Belief Propagation and H-infinity Controller for Microgrid State Estimation and Stabilization Using Internet of Things Technologies

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***Abstract*—Due to the global warming and increasing of green house gas emissions, the renewable distributed energy resources (DERs) are going to be integrated into the smart grid. As the grid can spread the intelligent energy management system to the long-distance remote areas, thus it requires a real-time dynamic state estimation and stabilization algorithm for monitoring and maintaining stability of these intermittent DERs. This paper proposes a belief propagation algorithm and H-infinity controller for system state estimation and stabilization using the internet of things (IoT) communication network. Basically, the IoT based smart sensors are deployed to gather the measurement information where the binary phase shift-keying are used for modulation. The system state and it error covariance are propagated between root and leave nodes of the considered Baysian tree network. Using forward and backward propagation of the these variables, an accurate state estimation is obtained. Using Parseval's theorem, bounded real lemma and Schur's complement, the discrete-time H-infinity controller is designed. The numerical simulation results demonstrates that the algorithms can effectively estimate and stabilize the microgrid states.**

***Keywords*—Belief propagation, distributed energy resources, dynamic state estimation, H_∞ controller, Internet of Things (IoT), microgrid.**

I. Introduction

The microgrid has been widely deployed in residential areas due to sustainable resources, and reduce energy cost [1], [2], [3]. As their generation patterns are random in nature, so they will need to be closely monitored. To do this, the internet of things (IoT) is the potential network for transmitting massive amount information to the control centre [2], [4], [5], [6], where the state estimation and stabilization can be performed to know the operating conditions of microgrids incorporating distributed energy resources (DERs). The IoT consists of sensing, actuating and communication elements [7]. The designing the IoT communication network is one the biggest challenges nowadays as they can be applied in many different applications such as smart grid, transportation systems, vehicle automation, communication, and smart health-care [8], [9], [10], [11]. From digital communication point of view, this paper proposes the IoT communication network for microgrid state estimation and stabilization.

Basically, the Kalman filter (KF) based dynamic state estimation (SE) is extensively used in the literature that provides an iterative update of the state variables [12], [13], [14]. Unfortunately, it requires high sampling measurement data, and the process and measurement noises covariances are required to be known. For improving the estimation performance, the accuracy dependent-KF scheme is proposed in [15], [16]. Moreover, the extended KF, unscented KF, and cubature KF algorithms for non-linear system stare estimation are deigned in [17], [18], [19]. However, taking the partial derivative of measurement function with respect to the state variables and required transformations are mathematically difficult.

The static state estimation using belief propagation (BP)algorithm for distribution power system is presented in [20], [21]. In fact, a factor graph based estimation process for unregulated dynamic system is explored in [22], [23]. Unfortunately, the system states are continuously changing over time and requiring to monitor them effectively. These type of algorithms are extensively applied in different applications such as smart grid, microgrid, and satellite position estimation [24], [25], [26], [27], [28]. Moreover, the system state estimation considering fading channel and IoT network are proposed in [29], [30], [31].

For maintaining stability of the islanded microgrid, the H_2 controller is designed in [32], [6], [13]. The idea is extended in [33], [34], where the controller is applied for estimation and stability of wind turbine. The semidefinite programming approach for system stabilization is presented in [35], [36]. Furthermore, the H_∞ controller with non-realtime application is proposed in [37]. For application point of view, the H_∞ controller for non-isolated converter is designed in [38]. In addition, the digitally controlled dual active bridge converter for distributed power system is presented in [39]. The nonlinear system model with capacitor is modelled first then the controller is applied for stability analysis. Moreover, the generalized discrete-time controller for a regional power system stability is presented in [40]. The discrete-time linear quadratic controller is explored [12], [41].

This paper proposes a BP algorithm and H_∞ controller for system state estimation and stabilization using the IoT network. The microgrid state and it error covariance are rectified between root and leave nodes of the Baysian tree network. Using the bounded real lemma and Schur's complement, the proposed H_∞ controller is developed. The numerical simulation results show that the algorithms can effectively estimate and stabilise the system states.

Organisation: The microgrid model is illustrated in Section II, which follows the proposed algorithms. The simulation results and conclusion are in Section IV and V.

Notations: The upper and lower bold letters are represented matrix and vector, respectively.

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II. Microgrid Model and IoT Communication Network

The block diagram of a microgrid incorporating multiple DERs is illustrated in Fig. 1 [42], [32]. There are N interconnected DERs in the microgrid where each DER is represented

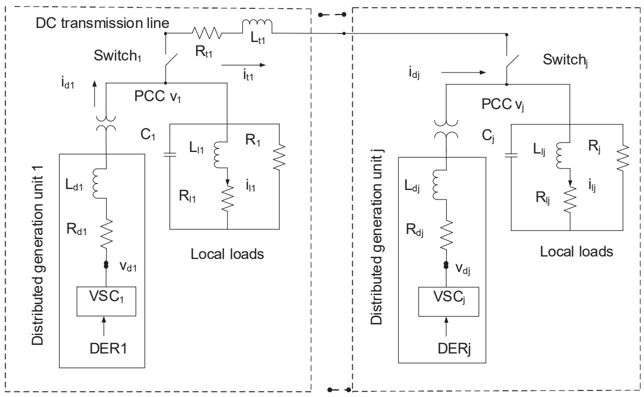

Fig. 1. Microgrid integrating multiple DERs [42], [32].

by a DC voltage source with a voltage source converter (VSC). For simplicity, this paper considers that three DERs and the system can be written in the following discrete form:

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

where $\mathbf{x} = [\Delta i_{l1}\ \Delta i_{d1}\ \Delta i_{t1}\ \Delta v_1 \Delta i_{l2}\ \Delta i_{d2}\ \Delta i_{t2}\ \Delta v_2\ \Delta i_{l3}\ \Delta i_{d3}\ \Delta v_3]'$, $\mathbf{u} = [\Delta v_{d1}\ \Delta v_{d2}\ \Delta v_{d3}]'$, $\mathbf{A}_d = \mathbf{I} + \mathbf{A}\Delta t$, $\mathbf{B}_d = \mathbf{B}\Delta t$ and Δt is the sampling period. The system state $\mathbf{A}$ and input matrices are given in [42], [32]. Here, Δi_{dj},Δi_{tj} and Δi_{lj} are the current deviation of DER_j, transmission line and load, respectively and Δv_j is the Point of Common Coupling (PCC) bus voltage deviation. The symbol $\mathbf{n}$ is the Gaussian process uncertainty with covariance $\mathbf{\Sigma_n}$ [21].

The sensors (IoT elements) are deployed to measurer system state as [2], [5]:

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{w}(k), \qquad (2)$$

where $\mathbf{y}(k)$ and $\mathbf{C}$ are the observation and it matrix, and $\mathbf{w}$ is the zero mean Gaussian process noise whose covariance is $\mathbf{\Sigma_w}$ [21]. The sensing information by the IoT based sensors is transmitted to the nearby base station that is also connected to the internet [43], [43], [6], [16], where sequence of bits $\mathbf{b}(k)$ are obtained by quantizer. To illustrate, Fig. 2 shows IoT based communication network and microgrid state estimation process [21], [44], [24], [25]. For long-distance data transmission via the internet, this paper uses binary phase shift keying (BPSK) as a modulation technique, which is generally not possible in the low rate power line communication (PLC). The received signal, $\mathbf{r}$(k), is given by:

$$\mathbf{r}(k) = \mathbf{s}(k) + \mathbf{e}(k), \qquad (3)$$

where $\mathbf{e}(k)$ and $\mathbf{s}(k)$ are the additive white Gaussian noise and modulated signal.

III. Proposed algorithms

The factor graph (FG) is a message passing scheme to achieve the optimal estimation [44], [24], [25]. In this process,

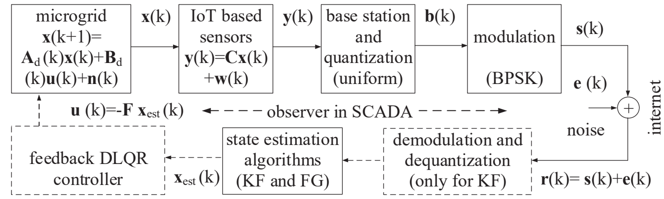

Fig. 2. Communication with state estimation process.

the π (priori information) and λ (likelihood) terms are the messages sent to the virtual node x from its parents $u_1, u_2, \ldots, u_m$ and children $y_1, y_2, \ldots, y_n$, respectively [21], [44], [24], [25]. The priori message passing from parents u_m to children x is $\pi_{u_m,x}(u_m)$ where $\pi_{u_m,x}(u_m)$ denotes the π message sent between u and x. Based on the Bayesian tree network Fig.

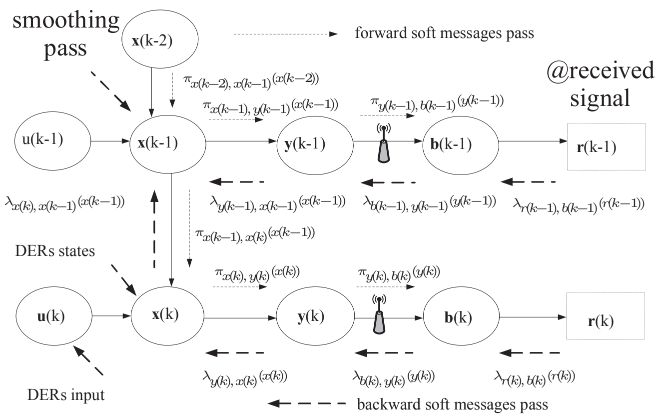

Fig. 3. Messages exchange in the factor graph [24], [25].

3, the system state is passed between forward, backward and smoothing. In each step, the state and error covariance are determined based on forward, backward and smoothing rules which are described in [44], [24], [25]. The calculated state and error covariance are rectified in this tree structure from root to leaf. When the estimated states match to the actual state then the algorithm is stop or user can define the iteration step. The detail process is described in [24], [25], where the communication system is not considered.

Using separation principle, the feedback control law is defined as [45]:

$$\mathbf{u}(k) = -\mathbf{F}\mathbf{x}(k). \qquad (4)$$

Here, $\mathbf{F}$ is the state feedback gain. The following two lemmas are used to obtain $\mathbf{F}$ in Theorem 1.

Lemma 2: If the system (1) and (2) is stable, then the following inequality holds [37]:

$$\sum_{k=0}^{\infty}[\mathbf{y}'(k)\mathbf{y}(k) - \delta\mathbf{u}'(k)\mathbf{u}(k)] > 0. \qquad (5)$$

Proof: See Appendix A.

Lemma 3: The system is stable, if there exists $\mathbf{P} > \mathbf{0}$ and $||\mathbf{C}(z\mathbf{I} - \mathbf{A}_d)^{-1}\mathbf{B}_d||_\infty \leq \beta$ such that Bounded Real Lemma holds:

$$\begin{bmatrix} -\mathbf{P} & \mathbf{PA}_d & \mathbf{PB}_d & \mathbf{0} \\ \mathbf{A}_d'\mathbf{P} & -\mathbf{P} & \mathbf{0} & \mathbf{C}' \\ \mathbf{B}_d'\mathbf{P} & \mathbf{0} & -\beta\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{C} & \mathbf{0} & -\beta\mathbf{I} \end{bmatrix} < \mathbf{0}. \tag{6}$$

Proof: In Appendix B.

Theorem 1: The system is stable with $\mathbf{F} = \mathbf{YX}^{-1}$, if there exists a slack variable $\mathbf{Y}$ and $\beta > 0$ such that the following equality holds:

$$\begin{bmatrix} -\mathbf{X} & \mathbf{A}_d\mathbf{X} - \mathbf{B}_d\mathbf{Y} & \mathbf{B}_d & \mathbf{0} \\ \mathbf{XA}_d' - \mathbf{Y}'\mathbf{B}_d' & -\mathbf{X} & \mathbf{0} & \mathbf{XC}' \\ \mathbf{B}_d' & \mathbf{0} & -\beta\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{CX} & \mathbf{0} & -\beta\mathbf{I} \end{bmatrix} < \mathbf{0}. \tag{7}$$

Proof: See Appendix C.

IV. Simulation results

The simulation parameters are shown in Table I [42]. The simulation is conducted using Matlab and YALMIP [46]. From Fig. 4, it is clearly seen that the proposed algorithm

TABLE I. System parameters [42], [32], [20], [21].

Parameters	Values	Parameters	Values	Parameters	Values
R_{lj}	76 Ohm	R_j	76 Ohm	i_{d1}	300 Amp
i_{lj}	76 Amp	R_{t1}	1 Ohm	i_{d2}	900 Amp
R_{t2}	5 Ohm	R_{t3}	10 Ohm	i_{d3}	1500 Amp
i_{t1}	0.1 Amp	i_{t2}	10 Amp	C_j	0.9 F
Quantization	16 bits	R_{d1}	1.5 Ohm	L_j	76 H
R_{d2}	6 Ohm	R_{d3}	10 Ohm	Δt	0.02 sec
$\mathbf{\Sigma_n}$	0.01*$\mathbf{I}$	$\mathbf{\Sigma_w}$	0.1*$\mathbf{I}$	Modulation	BPSK

achieves significant performance improvement compared with the existing KF technique [9]. This is due to the fact the system state and error covariance are propagated between root and leave nodes of the considered Baysian tree network. Using forward and backward propagation, they are rectified which leads to an accurate estimation. On the other hand, the existing KF has only a node where the estimation can perform. Technically, the proposed algorithm has many steps but it can be computed in a nature of distributed way in the tree structure.

From the simulation result in Fig. 5, it is revealed that the proposed controller is able to keep PCC voltage deviations driven towards zero within a short period of time. This is due to the fact that designed H_∞ controller can find the optimal gain to stabilise the system states.

V. Conclusion

This paper proposes a belief propagation algorithm and H_∞ controller. In each step of the considered tree network, the estimation error is minimized which leads to an accurate estimation results. The numerical results show that proposed controller can regulate the microgrid states. In future, we will consider the delay in the measurement and will propose the data-drive cyber-resilient state estimation algorithm [47], [48].

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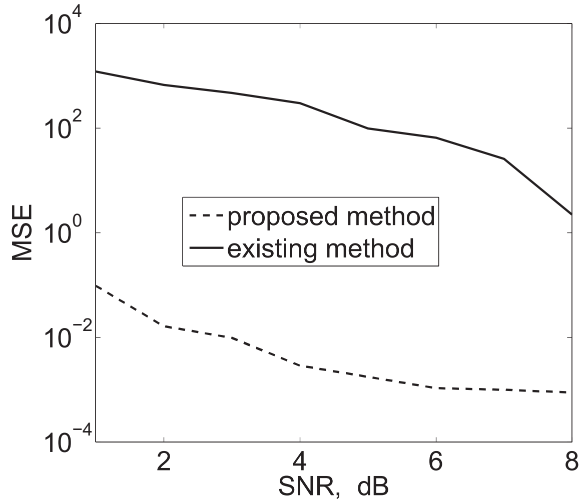

Fig. 4. Mean squared error (MSE) vs signal to noise ratio (SNR).

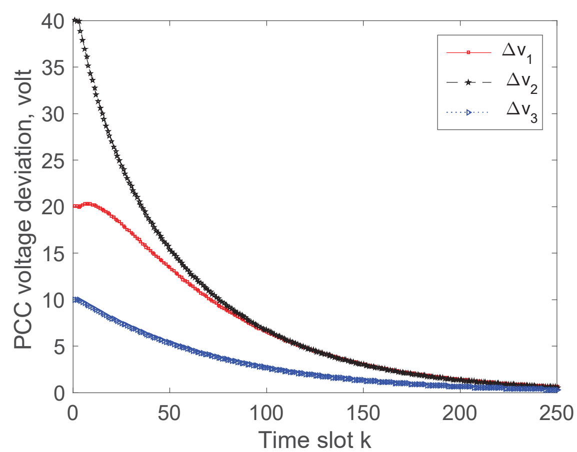

Fig. 5. Controlling the system states.

Appendix A (Proof of Lemma 2)

Generally speaking, the system is asymptotically stable regardless of inputs or disturbances. Basically, the transfer function of the considered system without noises is given by:

$$\mathbf{H}(z) = \mathbf{C}(z\mathbf{I} - \mathbf{A}_d)^{-1}\mathbf{B}_d. \tag{8}$$

Let's $\tilde{\mathbf{y}}(\mathbf{z})$ and $\tilde{\mathbf{u}}(\mathbf{z})$ represent for the Z-transform of m-dimensional output vector and r-dimensional input vector [37]. Indeed, the following input and output relationship is true:

$$\tilde{\mathbf{y}}(\mathbf{z}) = \mathbf{H}(z)\tilde{\mathbf{u}}(\mathbf{z}). \tag{9}$$

$$||\tilde{\mathbf{y}}(\mathbf{z})|| \leq ||\mathbf{H}(z)||\ ||\tilde{\mathbf{u}}(\mathbf{z})||. \tag{10}$$

Here, $||\mathbf{H}(z)||$ is the H_2 norm of the transfer function $\mathbf{H}(z)$. Mathematically, H_2 norm property states as follows:

$$\frac{1}{\sqrt{m}}\ ||\mathbf{H}(z)||_\infty \leq ||\mathbf{H}(z)|| \leq \sqrt{r}\ ||\mathbf{H}(z)||_\infty. \tag{11}$$

According to the Parseval's theorem and $||\mathbf{H}(z)||_\infty = \sqrt{\delta}$ with (10), it can be written as follows:

$$
\begin{aligned}
&\frac{1}{\sqrt{m}} \leq \frac{1}{\sqrt{\delta}}||\mathbf{H}(z)|| \leq \sqrt{r} \\
&\Rightarrow 1 < \frac{||\tilde{\mathbf{y}}(\mathbf{z})||}{\sqrt{\delta}||\tilde{\mathbf{u}}(\mathbf{z})||} = \frac{\sqrt{\sum_{k=0}^{\infty}\mathbf{y}'(k)\mathbf{y}(k)}}{\sqrt{\delta}\sqrt{\sum_{k=0}^{\infty}\mathbf{u}'(k)\mathbf{u}(k)}} \\
&\Rightarrow \sum_{k=0}^{\infty}[\mathbf{y}'(k)\mathbf{y}(k) - \delta\mathbf{u}'(k)\mathbf{u}(k)] > 0. \qquad (12)
\end{aligned}
$$

Appendix B (Proof of Lemma 3)

Since (5) is positive for sufficient large k, so we consider the following Lyapunow function $\mathbf{v}[\mathbf{x}(k)]$ [37]:

$$V[\mathbf{x}(k)] = \mathbf{x}'(k)\mathbf{P}\mathbf{x}(k) + \beta^{-1}\sum_{j=0}^{k-1}[\mathbf{y}'(j)\mathbf{y}(j) - \beta^2\mathbf{u}'(j)\mathbf{u}(j)] > 0.$$

Now, the forward difference along the solution of the system is expressed as follows:

$$
\begin{aligned}
\Delta V &= [\mathbf{x}'(k+1)\mathbf{P}\mathbf{x}(k+1) + \beta^{-1}\mathbf{y}'(k)\mathbf{y}(k) - \\
&\quad \beta\mathbf{u}'(k)\mathbf{u}(k) - \mathbf{x}'(k)\mathbf{P}\mathbf{x}(k)] < 0 \\
&= \{[\mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k)]'\mathbf{P}[\mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k)] + \beta^{-1}\mathbf{x}'(k) \\
&\quad \mathbf{C}'\mathbf{C}\mathbf{x}(k) - \beta\mathbf{u}'(k)\mathbf{u}(k) - \mathbf{x}'(k)\mathbf{P}\mathbf{x}(k)\} < 0 \\
&= \{[\mathbf{x}'(k)\ \mathbf{u}'(k)]\begin{bmatrix} -\mathbf{P} + \mathbf{A}_d'\mathbf{P}\mathbf{A}_d + \beta^{-1}\mathbf{C}'\mathbf{C} & \mathbf{A}_d'\mathbf{P}\mathbf{B}_d \\ \mathbf{B}_d\mathbf{P}\mathbf{A}_d & -\beta\mathbf{I} + \mathbf{B}_d\mathbf{P}\mathbf{B}_d \end{bmatrix} \\
&\quad [\mathbf{x}(i)\ \mathbf{u}(i)]\} < 0 \\
&= \{[\mathbf{x}'(k)\ \mathbf{u}'(k)]\begin{bmatrix} -\mathbf{P} & \mathbf{0} & \mathbf{C}' \\ \mathbf{0} & -\beta\mathbf{I} & \mathbf{0} \\ \mathbf{C} & 0 & -\beta\mathbf{I} \end{bmatrix} + \begin{bmatrix} \mathbf{A}_d'\mathbf{P} \\ \mathbf{B}_d'\mathbf{P} \\ \mathbf{0} \end{bmatrix} \\
&\quad \mathbf{P}^{-1}[\mathbf{P}\mathbf{A}_d\ \mathbf{P}\mathbf{B}_d\ \mathbf{0}][\mathbf{x}(k)\ \mathbf{u}(k)]\} < 0. \qquad (13)
\end{aligned}
$$

Using the Schur's complement leads to the Lemma 3.

Appendix C (Proof of Theorem 1)

The $\mathbf{H}_{cl}(z)$ of $\mathbf{A}_{cl} = \mathbf{A}_d - \mathbf{B}_d\mathbf{F}$ is given by [37]:

$$\mathbf{H}_{cl}(z) = \mathbf{C}(z\mathbf{I} - \mathbf{A}_{cl})^{-1}\mathbf{B}_d. \qquad (14)$$

Considering the transfer functions in (8) and (14), we can substituting $\mathbf{A}_{cl}$ into the Lemma 3 yields:

$$\begin{bmatrix} -\mathbf{P} & \mathbf{P}(\mathbf{A}_d - \mathbf{B}_d\mathbf{F}) & \mathbf{P}\mathbf{B}_d & \mathbf{0} \\ (\mathbf{A}_d - \mathbf{B}_d\mathbf{F})'\mathbf{P} & -\mathbf{P} & \mathbf{0} & \mathbf{C}' \\ \mathbf{B}_d'\mathbf{P} & \mathbf{0} & -\beta\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{C} & \mathbf{0} & -\beta\mathbf{I} \end{bmatrix} < \mathbf{0}. \qquad (15)$$

Define $\mathbf{X} = \mathbf{P}^{-1}$ and multiplying (15) by diag ($\mathbf{X}\ \ \mathbf{X}\ \ \mathbf{I}\ \ \mathbf{I}$):

$$\begin{bmatrix} -\mathbf{X} & (\mathbf{A}_d - \mathbf{B}_d\mathbf{F})\mathbf{P} & \mathbf{B}_d & \mathbf{0} \\ \mathbf{X}(\mathbf{A}_d - \mathbf{B}_d\mathbf{F})' & -\mathbf{X} & \mathbf{0} & \mathbf{X}\mathbf{C}' \\ \mathbf{B}_d' & \mathbf{0} & -\beta\mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{C}\mathbf{X} & \mathbf{0} & -\beta\mathbf{I} \end{bmatrix} < \mathbf{0}. \qquad (16)$$

By denoting $\mathbf{Y} = \mathbf{F}\mathbf{X}$, (16) leads to the Theorem 1.

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