Renewable Microgrid State Estimation using the Internet of Things Communication Network

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***Abstract*—Given the huge concerns all over the world regarding carbon emissions from fossil fuels, energy crisis and global warming, the renewable distributed energy resources (DERs) are going to be integrated in electricity grids, which will make the energy supply more reliable and decrease transmission losses. Regrettably, one of the main practical defies in smart grid planning, control and operation with DERs is the voltage regulation at the distribution field level. This problem motivates the deployment of sensors and actuators in electricity grids so that the voltage regulation can be controlled at the desired level. To do that the measurements from the renewable microgrid state information is transmitted to an energy management center via the internet of things (IoT) based communication network. In other words, the proposed IoT communication infrastructure provides an opportunity to address the voltage regulation challenge by offering the two-way communication links for microgrid state information collection and estimation. Based on this smart grid communication infrastructure, we propose a Kalman filter based state estimation method for voltage regulation of the microgrid. Finally, the effectiveness of the Kalman filter based state estimation method is illustrated using the linear state space model of a microgrid incorporating DERs.**

***Index Terms*—Communication network, distributed energy resource, internet of things, Kalman filter, microgrid, smart grid, state estimation.**

I. INTRODUCTION

All over the world, the global warming in one of the major concerns. The key reason behind is the dramatically swelling greenhouse gas emissions from burning fossil fuels and vehicles [1]. In order to diminish this problem, the renewable distributed energy resource (DER) is considered as one of the future electricity generation units [1], [2]. Based on the incentives from governments all over the world, the penetration of DERs is growing promptly. Thus, electricity consumer are participating in the eco-aware global community and the excess amount of energy is sell to the smart grid. Nevertheless, there are significant technical challenges arise in the planning, operation and control of DERs, due to the randomness and weather-dependence in the power generation patterns [3]. Therefore, an unacceptable voltage level may frequently occur at the point common coupling (PCC). This can lead to over-voltage or under-voltage problems for the power network, with undesired voltages appearing at buses of the distribution power network [4], [5]. Driven by this factors, voltage regulators should be installed at planned positions of the distributed feeders [2], [5]. Remarkably, the bidirectional smart grid communication infrastructure between the microgrid and the energy management center can be leveraged to facilitate voltage regulation issues [4]. The key concepts of such intelligent energy management systems are parallel to those of the internet of things (IoT) which can exploit reasonable security and privacy of DERs measurements, seamless interoperability and far-reaching connectivity. To accomplish the goals, the fifth generation (5G) communication network will be the future infrastructure assisting the objectives of the IoT.

A. Related Research

Based on the information and communication network, the smart grid can spread the intelligence from the central control center to the distributed control center, thus enabling accurate state estimation (SE) and wide-area real-time monitoring of the renewable energy sources [6] [7]. First of all, power system SE often practices the weighted least square method that minimizes the sum square of the weighted residuals errors; however, the gain matrix may be ill-conditioned [8]. Later, a comparison between the extended Kalman filter (EKF) and nonparametric belief propagation (NBP) has been implemented for distributed dynamic state estimation [9]. More specially, a NBP method to compute the power system state is developed, showing that the performance of the NBP is better than that of EKF algorithm. In [10], [11], a factor graph based message-passing algorithm for power system state estimation is proposed. Generally, the factor graph entails of variable and factor nodes. The factor nodes are the logical representation of the sensor measurement, whereas the variable nodes do not exists actually [10]. The information can be processed and passed between the variable and factor nodes with definite sum product rules [10], [11]. A BP algorithm has interesting structural properties corresponding to nonlinear feedback dynamical systems in the context of decoding the received signal [12]. Generally, the BP based statistical estimation techniques can provide a better performance if there

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is no cycle in the graph [13]. This method can converge to the actual system states in the tree like configuration. When cycles are present in the graph, the technique may cause fluctuation and the estimated state may diverge from the actual state [13], [14].Furthermore, the ensemble KF approach uses the probability distribution function of the system state and the data likelihood [15]. Due to the use of stochastic measurement rather than of the whole available data set, it is computationally faster and performs satisfactorily for highly stochastic systems.

B. Key Contributions

This paper proposes an approach for microgrid state estimation using the IoT networks. First of all, a renewable microgrid incorporating multiple DERs is modelled as a continuous linear state space model. This model is transformed to the discrete linear state space system considering the uncertainty. Then the smart sensors are positioned around the microgrid to obtain the measurements. Afterward, the measurements from the microgrid is transmitted to an energy management center via the IoT based 5G communication network. This IoT communication technology affords an opportunity to address the estimation challenge by offering the two-way communication links for microgrid state information collection and estimation. Based on this smart grid communication infrastructure, we propose a KF algorithm for state estimation. The effectiveness of the KF method is verified by numerical simulations using a microgrid incorporating DERs.

The remaining of this manuscript is organized as follows. The fundamental description of the IoT and its vision is described in Section II. Section III explores the IEEE 4-bus distribution system with microgrid model and IoT communication network. In addition, the proposed KF based dynamic SE scheme is described in Section IV, followed by the simulation results and discussions in Section V. This is followed by the conclusion in Section VI.

Notation: Bold face lower and upper case letters are used to represent vectors and matrices, respectively; and **I** is the identity matrix.

II. ARCHITECTURE AND VISION OF THE IOT

The IoT is a vision that encompasses and surmounts several technologies at the confluence of power systems, information technology, medicines, nanotechnology and biotechnology [16], [17]. In fact, the application scenarios of the IoT in diverse areas is illustrated in Fig. 1. The IoT has been considered as the latest revolution in the digital technology after the invention of computers and the internet [16], [18]. From the aspect of electricity network, it brings major benefits to the smart grid infrastructure design. Technically, it represents a world-wide network of heterogeneous things such as smart devices, smart objects, smart sensors, smart actuators, radio frequency identification (RFID) tags and readers, global positioning systems (GPS) and embedded computers [18]. Such things can be deployed and exploited in different physical environments to support diversified cyber physical applications such as information collection, information processing, identification, control and actuation [18], [19]. For clarify of understanding, Fig. 2 shows the information flow between the cyber and physical space using the IoT infrastructure. It can be seen that the information produced in the physical space is transmitted to the cyber space for interpretation, which in turn affects the physical environment such as plug in hybrid electric vehicle and smart grid communications [18].

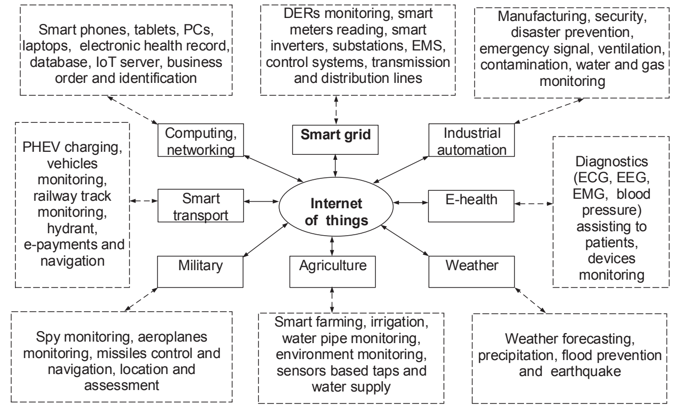

Fig. 1. The application scenarios of the IoT [16].

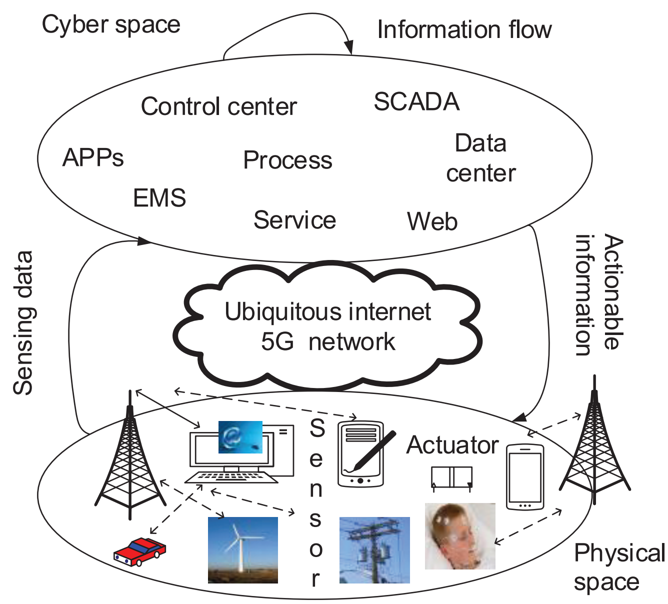

Fig. 2. Information flow between the cyber and physical space using the IoT with 5G networks [18].

Due to the economic, environmental as well as technical reasons, the energy sector has a growing awareness of smart grid technologies to enhance the efficiency and reliability of electricity networks [1], [20]. From this perspective, renewable DERs such as solar cells, photovoltaic arrays and wind turbines, have been integrated into the grid in the form of smart distribution grids. From the aspect of smart devices and smart metering, they play a vital role for remote monitoring and power systems' state estimation [21]. The reliable state estimation is a key technique to fulfil the automation of power grids. In order to monitor the DER state, the proposed IoT based communication network architecture for sensing the DER states describes in the next section.

III. DERs Model and IoT Communication Network

This section illustrates the multiple DERs model that is connected to the IEEE 4-bus distribution system, observation model, uniform quantization and IoT communication systems.

A. *DERs Connected to the IEEE 4-bus distribution system*

Fig. 3 shows IEEE 4-bus distribution test feeders that are interfaced to the local load through converter [22]. We adopt

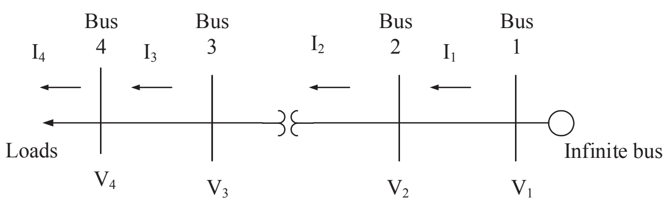

Fig. 3. An illustration of the IEEE 4-bus distribution system.

the model of interconnected DERs from [23], [22], as shown in Fig 4. It is assumed that four DERs are modelled as

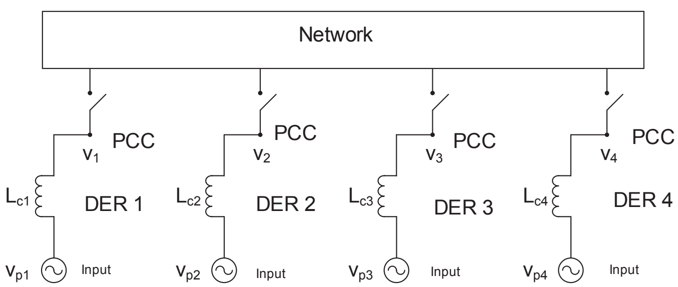

Fig. 4. Four DERs are connected to the power network [22].

voltage sources whose input voltages are denoted by $\mathbf{v}_p = (v_{p1}\ v_{p2}\ v_{p3}\ v_{p4})^T$, where v_{pi} is the i-th DER input voltage. The four DERs are connected to the main power network at the corresponding Point of Common Coupling (PCCs) whose voltages are denoted by $\mathbf{v}_s = (v_1\ v_2\ v_3\ v_4)^T$, where v_i is the i-th PCC voltage. In order to maintain the proper operation of DERs, these PCC voltages need to be kept at their reference values. A coupling inductor exists between each DER and the rest of the electricity network. Now applying the Laplace transformation in this microgrid to obtain the nodal voltage equations. The nodal voltage equation is given by:

$$\mathbf{Y}(s)\mathbf{v}_s(s) = \frac{1}{s}\mathbf{L}_c^{-1}\mathbf{v}_p(s), \tag{1}$$

where $\mathbf{L}_c = diag(L_{c_1},\ L_{c_2},\ L_{c_3},\ L_{c_4})$ and $\mathbf{Y}(s)$ is the admittance matrix of the power network. Based on the typical assumptions of the IEEE 4-bus distribution feeder [22], the admittance matrix is given in (2). Now we can transform the Laplacian form into the linear state space model. The brief conversion can be found in [22]. Normally, the dynamic of the physical state space system is given by:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{n}(t), \tag{3}$$

where $\mathbf{x}(t) = \mathbf{v}_s - \mathbf{v}_{ref}$ is the PCC state voltage deviation, $\mathbf{v}_{ref}$ is the PCC reference voltage, $\mathbf{u}(t) = \mathbf{v}_p - \mathbf{v}_{pref}$ is the DER control input deviation, $\mathbf{v}_{pref}$ is the reference control effort, $\mathbf{n}(t)$ is the zero mean process noise whose covariance matrix is $\mathbf{Q}_n$, the state matrix $\mathbf{A}$ and input matrix $\mathbf{B}$ are given by:

$$\mathbf{A} = \begin{bmatrix} 175.9 & 176.8 & 511 & 103.6 \\ -350 & 0 & 0 & 0 \\ -544.2 & -474.8 & -408.8 & -828.8 \\ -119.7 & -554.6 & -968.8 & -1077.5 \end{bmatrix}, \tag{4}$$

$$\mathbf{B} = \begin{bmatrix} 0.8 & 334.2 & 525.1 & -103.6 \\ -350 & 0 & 0 & 0 \\ -69.3 & -66.1 & -420.1 & -828.8 \\ -434.9 & -414.2 & -108.7 & -1077.5 \end{bmatrix}. \tag{5}$$

The continuous state space model (3) can be written into the following discrete state space form:

$$\mathbf{x}(k+1) = \mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k) + \mathbf{n}_d(k), \tag{6}$$

where $\mathbf{A}_d = \mathbf{I} + \mathbf{A}\Delta t$, Δt is the discretization step value, $\mathbf{B}_d = \mathbf{B}\Delta t$ and $\mathbf{n}_d(k) = \Delta t\mathbf{n}(k)$ with the variance $\mathbf{Q}_{nd}$ [24], [25]. The smart sensors can sense the microgrid states to form an observer model as follows:

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) + \mathbf{w}(k), \tag{7}$$

where $\mathbf{y}(k)$ is the measurement, $\mathbf{C}$ is the measurement matrix and $\mathbf{w}(k)$ is the measurement noise whose variance is $\mathbf{Q}_{wd}$. The observation noise comes from the distributed wireless sensors measurements. The observation information by the wireless sensor networks (WSN) powered by 5G technologies is transmitted to the nearby base station (BS) as shown in Fig. 5. The uniform quantizer of this base station maps each measurement signals to a sequence of bits.

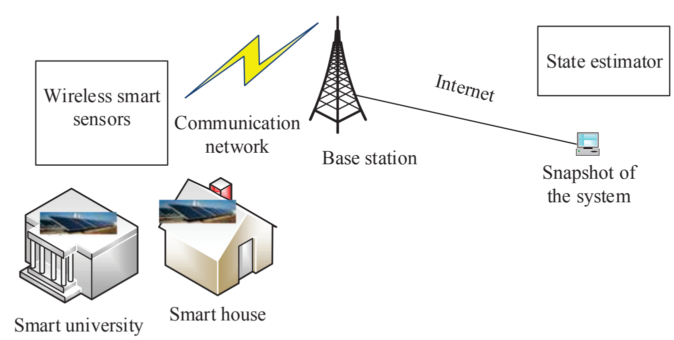

Fig. 5. Interfacing microgrid measurements to the base station.

B. *IoT Communication Network*

For transmitting the microgrid state information to the energy management system, we used binary phase shift keying (BPSK) as a modulation technique. The bit sequence $\mathbf{b}(k)$ is goes through a BPSK and get modulated signal $\mathbf{s}(k)$. The $\mathbf{s}(k)$ goes through the internet and add noise. To demonstration, Fig. 6 shows the IoT communication network and dynamic state estimation process. The received signal at the energy

$$\mathbf{Y}(s) = (\mathbf{L}_c s)^{-1} + \begin{bmatrix} \frac{1}{0.1750+0.0005s} & \frac{-1}{0.1750+0.0005s} & 0 & 0 \\ \frac{-1}{0.1750+0.0005s} & \frac{1}{0.1750+0.0005s} + \frac{1}{0.1667+0.0004s} & \frac{-1}{0.1667+0.0004s} & 0 \\ 0 & \frac{-1}{0.1667+0.0004s} & \frac{1}{0.1667+0.0004s} + \frac{1}{0.2187+0.0006s} & \frac{-1}{0.2187+0.0006s} \\ 0 & 0 & \frac{-1}{0.2187+0.0006s} & \frac{1}{0.2187+0.0006s} + \frac{1}{12.3413+0.0148s} \end{bmatrix}. \tag{2}$$

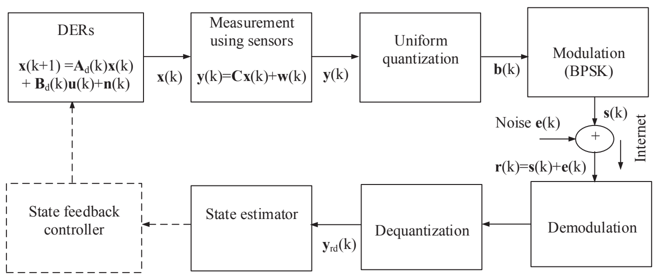

Fig. 6. The IoT communication network and microgrid dynamic state estimation process.

management system is given by

$$\mathbf{r}(k) = \mathbf{s}(k) + \mathbf{e}(k), \tag{8}$$

where $\mathbf{e}(k)$ is additive white Gaussian noise AWGN noise. Then the received sequence is followed by dequantization and finally KF algorithm is used for this microgrid.

IV. Kalman filter based microgrid state estimation method

This section tries to answer the following question: (i) What is the optimal smart grid SE method for the microgrid incorporating multiple DERs?

The discrete time KF is a set of recursive mathematical equations that provides an efficient recursive means to estimate the state of a process in a way that minimizes the mean squared error between the measurement and prediction. The KF operates recursively on streams of the noisy measurers to produce a statistically optimal estimate of the underlying microgrid system states. This method works in two-steps (prediction and correction step). The energy management system computes the following steps [26]:

$$\hat{\mathbf{x}}^-(k) = \mathbf{A}_d\hat{\mathbf{x}}(k-1) + \mathbf{B}_d\hat{\mathbf{u}}(k-1), \tag{9}$$

where $\hat{\mathbf{x}}^-(k)$ is the microgrid estimate states of the earlier step. The predicted estimate covariance matrix is given by:

$$\mathbf{P}^-(k) = \mathbf{A}_d\mathbf{P}^-(k-1)\mathbf{A}_d^T + \mathbf{Q}_{nd}, \tag{10}$$

where $\mathbf{P}^-(t)$ is the microgrid estimate covariance matrix of the earlier step. The microgrid estimated update state (correction step) is given by

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^-(k) + \mathbf{K}(k)[\mathbf{y}_{rd}(k) - \mathbf{C}\hat{\mathbf{x}}^-(k)], \tag{11}$$

where $\mathbf{y}_{rd}(k)$ is the dequantized and demodulated output bit sequences and the Kalman gain $\mathbf{K}(t)$ is given by:

$$\mathbf{K}(k) = \mathbf{P}^-(k)\mathbf{C}^T(\mathbf{C}\mathbf{P}^-(k)\mathbf{C}^T + \mathbf{Q}_{wd})^{-1}, \tag{12}$$

and

$$\mathbf{P}(k) = \mathbf{P}^-(k) - \mathbf{K}(k)\mathbf{C}\mathbf{P}^-(k). \tag{13}$$

Based on the KF steps, the energy management system can obtain the predicted distribution of the measurement which is a Gaussian distributed with the expectation given by Eq. (9) and the covariance matrix given by Eq. (10). Considering the aforementioned expressions taking into account, the flow chart for the KF state estimation algorithm is sketched in Fig. 7.

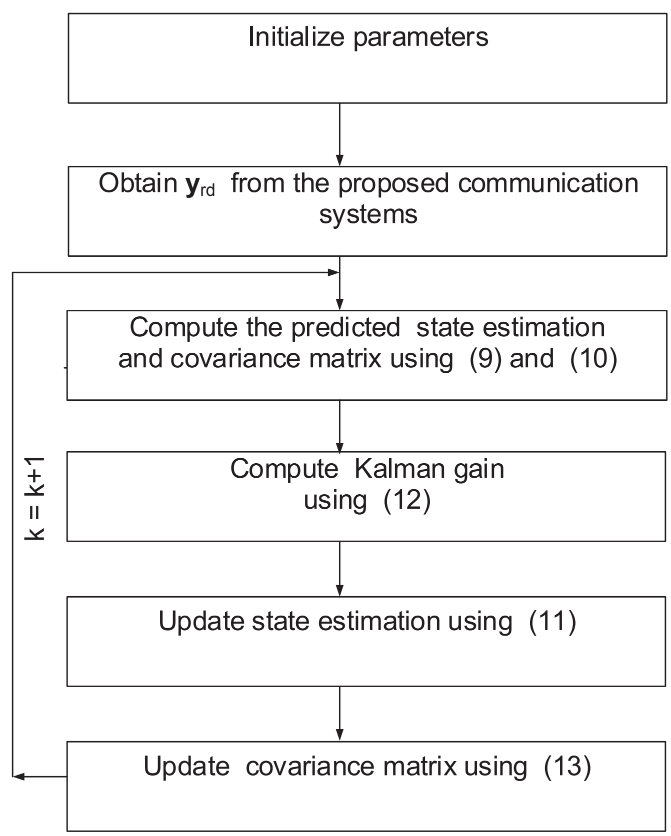

Fig. 7. The flow chart for the Kalman filter based microgrid state estimation.

V. Performance Evaluations and Discussions

We consider four DERs in which the system state is a four-dimensional vector. Each DER is connected to the IEEE 4-bus distributed systems operated as an island mode [27]. The continuous state space system has been approximated to the discrete time state space system with a small step size parameter. The simulation parameters of the IoT networks are summarized in Table I. The simulation of this proposed KF

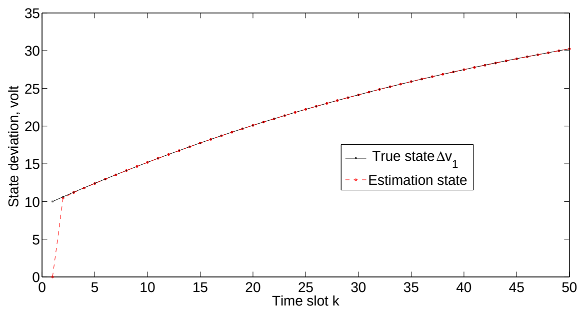

Fig. 8. Δv_1 comparison between the true and estimated state using 4 sensors.

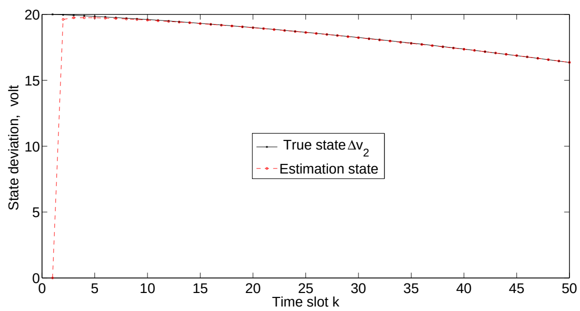

Fig. 9. Δv_2 comparison between the true and estimated state using 4 sensors.

based microgrid SE for the IoT communication network is carried out for two different sensing scenarios.

TABLE I
THE SYSTEM PARAMETERS AND ASSUMPTIONS USING MATLAB.

Parameters	Values	Parameters	Values
Step size Δt	0.00001	Quantization	Uniform
Modulation	BPSK	Channel	AWGN
Time slots	50	Quantization	Uniform 16 bits

A. *Number of sensors equal to states*

First of all, it assumes that the four voltage sensors can sense the four PCC voltage states directly. From the simulation results as shown in Figs. 8 to 11, it can be seen that the proposed KF is able to estimate the PCC state voltages properly and it needs few iterations to track the original states. However, in practical scenario there are the possibility that the smart sensors battery gets low so that they cannot sense the system state properly.

B. *Number of sensors less than states*

When the smart sensors battery gets low and it cannot sense the system state properly. In this case, one assumes that the two voltage sensors are out of order among four sensors to sense the four PCC voltage states. From the simulation results as shown in Figs. 12 to 15, it can be seen that the proposed KF is able to estimate system states properly and it needs more iterations to track the original states. Due the two sensors sensing problems, the PCC state voltages v_2 and v_3 are not

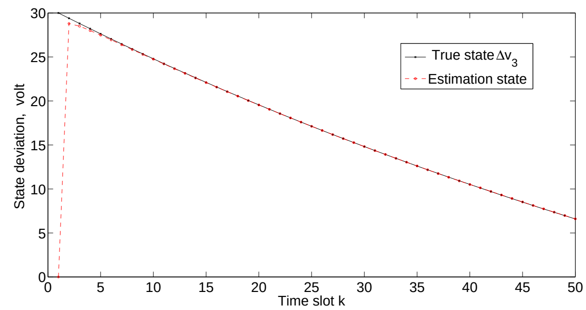

Fig. 10. Δv_3 comparison between the true and estimated state using 4 sensors.

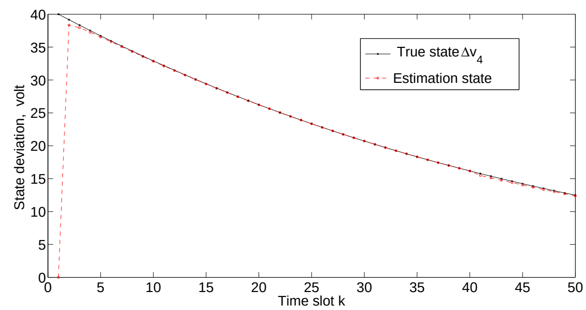

Fig. 11. Δv_4 comparison between the true and estimated state using 4 sensors.

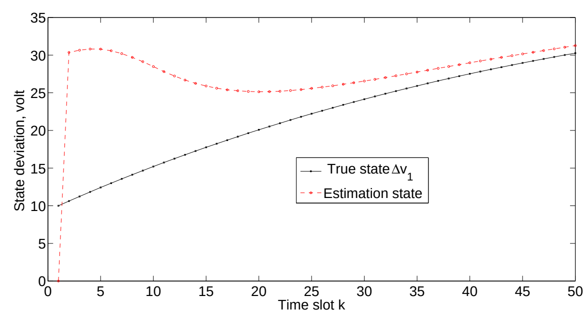

Fig. 12. Δv_1 comparison between the true and estimated state using 2 sensors.

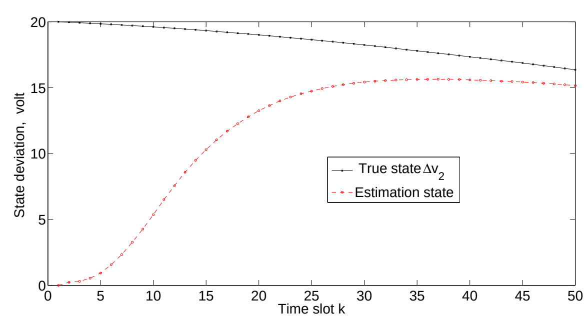

Fig. 13. Δv_2 comparison between the true and estimated state using 2 sensors.

able to be sensed directly by the corresponding sensors. But the KF is able to track these states with small considerable errors. However, there are the possibility that the number of

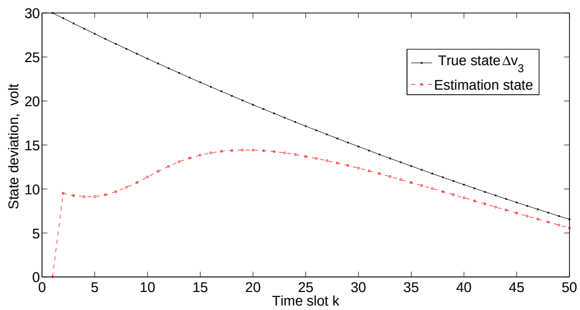

Fig. 14. Δv_3 comparison between the true and estimated state using 2 sensors.

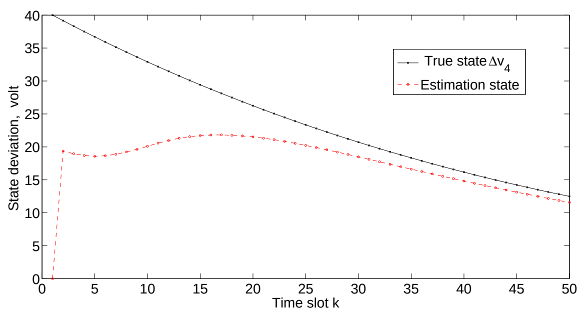

Fig. 15. Δv_4 comparison between the true and estimated state using 2 sensors.

smart sensors is greater than the system states.

C. Number of sensors greater than states

Finally, we assume that the number of sensors is greater than the system states. This simulation it is assumed that the observation matrix has eight sensors. From the simulation results as shown in Fig. 16 to 19, it can be seen that the proposed KF is able to estimate system states properly and it needs few iterations to track the original states. Due the more sensors, the PCC voltage are not able to sense by the the sensors correctly. But using the proposed KF is able to track these states with very small errors. Therefore, it is better to use same number of sensors and states to properly estimate system states in the IoT communication network.

VI. Conclusions

This paper addresses the voltage regulation issue from the communication perspective. To do so, wireless sensor network components such as sensors and actuators have been applied into the microgrid to coordinate DER states regulation. In order to transmit the sensing information to the observer, the proposed innovative communication systems have been utilized. Based on this infrastructure, this paper proposes a KF algorithm for centralized DER state estimation. Finally, the effectiveness of the developed approaches is verified by numerical simulations. In the future, we will use least square based Kalman filter in order to obtain the better initial state value.

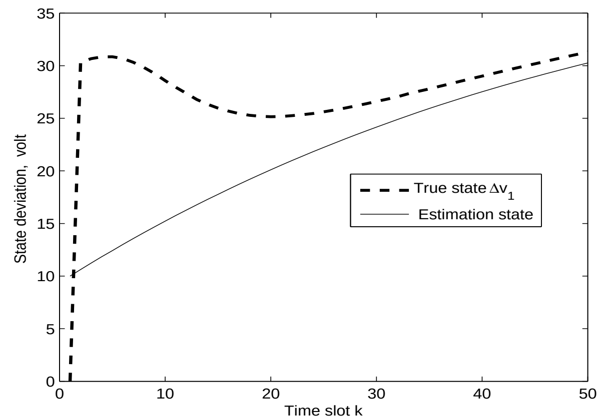

Fig. 16. Δv_1 comparison between the true and estimated state using 8 sensors.

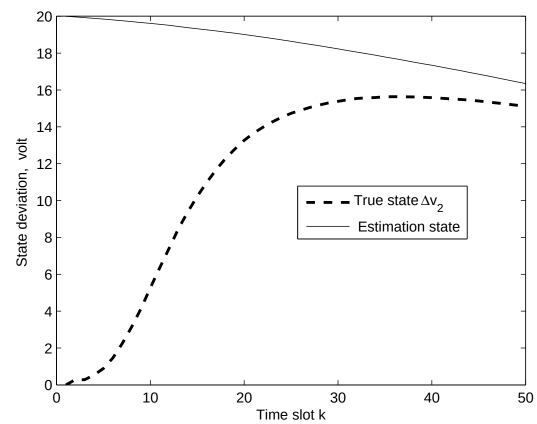

Fig. 17. Δv_2 comparison between the true and estimated state using 2 sensors.

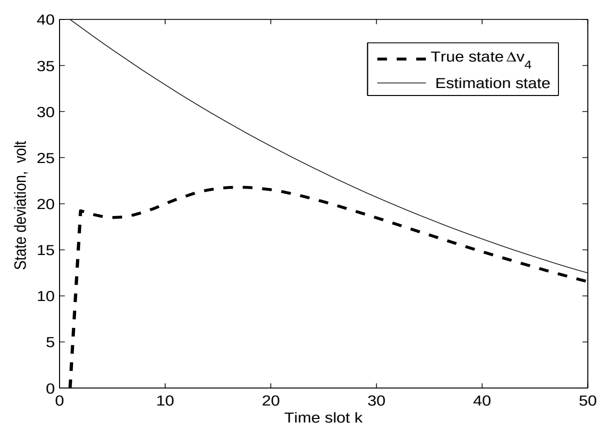

Fig. 18. Δv_3 comparison between the true and estimated state using 8 sensors.

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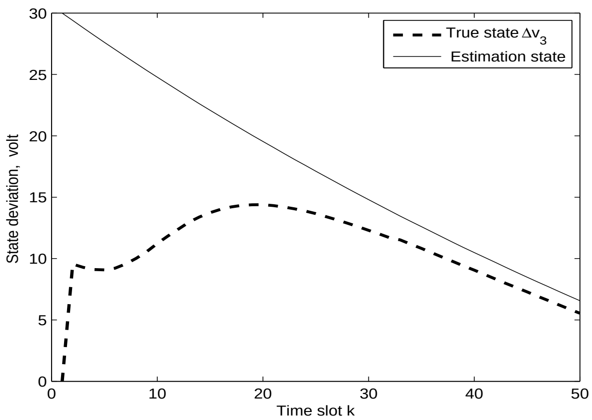

Fig. 19. Δv_4 comparison between the true and estimated state using 8 sensors.

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