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Smart grid state estimation and stabilisation

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ABSTRACT

This paper proposes a smart grid state estimation and stabilisation algorithm. It relies on the principle of Bayesian filter structure where the smart grid state information is estimated in an iterative way. This approach assumes that the system state is a set of stochastic variables with mean and covariance values, which are shifted between the factor and variable nodes to obtain an accurate estimation. Afterwards, a semidefinite programming based optimal feedback controller is designed to stabilise the system states. Using the standard Schur complement, the system state matrix is written into the linear matrix inequality form. After solving the proposed convex optimisation problem, the designed feedback gain can stabilise the system states. Numerical results illustrate that the proposed scheme is able to estimate and stabilise the system states within a very short time.

1. Introduction

The growing use of renewable green energy on one hand and the rise of interconnectivity in the grid side on the other hand put focus on the significance of state estimation and stability issues [1]. This is due to the fact that the microgrid integrates multiple distributed renewable energy resources, which are generally intermittent in nature. Therefore, it requires to know the microgrid operating conditions for proper operations. This can only be achieved by state estimation and stabilisation approaches [2,3]. In contrast to the traditional estimation schemes, this paper proposes a message passing algorithm and optimal feedback controller for smart grid state estimations and stabilisation.

Generally speaking, the distributed renewable energy resources such as micro-turbines and solar cells are penetrated into the smart grid due to portable, reliable and low green house gas emissions [4]. As their generation pattern are generally intermittent, so these devices need to be closely monitored for proper operations and services. Basically, the weighted least squared (WLS) based power system state estimation is widely used in the literature [5]. [6]. After utilizing all measurements, the WLS algorithm aims to estimate the system states in one-run [7]. In order to estimate the system states in a recursive way, the Kalman filter (KF) is extensively used more than 45 years [8,9]. On the other hand, the nonlinear systems are tracked using the extended KF (EKF), fractional order EKF and unscented KF (UKF) algorithms [10–12].

In the information theory specifically in the context of iterative decoding of low-density parity-check codes, the belief propagation (BP) algorithm is commonly used [13,14]. Recently, the BP based power system static estimation is proposed in [15]. The state estimation is considered as a probabilistic domain where mean and covariance are propagated between variable and factor nodes [16]. The factor nodes are the logical representation of the sensors while variable nodes do not exist physically [7]. Virtually adding the variable nodes create the communication links/message propagation among them to reduce the estimation errors. From the wireless communication point of view, the BP algorithm is proposed for the unregulated power system [17,13]. In this scheme [17], the system dynamic is considered the outer code and recursive systematic channel is the inner code, which adds redundancy into the system states. At the receiver end, the log-maximum a posteriori (Log-MAP) decoding scheme with BP is used to estimate the systems states. Moreover, the message passing algorithm for unregulated smart grid incorporating turbines and vehicles is presented in [18] From the signal processing perspective, the BP based distributed message passing algorithm is presented in [19,7]. The idea is then extended in [20] where the loopy Gaussian BP is used for the distributed state estimation. From the signal processing point of view, the convergence of the BP is also analysed [21]. All of the aforementioned papers consider the unregulated power systems or developed a algorithm based on communication perspectives.

Many feedback control approaches have been proposed to regulate the system states. To begin with, the linear quadratic Gaussian controller for a linear system is proposed in [22,23]. In [24], a new strategy is recommended for designing a communication and control infrastructure in a distribution system based on the virtual microgrid concept. It is shown in [25,26] that designing a state feedback control framework for a general case of polynomial discrete-time system is quite challenging because the solution is non-convex. Thus, the convex

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method based controller design has gained growing interest in the research community. In order to guarantee and expand the stability region of microgrids, the convex optimization based semidefinite programming (SDP) controller is proposed in [27]. In [28] proposes a SDP approach for designing repetitive controllers applied to uninterruptible power supplies. Moreover, the SDP based model predictive control strategy is developed for linear dynamic systems with input saturation [29]. Furthermore, the SDP based distributed controller for consensus networks of single-integrators is presented in [30]. Driven by aforementioned motivations, this paper proposes a smart grid state estimation and stabilisation algorithm. The key contributions of this paper are highlighted as follows:

- The mathematical dynamic model of the DC microgrid is represented by a state-space framework where sensors are deployed to obtain measurements for state estimation and stabilisation purposes.
- Proposed a message passing algorithm to achieve the global inference on the Bayesian structure. In this framework, the state information is considered the mean and covariance, and they are computed from the root-to-leaf in the Bayesian tree. In this way, the messages are rectifies in each step, so it minimizes the estimation errors leads to an accurate estimation.
- In order to stabilise the system states, proposes an optimal feedback controller based on the semidefinite programming approach. Using the standard Schur complement, the system state matrix is written into the linear matrix inequality (LMI) form. After solving the proposed convex optimisation problem, the designed feedback gain can stabilise the system states.
- Simulation results demonstrate that the developed scheme can be well estimated and stabilised system states within a very short time.

This paper is organized in four sections. The microgrid model is described in Section 2. The developed state estimation and stabilisation approaches are presented in Sections 3 and 4, respectively. The numerical simulation result is demonstrated in Section 5. Section 6 draws the conclusion and presents the future work.

Notations: Generally, $\boldsymbol{N}(\mathbf{y},\boldsymbol{\mu},\boldsymbol{\Sigma})$ be the probability density function of $\mathbf{y}$ whose mean $\boldsymbol{\mu}$ and covariance $\boldsymbol{\Sigma}$. $\mathbf{I}$ denotes the identity matrix.

2. Microgrid state-space representation

Fig. 1 shows a typical modern power system where different microsources and loads are connected into the main bus bar. The modern power systems are embedded in hybrid AC and DC sources, power electronics interfaced and loads. In order to supply energy to the grid, the source converter are utilised. The different kinds of loads such as electric motors, constant power loads (CPLs) and storage battery systems are used [31,32]. Indeed, due to climate change, energy crisis and reduce the green house gas emissions, the renewable microsources are widely integrated into the smart grid.

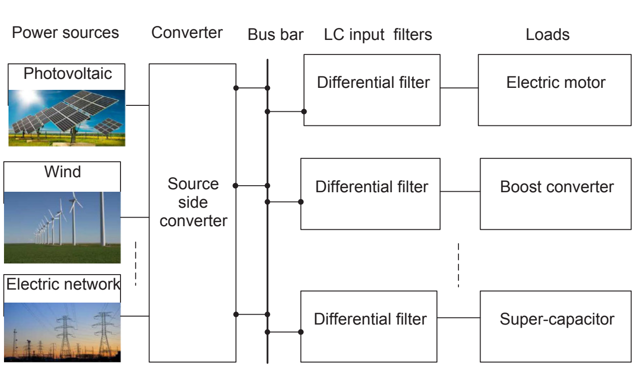

Fig. 1. Modern electric power systems and its interfaced.

Basically, the DC microgrids facilitate integrating the DC renewable resources such as fuel cells or energy storage devices such as supercapacitors by eliminating the redundant energy conversion [33]. From the practical and higher efficiency point of views, such kind of renewable resources are widely integrated into the smart grid and smart buildings. Basically, the DC microgrid with a source converter, LC filters and three loads is used for this study. Fig. 2 shows the schematic diagram of the considered DC microgrid [4,34]. It consists of DC voltage source (representing renewable power generation), series filters and loads. The source-connected converter provides a regulated DC voltage on the distribution bus, and the load converters transfer the DC bus voltage to tightly regulated power [33]. The source converter is a buck DC-DC converter. In the system model, the line filters are used to reject the current/voltage harmonics and limit the electromagnetic interferences [33]. The first load is a nonsalient permanent magnet synchronous motor supplied by the pulsewidth modulated (PWM) tightly controlled DC-AC converter. The second load is a resistive load connected to the DC link through a PWM tightly controlled DC-DC converter. The load power is absorbed from the DC link remain constant with the DC voltage variations [32].

The equivalent circuit diagram of the considered DC microgrid is illustrated in Fig. 3 [4,34]. Apply the Kirchhoff's laws, the differential equations of the microgrid can be written as follows [4,34]:

$$\Delta\dot{I}_n = (-R\Delta I_n - \Delta V_n)/L. \tag{1}$$

$$\Delta\dot{I}_1 = (-R_1\Delta I_1 + \Delta V_n - \Delta V_1)/L_1. \tag{2}$$

$$\Delta\dot{I}_2 = (-R_2\Delta I_2 + \Delta V_n - \Delta V_2)/L_2. \tag{3}$$

$$\Delta\dot{V}_n = (\Delta I - \Delta I_1 - \Delta I_2 + \Delta I_{lsc})/C_n. \tag{4}$$

$$\Delta\dot{V}_1 = (\Delta I_1 + \Delta I_{l1})/C_1. \tag{5}$$

$$\Delta\dot{V}_2 = (\Delta I_2 + \Delta I_{l2})/C_2. \tag{6}$$

Here, (L,R),(L_1,R_1) and (L_2,R_2) are the inductance and resistance of converter, filter 1 and 2, respectively. (I_n,I_1,I_2) are the current of converter, filter 1 and 2, respectively. (V_n,V_1,V_2) are the voltage of converter, filter 1 and 2, respectively. (C_n,C_1,C_2) are the capacitance of converter, filter 1 and 2, respectively. (I_{lsc},I_{l1},I_{l2}) are the load current of super-capacitor, filter 1 and 2, respectively. The system state variables are described as a deviation of the physical variables around the operating points [1] i.e., $\Delta\mathbf{x} = \mathbf{x} - \mathbf{x}_0$, where $\mathbf{x}_0$ stand for the system state $\mathbf{x}$ at the operating points.

The partial differential equations of microgrid can be written in the following discrete form:

$$\mathbf{x}(k+1) = \mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k) + \mathbf{n}(k), \tag{7}$$

where $\mathbf{x} = [\Delta I_n\ \Delta I_1\ \Delta I_2\ \Delta V_n\ \Delta V_1\ \Delta V_2]'$, $\mathbf{u} = [\Delta I_{lsc}\ \Delta I_{l1}\ \Delta I_{l2}]'$, $\mathbf{A}_d = \mathbf{I} + \mathbf{A}\Delta t$, $\mathbf{B}_d = \mathbf{B}\Delta t$ and Δt is the sampling period. The system state matrix is given by

$$\mathbf{A} = \begin{bmatrix} \frac{-R}{L} & 0 & 0 & \frac{-1}{L} & 0 & 0 \\ 0 & -\frac{R_1}{L_1} & 0 & \frac{1}{L_1} & -\frac{1}{L_1} & 0 \\ 0 & 0 & -\frac{R_2}{L_2} & \frac{1}{L_2} & 0 & -\frac{1}{L_2} \\ \frac{1}{C_n} & -\frac{1}{C_n} & -\frac{1}{C_n} & 0 & 0 & 0 \\ 0 & \frac{1}{C_1} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{C_2} & 0 & 0 & 0 \end{bmatrix}, \tag{8}$$

and the non-zero element of $\mathbf{B}$ are: $B_{4,1} = 1/C_n$, $B_{5,2} = 1/C_1$ and $B_{6,3} = 1/C_2$. $\mathbf{n}$ is the process noise which is considered as a Gaussian distribution with $\boldsymbol{\Sigma}_n$ covariance.

In order to facilitate the two-way communication between microgrids and utilities, the service provider deploys a set of sensors to monitor electricity grid [35,36]. We assume that time data are collected