A. Local Model for the Local KF

We assume that the local KF associated with each generation unit has only local information about the network. This led to a local model for the KF, as illustrated in Fig. 7. Compared with the model in Fig. 5, the branches connected to the bus are neglected. Instead, a current source $I_{d,i}$ is added as a virtual disturbance model. This assumes that there is an inherent modeling error of the local model in comparison to the true DG model. Moreover, we assume that the measurement of the bus voltage in the local model denoted by V_i^* is available to the local KF.

Therefore, the state space model for the local KF according to Fig. 7 turns out to be

$$\frac{d}{dt}\mathbf{x}_i = \mathbf{A}_i\mathbf{x}_i + \mathbf{B}_i V_{\text{conv},i} + \mathbf{N}_i I_{d,i} \tag{16}$$

with $\mathbf{A}_i$, $\mathbf{B}_i$ defined in (13) and

$$\mathbf{N}_i = \begin{bmatrix} 0 & 0 & \frac{R_{Li}}{L_{si}} \end{bmatrix}^T. \tag{17}$$

The local measurement that is available to the local KF is given by

$$y_i = V_i^* + v_i = \mathbf{C}_i\mathbf{x}_i - R_{Li}I_{di} + v_i \tag{18}$$

where v_i is a white Gaussian measurement noise with zero mean and variance σ_{vi}^2. The matrix $\mathbf{C}_i$ is defined in (14).

Comparing (16) and (18) with (12) and (14), one can see that the terms $\mathbf{F}_i \sum_{j=k,j\neq i}^{m} I_{ij}$ and $R_{Li}\sum_{j=k,j\neq i}^{m} I_{ij}$ corresponding to the branch current flows are represented by terms dependent on the virtual disturbance $I_{d,i}$. Consequently, the local KF does not depend on the network topology and parameters anymore and can operate in an independent way.

As discussed before, we consider the virtual disturbance $I_{d,i}$ as an additional state to estimate. In the following, we apply the two dynamic models of the virtual disturbance introduced in Section III for state estimation in dc and ac power networks.

B. DC Power Network

Applying the virtual disturbance for the dc network in (6), we extend the state estimation of the local system in (16) and (18) by considering $I_{d,i}$ as an additional state to estimate and obtain

$$\begin{aligned} \frac{d}{dt}\mathbf{x}_{i,\text{ext}}^{\text{dc}} &= \mathbf{A}_{i,\text{ext}}^{\text{dc}}\mathbf{x}_{i,\text{ext}}^{\text{dc}} + \mathbf{B}_{i,\text{ext}}^{\text{dc}} V_{\text{conv},i} + \mathbf{N}_{i,\text{ext}}^{\text{dc}} w_i \\ y_i &= \mathbf{C}_{i,\text{ext}}^{\text{dc}}\mathbf{x}_{i,\text{ext}}^{\text{dc}} + v_i \end{aligned} \tag{19}$$

with

$$\mathbf{x}_{i,\text{ext}}^{\text{dc}} = \begin{bmatrix} \mathbf{x}_i \\ I_{d,i} \end{bmatrix};\ \mathbf{A}_{i,\text{ext}}^{\text{dc}} = \begin{bmatrix} \mathbf{A}_i & \mathbf{N}_i \\ \mathbf{0} & -a_{di} \end{bmatrix};\ \mathbf{B}_{i,\text{ext}}^{\text{dc}} = \begin{bmatrix} \mathbf{B}_i \\ \mathbf{0} \end{bmatrix};$$
$$\mathbf{N}_{i,\text{ext}}^{\text{dc}} = [\,\mathbf{0} \quad b_{di}\,]^T;\ \mathbf{C}_{i,\text{ext}}^{\text{dc}} = [\,\mathbf{C}_i \quad -R_{Li}\,]. \tag{20}$$

The local KF with augmented state estimate $\hat{\mathbf{x}}_{i,\text{ext}}^{\text{DC}}$ is then given by

$$\frac{d}{dt}\mathbf{x}_{i,\text{ext}}^{\text{dc}} = \mathbf{A}_{i,\text{ext}}^{\text{dc}}\hat{\mathbf{x}}_{i,\text{ext}}^{\text{dc}} + \mathbf{B}_{i,\text{ext}}^{\text{dc}} V_{\text{conv},i} + \mathbf{K}_i^{\text{dc}}\left(y_i - \mathbf{C}_{i,\text{ext}}^{\text{dc}}\hat{\mathbf{x}}_{i,\text{ext}}^{\text{dc}}\right) \tag{21}$$

which assumes the observability of the augmented local system. Since we consider the system in steady state, the Kalman gain $\mathbf{K}_i^{\text{DC}}$ can be determined by the standard algebraic Riccati equation [15].

C. AC Power Network

Equivalently, for the ac network, we apply the model in (10) for the virtual disturbance $I_{d,i}$, which is also a sinusoidal wave. The augmented model for the local KF in this case turns out to be

$$\begin{aligned} \frac{d}{dt}\mathbf{x}_{i,\text{ext}}^{\text{ac}} &= \mathbf{A}_{i,\text{ext}}^{\text{ac}}\mathbf{x}_{i,\text{ext}}^{\text{ac}} + \mathbf{B}_{i,\text{ext}}^{\text{ac}} V_{\text{conv},i} + \mathbf{N}_{i,\text{ext}}^{\text{ac}} w_i \\ y_i &= \mathbf{C}_{i,\text{ext}}^{\text{ac}}\mathbf{x}_{i,\text{ext}}^{\text{ac}} + v_i \end{aligned} \tag{22}$$

with

$$\mathbf{x}_{i,\text{ext}}^{\text{ac}} = \begin{bmatrix} \mathbf{x}_i \\ x_{d1} \\ x_{d2} \end{bmatrix};\ \mathbf{A}_{i,\text{ext}}^{\text{ac}} = \begin{bmatrix} \mathbf{A}_i & \mathbf{N}_i & \mathbf{0} \\ \mathbf{0} & 0 & 1 \\ \mathbf{0} & -(2\pi f)^2 & 0 \end{bmatrix};$$
$$\mathbf{B}_{i,\text{ext}}^{\text{ac}} = \begin{bmatrix} \mathbf{B}_i \\ 0 \\ 0 \end{bmatrix};$$
$$\mathbf{N}_{i,\text{ext}}^{\text{ac}} = [\,\mathbf{0} \quad b_{di} \quad 0\,]^T;\ \mathbf{C}_{i,\text{ext}}^{\text{ac}} = [\,\mathbf{C}_i \quad -R_{Li} \quad 0\,]. \tag{23}$$

Assuming the observability of the augmented local model in (22), the local KF for the ac power network and the Kalman gain $\mathbf{K}_i^{AC}$ can be obtained as in the previous section.

It should also be noted that the white noise w_i in both dc and ac disturbance models can be interpreted as the process noise of the augmented local system in (19) and (22).

D. Analysis of the Augmented State Estimation

According to the definition of the local measurement in (18), the local KF considers the local measured voltage V_i^* nominally only dependent on the single current injected by the local DG perturbed by the virtual disturbance source $I_{d,i}$. However, the true measured voltage V_i defined in (14) depends on all the current injections from the power source and the branches into the bus. As mentioned before, the terms related to the branch current flows in the true DG model are replaced by terms dependent on the virtual disturbance $I_{d,i}$ in the local model. Therefore, the virtual disturbance obtained by the local augmented state estimation is related to the branch current flows.

For each local KF, the local measurement of the bus voltage in (18) should be equal to the true bus voltage in (14) despite the measurement noise v_i with zero mean according to

$$V_i = E[y_i] = V_i^* \tag{24}$$

where $E[\bullet]$ is the expected value.

Inserting (14) and (18) into (24) and solving with respect to $I_{d,i}$, the locally estimated virtual disturbance is obtained as

$$\hat{I}_{d,i} = -\sum_{j=k,j\neq i}^{m} I_{ij}. \tag{25}$$

Thus, the locally estimated virtual disturbance in (25) is equal to the negative sum of the current flows injected into the bus. This indicates that the local KF is able to implicitly learn the unknown branch current flows of the power network in an

TABLE I
SYSTEM PARAMETERS

Parameters	Subsystem 1&3	Subsystem 2
L_{fi}	10uH	1mH
R_{fi}	0.2Ω	0.2Ω
C_{fi}	2uF	200uF
L_{si}	5uH	10mH
R_{si}	0.3Ω	0.3Ω

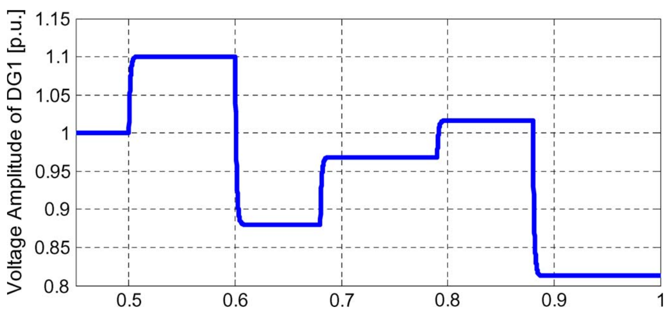


Fig. 8. Sequence of random changes in the voltage amplitude of DG1.

aggregated way. The negative sign is due to the chosen current flow direction of the virtual disturbance model.

VI. Simulation Results

The parameters of the three DGs are chosen as given in Table I. The chosen parameters imply that the dynamics of the subsystem 1 and 3 are much faster than the dynamic of subsystem 2.

The transmission lines of the power network are modeled by simple serial RL components. The value for R_i and L_i are also chosen arbitrarily, with all three branches having $R_i = 0.5\ \Omega$ and $L_i = 0.1$ mH. All the three loads R_{Li} are chosen equal to 5 Ω. The nominal amplitudes of the output voltages $V_{\text{conv},i}$ of the three power converters are chosen equal to 402, 403, and 398 V, respectively. We assume the uncertainty of the measurement devices with uniform distribution, and the devices have an accuracy of 0.25%. The white Gaussian measurement noise thus has a variance of $\sigma_{vi}^2 = 0.3V^2$ for all local KFs.

In the simulation, the changes in branch current flows that also imply the changes in the virtual disturbance is stimulated by random step changes of the output voltage amplitude of the DG1 in Fig. 6 with a correlation time of $\tau_{di} = 100$ ms for both dc and ac cases. The sequence of changes normalized on the initial output voltage starting at $t = 0.5$ s is shown in Fig. 8. It is noted that these changes also cause the changes of all the system states. We also assume that for $t < 0.5$ s, all the local KFs are settled according to the initial steady state of the system.

For the resulted random changes in branch current flows, we assume a variance of $\sigma_{di}^2 = 10^3 A^2$ for all three subsystems in both dc and ac cases, which also represents the variance of the plant noise. It is noticed that in this paper the variance of the model is heuristically chosen by observing the simulation results. In practice, the variance of the model can be determined, e.g., based on historical values of the load changes. Therefore,

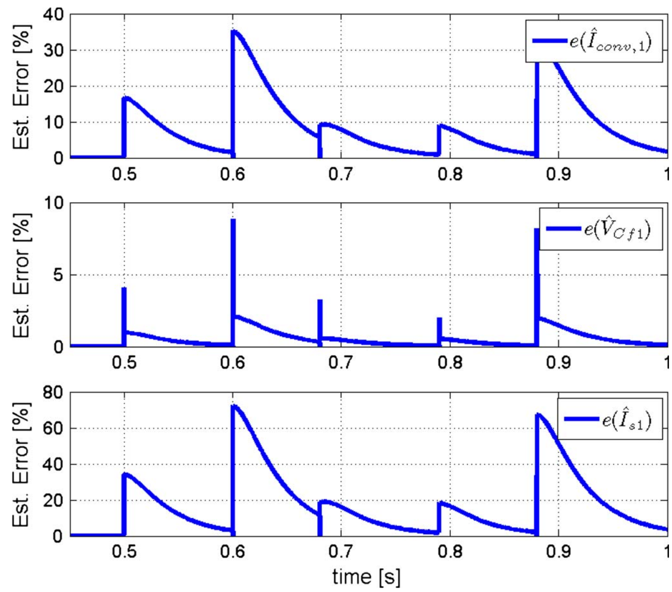


Fig. 9. State estimation error of DG1 with the filter parameters in the previous work for dc power network.

the parameters for the shaping filter and thus the dynamic model of the virtual disturbance for the three subsystems turns out to be

$$a_{di} = \frac{1}{\tau_{di}} = \frac{1}{100\ \text{ms}} = 10s^{-1};$$
$$b_{di} = \sqrt{2\sigma_{di}^2 a_{di}} = \sqrt{2}\cdot 100\ \text{A}. \qquad (26)$$

In addition, we define a percentage estimation error as

$$e(\hat{x}_i) = \frac{|x_i - \hat{x}_i|}{\bar{x}_i}\cdot 100\% \qquad (27)$$

where $\mathbf{x}_i$ is the instantaneous absolute value of the true state, $\hat{\mathbf{x}}_i$ is the instantaneous state estimate, and $\overline{\mathbf{x}}_i$ is the amplitude of the steady state.

A. DC Power Network

For comparison purpose, we first set the parameter of the virtual disturbance model to $a_{di} = 0$ and $b_{di} = 1$, as chosen in the previous work [14]. The state estimation errors of the DG1 following the sequential changes are shown as an example in Fig. 9.

According to (25), the local KF based on the augmented local model should be able to learn the negative sum of the branch currents flowing into the bus through the estimated virtual disturbance, in addition to the local state estimation. This effect is shown in Fig. 10, where the negative values of the individually estimated virtual disturbance $\hat{I}_{di}$ of all three local KFs are compared with the sum of the respective branch current.

It is obvious in Figs. 9 and 10 that the local KFs do not provide satisfied performance to track the sequential changes in the system states and the virtual disturbances that are aggregated to the branch currents. On the other hand, it can easily be observed in Fig. 10 that the changes of the current flows

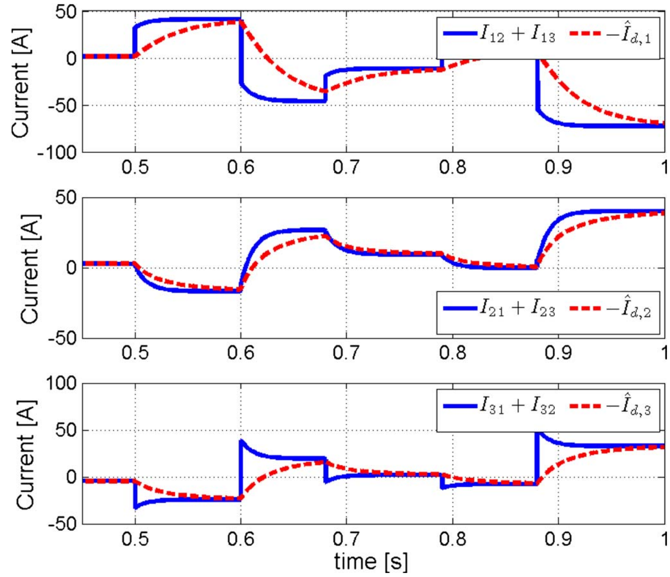


Fig. 10. Learning of the aggregated branch currents via the virtual disturbance estimation with the filter parameters in the previous work for dc power network.

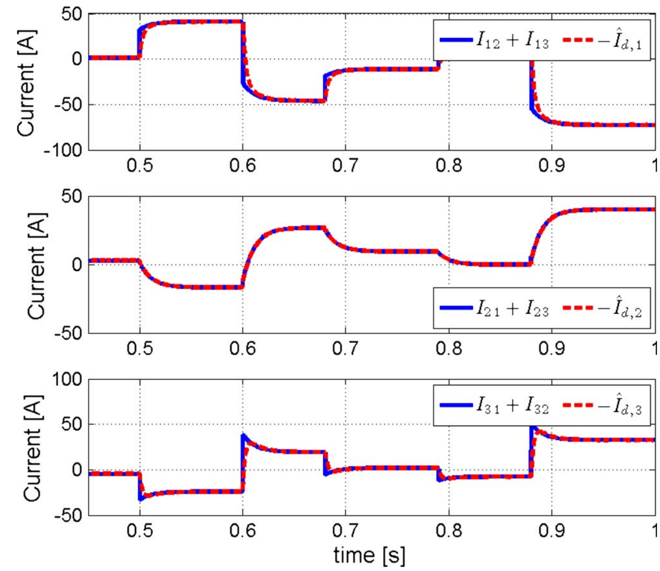


Fig. 12. Learning of the aggregated branch currents via the virtual disturbance estimation at systematic design of the virtual disturbance for dc power network.

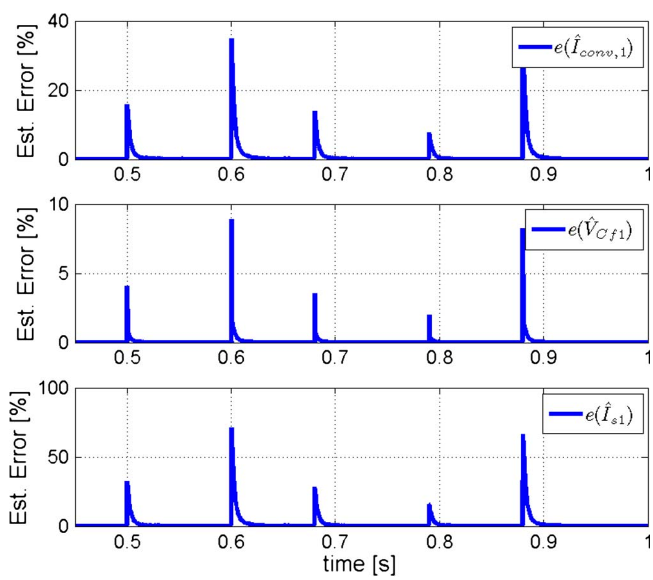


Fig. 11. State estimation error of DG1 with systematic design of the virtual disturbance for dc power network.

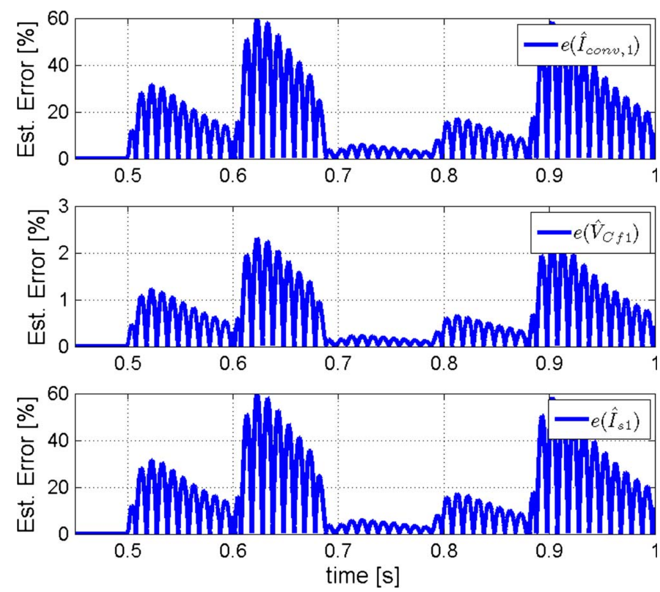


Fig. 13. State estimation error of DG1 with the filter parameters in the previous work for ac power network.

injected into buses 1 and 3 (the upper and lower subplots) are fast, whereas the changes of the current injection into bus 2 (the middle subplot) are slow. This is caused by the different dynamics of each subsystem according to the chosen system parameters, as previously shown.

Then, we apply the systematically determined filter parameters in (26) to the virtual disturbance model, and the simulation results are shown Figs. 11 and 12. It is shown that with the new designed parameters the local KFs show very good performance in tracking the states and the current flow changes.

B. AC Power Network

The same investigations as in the previous section are carried out for the ac case with the local KF defined in Section V-C. The system inputs, i.e., output voltages of the three power converters $V_{\text{conv},i}$, are chosen as sinusoids with a frequency of 50 Hz. Please note that only the parameter b_{di} is needed for the ac power network. Since the same disturbance and the same plant variance are assumed for both dc and ac cases, the same value of b_{di} in (26) is also applied to the ac case.

First, we set again the parameter $b_{di} = 1$ as in the previous work [14]. The same effect as in the dc case is observed that the local KFs cannot track the fast changes of the states and the branch current flows (Figs. 13 and 14).

It should be noted that the decaying sinusoidal oscillation in the estimation errors in Fig. 13 is caused by the estimation error of amplitude and phase during the settling time of the local KF.

Then, we use the filter parameters b_{di} in (26) for the virtual disturbance model in the ac case. The simulation results in Figs. 15 and 16 show again that with the designed parameters

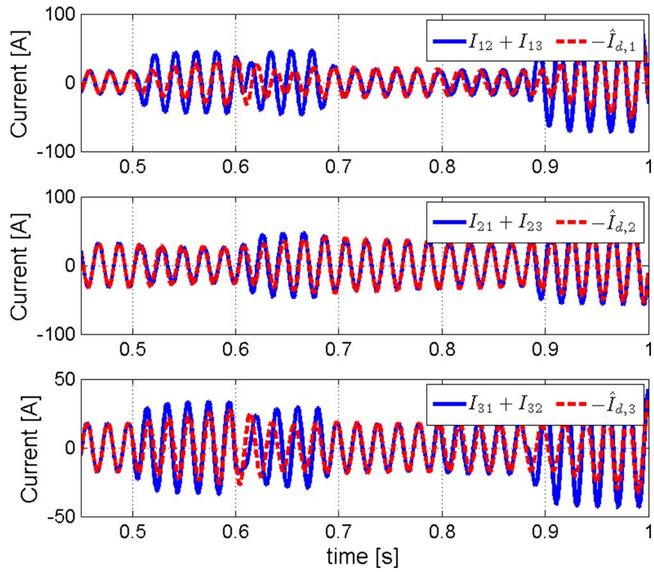


Fig. 14. Learning of the aggregated branch currents via the virtual disturbance estimation with the filter parameters in the previous work for ac power network.

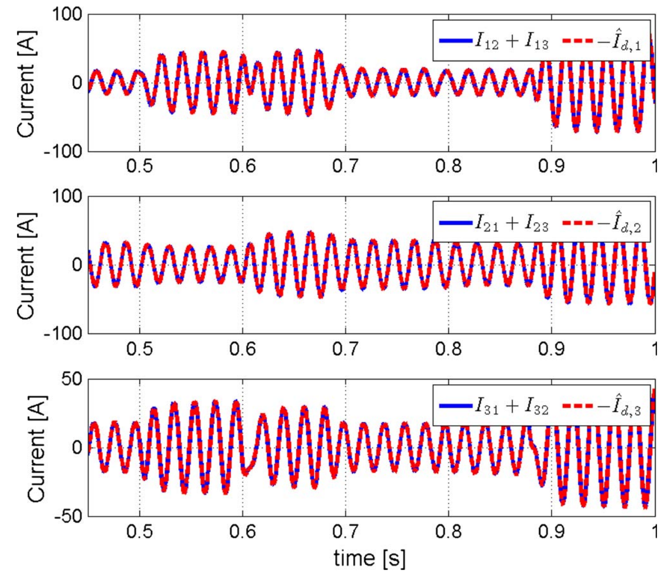


Fig. 16. Learning of the aggregated branch currents via the virtual disturbance estimation at systematic design of the virtual disturbance for ac power network.

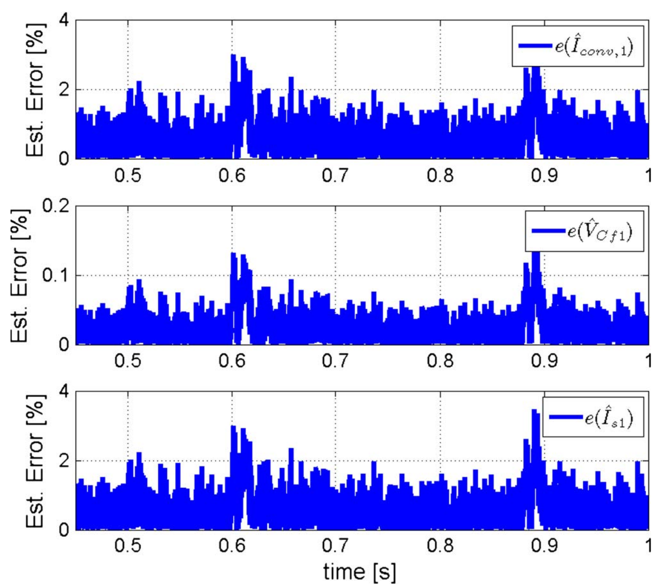


Fig. 15. State estimation error of DG1 with systematic design of the virtual disturbance for ac power network.

the local KFs provide very good performance in tracking the states and the aggregated branch current flows.

VII. Conclusion

In this paper, we have proposed independent local KFs based on local models with a virtual disturbance source. The model of the virtual disturbance is designed in a systematic way based on the principle of nonwhite noise generation using a shaping filter. The state estimation with the proposed KF is carried out in an independent way without communication. The local KFs based on the systematic designed disturbance model show very good performance in tracking the fast changes of the system states compared to the previous work. The presented estimation approach forms the basis for the decentralized grid control, as shown in [13]. As shown in the simulation results, the local KF can track the system states caused the random changes of maximal about 20% of the voltage amplitude of the DG, and the proposed method is not limited in small variations of operating conditions.

It is noted that the stationarity hypothesis of the stochastic process of the virtual disturbance model is assumed in terms of a constant variance over time in this paper. In practice, the change of the variance of the virtual disturbance model can be taken into account by updating the parameters of the shaping filter and then also its bandwidth according to current knowledge about the changes of system, such load changes. The update of the filter parameters also leads to an update of the Kalman gain.

As future work, it is interesting to include the estimation of harmonics in the power network. This would be possible by applying an appropriate model of the sinusoidal wave with given frequencies for the virtual disturbance.

References

[1] F. C. Schweppe and E. J. Handschin, "Static state estimation in electric power systems," *Proc. IEEE*, vol. 62, no. 7, pp. 972–982, Jul. 1974.

[2] A. Monticelli, "Electric power system state estimation," *Proc. IEEE*, vol. 88, no. 2, pp. 262–282, Feb. 2000.

[3] A. S. Debs and R. E. Larson, "A dynamic estimator for tracking the state of a power system," *IEEE Trans. Power App. Syst.*, vol. PAS-89, no. 7, pp. 1670–1678, Sep. 1970.

[4] K. R. Shih and S. J. Huang, "Application of a robust algorithm for dynamic state estimation of a power system," *IEEE Trans. Power Syst.*, vol. 17, no. 1, pp. 141–147, Feb. 2002.

[5] A. T. Alexandridis and G. D. Galanos, "Design of an optimal current regulator for weak AC/DC systems using Kalman filtering in the presence of unknown inputs," *Proc. Inst. Elect. Eng.—Gener., Transm. Distrib.*, vol. 136, pt. C, no. 2, pp. 57–63, Mar. 1989.

[6] H. Fujimoto, "Visual servoing of 6 DOF manipulator by multirate control with depth identification," in *Proc. 42nd IEEE Conf. Decision Control*, 2003, vol. 5, pp. 5408–5413.

[7] R. Olfati-Saber, "Distributed Kalman filtering for sensor networks," in *Proc. 46th IEEE Conf. Decision Control*, 2007, pp. 5492–5498.

[8] B. S. Rao and H. F. Durrant-Whyte, "Fully decentralised algorithm for multisensor Kalman filtering," *Proc. Inst. Elect. Eng.—Control Theory Appl.*, vol. 138, no. 5, pp. 413–420, Sep. 1991.

[9] S. Oruc, J. Sijs, and P. P. J. van den Bosch, "Optimal decentralized Kalman filter," in *Proc. 17th Mediterranean Conf. Control Autom.*, Thessaloniki, Greece, 2009, pp. 803–808.

[10] C.-S. Hsieh, "Robust two-stage Kalman filters for systems with unknown inputs," *IEEE Trans. Autom. Control*, vol. 45, no. 12, pp. 2374–2378, Dec. 2000.

[11] G. D'Antona, A. Monti, and F. Ponci, "A decentralized information filter for the state estimation in electrical power systems," in *Proc. IEEE IMTC*, 2007, pp. 1–5.

[12] A. Benigni, U. Ghisla, G. D'Antona, A. Monti, and F. Ponci, "A decentralized observer for electrical power systems," in *Proc. IEEE IMTC*, 2008, pp. 859–864.

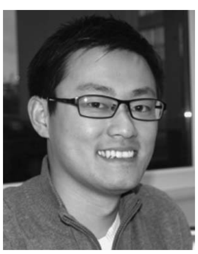
[13] J. Liu, D. Obradovic, and A. Monti, "Decentralized LQG control with online set-point adaptation for parallel power converter systems," in *Proc. IEEE Energy Convers. Congr. Expo.*, 2010, pp. 3174–3179.

[14] J. Liu, A. Benigni, D. Obradovic, S. Hirche, and A. Monti, "State estimation and learning of unknown branch current flows using decentralized Kalman filter with virtual disturbance model," in *Proc. IEEE Int. Workshop AMPS*, 2010, pp. 31–36.

[15] K. J. Astrom and R. M. Murray, *Feedback Systems—An Introduction for Scientists and Engineers*. Princeton, NJ: Princeton Univ. Press, 2008.

[16] J. B. Burl, *Linear Optimal Control—H_2 and $\mathrm{H}\infty$ Methods*. Englewood Cliffs, NJ: Prentice-Hall, 1998.

[17] M. Elbuluk and N. R. N. Idris, "The role power electronics in future energy systems and green industrialization," in *Proc. IEEE 2nd Int. PECon*, Dec. 2008, pp. 1–3.



Junqi Liu (S'10) received the Dipl.-Ing. (FH) degree from the University of Applied Sciences Munich, Munich, Germany, in 2007 and the M.Sc. degree from Technische Universität München (TUM), Munich, in 2009. He is currently working toward the Ph.D. degree with the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University, Aachen, Germany.

He is currently a Research Associate with the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University. His research interests include advanced monitoring, control, and optimization techniques for next-generation power systems.

Andrea Benigni (S'09) received the M.S. degree from Politecnico di Milano, Milan, Italy, in 2008. He is currently working toward the Ph.D. degree with the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University, Aachen, Germany.

He was a Visiting Scholar and, from August 2008 to December 2008, a Ph.D. Student with the University of South Carolina, Columbia. Since January 2009, he has been a Research Associate with the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University. His research activities mainly concern state estimation and real-time simulation.

Dragan Obradovic received the B.E. and M.E. degrees in mechanical engineering from the University of Belgrade, Belgrade, Serbia, in 1980 and 1985, respectively, and the Ph.D. degree in mechanical engineering from the Massachusetts Institute of Technology, Cambridge, in 1990.

Until the end of 1991, he was a Postdoctoral Fellow with the Laboratory for Information and Decision Systems (LIDS). Since 1992, he has been with Corporate Technology, Siemens, Munich, Germany, where he is currently a Principal Research Scientist with the Intelligent Systems and Control Department, and working on system dynamics and control problems in the electric grid and industrial automation areas. He was an Industrial Lecturer at the Munich University of Technology (TUM), Munich, Germany, between 2001 and 2009, in the international "Masters of Science in Communication Engineering" program within the EE Department. Since 2009, he has been associated with the TUM Institute for Advance Study in the capacity of a Rudolf Diesel Fellow.

Sandra Hirche (M'07) received the Diploma Engineer degree in mechanical engineering and transport systems from the Technical University Berlin, Berlin, Germany, in 2002 and the Doctor of Engineering degree in electrical engineering and computer science from Technische Universitaet München (TUM), Munich, Germany, in 2005.

From 2005 to 2007, she was a Japanese Society for the Promotion of Science (JSPS) PostDoc with the Tokyo Institute of Technology, Tokyo, Japan. Since 2008 she has been an Associate Professor heading the Associate Institute for Information-oriented Control, Department of Electrical Engineering and Information Technology, Technische Universitaet München, Munich. Her research interests include control over communication networks, networked control systems, control of large-scale systems, cooperative control, human-in-the-loop control, robotics, and haptics.

Dr. Hirche has served as Chair for Student Activities in the IEEE Control System Society (CSS) since 2009 and as Chair of the CSS Awards Subcommittee on "CDC Best Student-Paper Award" since 2010 and has been elected member of the Board of Governors of IEEE CSS since 2010.

Antonello Monti (M'94–SM'02) received the M.S. and Ph.D. degrees in electrical engineering from Politecnico di Milano, Milano, Italy, in 1989 and 1994, respectively.

From 1990 to 1994, he was with the Research Laboratory, Ansaldo Industria of Milan, where he designed the digital control of large power drives. In 1995, he was an Assistant Professor with the Department of Electrical Engineering, Politecnico di Milano. From 2000 to 2008, he was an Associate Professor and then a Full Professor with the Department of Electrical Engineering, University of South Carolina, Columbia. He is currently the Director of the Institute for Automation of Complex Power Systems, E.ON Energy Research Center, RWTH Aachen University, Aachen, Germany.