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Microgrid State Estimation and Control Using Kalman Filter and Semidefinite Programming Technique

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Abstract – The design of environment-friendly microgrids at the smart distribution level requires a stable behaviour for multiple state operations. This paper develops a Kalman filter based optimal feedback control method for the microgrid state estimation and stabilization. First, the microgrid is modelled by a discrete-time state space equation. Then the cost-effective smart sensors are deployed in order to obtain the required system information. From the communication point of view, the recursive systematic convolution code is adopted to add the redundancy in the system. At the end, the soft output Viterbi decoder is used to recover the system information from the noisy measurements and transmission uncertainties. Thereafter, the Kalman filter is utilized to estimate the system states, which acts as a precursor for applying the control algorithm. Finally, this paper proposes an optimal feedback control method to stabilize the microgrid based on semidefinite programming. The performance of the proposed approach is demonstrated by extensive numerical simulations.

Keywords – Kalman filter, optimal feedback control, renewable microgrid, semidefinite programming, smart grid.

1. INTRODUCTION

Due to dramatically increasing energy demand, rising inadequacy of traditional fossil fuels and collective awareness of environments there needs a rethinking of today's electric power system [1], [2]. From this point of view, the sustainable electric power generation unit such as renewable microgrid is one of the potential resources in smart grids. Indeed, the microgrid is a small-scale energy generation unit that consists of distributed energy generation resources (DERs), local loads and power electronic interfaces. It can operate in either grid connected mode or islanded mode. To obtain an accurate snapshot of the overall power networks including microgrid, it will need to estimate the system states which is essential to know the operating conditions of the power networks. In order to maintain the stability and reliability of the power network, a suitable control technique also needs to be applied.

Interestingly, the goals and ideas of such intelligent energy management systems are parallel to those of the internet of things (IoT) network. Actually, the visions of smart grids and the IoT have recently been combined into the internet of energy (IoE) [3], [4]. To achieve the IoE objective, the wireless sensor network and internet protocol version six (IPV6) will allow appliances to be remotely coordinated in order to seamlessly monitor and control the microgrid states [4].

A number of studies in the literature have been focused on power system state estimation. To begin with, a least mean squares (LMS) based power system dynamic state estimation is implemented in [5], [6]. However, it is very difficult to tune the step size parameter of this LMS algorithm. The normalized LMS (NLMS) algorithm is explored for state estimations [5], [7]. This NLMS algorithm normalizes the input signal so that the step size parameter guarantees stability of the algorithm. Then a variable step size based LMS algorithm for system state estimation is proposed in [8], [9]. This method provides an optimum convergence rate but there is a trade-off between rate and performance. An artificial intelligence based dynamic state estimation is presented in [10]. This technique does not require a mathematical model. However, in stability analysis of large-scale power systems, it is often preferable to have an exact model. From this perspective, the physical model based Kalman filter (KF) algorithm is widely used for dynamic state estimations [11], [12], [13]. After estimating the system state, a control algorithm is required to stabilize the power network.

Many methods have been developed to control the power network properly. First of all, a classic linear quadratic Gaussian (LQG) controller for the power system is proposed in [12], [14], [15]. This controller is comprised of an LQ regulator and a KF that minimizes the error between the output signals and their estimations. Then the cooperative control problem of AC microgrids is proposed in [16]. This method uses a feed forward approach which only requires local state measurements and reference signals from neighbors. Furthermore, an output voltage differential feedback and output current differential feed forward control strategy is presented in [17]. This technique eliminates the output voltage steady-state errors so that it can improve dynamic system response under different load disturbances. Following that an adaptive sliding mode based robust control scheme for a multi-bus islanded microgrid is recommended in [18]. This method is performed based on local measurements and is designed independently from topology, parameters, and dynamics of the microgrid loads. Unfortunately, most of these methods require knowledge of the entire measurement history and assume perfect communication. In fact, the smart grid utilizes efficient estimation, communications, control, and sensor technologies to enhance the

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operation of the traditional electricity network [19]. The incorporation of advanced sensing devices and communication technologies in the smart grid has motivated the development and design of various estimations and controllers.

Driven by this motivation, this paper develops a KF based dynamic state estimation and optimal feedback control method for controlling the microgrid. Firstly, the environment-friendly renewable microgrid is modelled as a discrete-time state space model. Then the cost-effective smart sensors are deployed to obtain the system state information. The recursive systematic convolution code (RSC) is adopted to add redundancy in the system. After that, the observation from the multiple DERs information is transmitted to a control center. Secondly, in the energy management system, the soft output Viterbi algorithm is used to recover the state information from the noisy observations and transmission errors. Following that a KF is utilized to estimate the system states, which acts as a precursor to apply the control algorithm. Lastly, a semi definite programming based optimal feedback control method is proposed to stabilize the microgrid. The effectiveness of the proposed scheme is demonstrated through numerical simulations. Overall, this approach has its own significance for designing a green control center.

The rest of this paper is organized as follows. The architecture for sensing the DER states is proposed in Section 2, followed by the proposed dynamic state estimation and feedback control scheme in Section 3. The simulation results and discussions are given in Section 4. Finally, the technical note is wrapped up with conclusions in Section 5.

Notation: Bold face lower and upper case letters are used to represent vectors and matrices, respectively; superscripts $\mathbf{x}^T$ denotes transpose of $\mathbf{x}$, and $\mathbf{I}$ is the identity matrix

2. SYSTEM MODEL AND PROPOSED COMMUNICATION SYSTEMS

A microgrid incorporating DERs is a small-scale power generation unit that is used to deliver an alternative to or an enhancement of the traditional electricity network. So, a typical microgrid can be described as a cluster of DERs and local loads. These potential micro-sources improve the efficiency of energy supply and reduce the electricity delivery cost and carbon footprint [20], [21]. Generally, the microgrid is capable of operating in either islanded mode or grid-connected mode. A microgrid has a switch installed at the point of common coupling (PCC) at the utility side [22]. Under abnormal conditions, this switch can be opened in a very short time. In this case, DERs can still supply power for the load points in the islanded portion of the distribution network. In the case of grid connected mode, the microgrid is connected to the main grid at the PCC to deliver power to the grid or to receive the power from the grid [23]. Therefore, seamless transition is one of the technical challenges in the microgrid control. To illustrate, Figure 1 displays a typical distributed system incorporating microgrid with DERs [20].

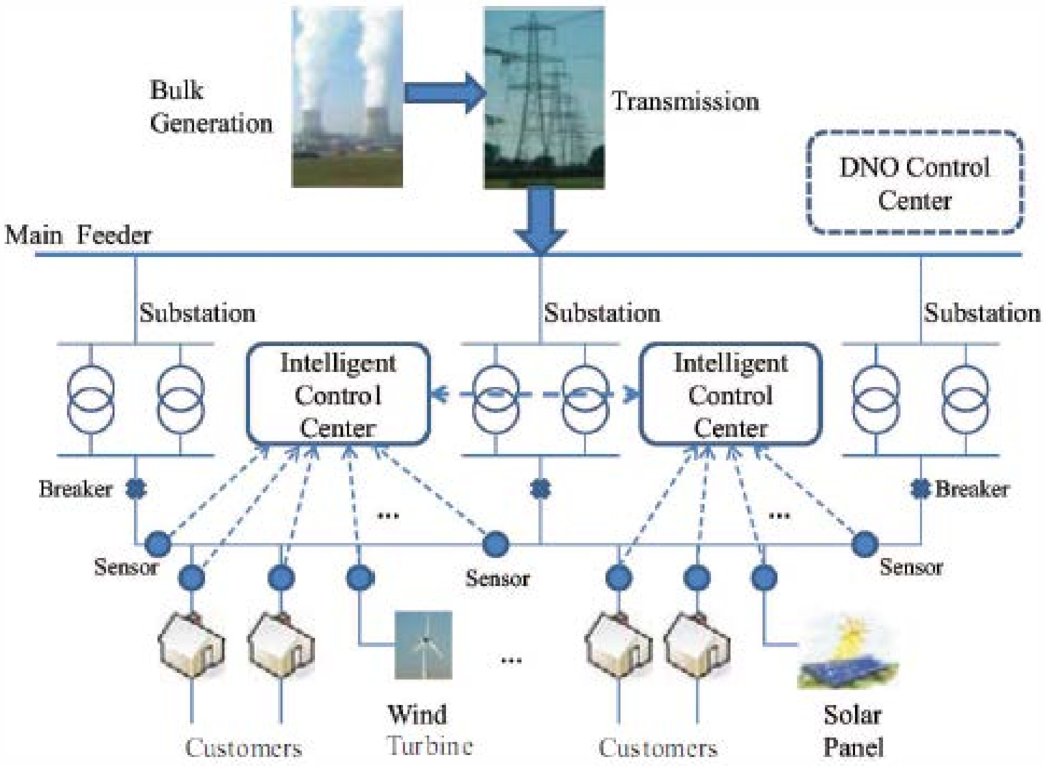

Fig. 1. An illustration of the distributed system incorporating microgrid with DERs [20].

The smart sensors and actuators are deployed for monitoring, automatic control and two-way communication functionalities. In other words, the multiple smart sensors detect the voltage fluctuation at the PCCs, and they will transmit the information to the nearby intelligent control center. Based on the received signal, the control center estimate the system state deviation from a pre-defined reference value. The estimated states are then used by voltage regulators to control the state deviations. If necessary, the control center can immediately turning on/off the related DERs to stabilize the power supply [22], [20]. The above iterative process continues until the state deviations are within a desired range [22]. For demonstration, Figure 2 shows the impact of DERs on the voltage regulation in smart grids [20]. It can be seen that without reasonable coordination, the voltage is not stable after introducing the DERs in the grid [20].

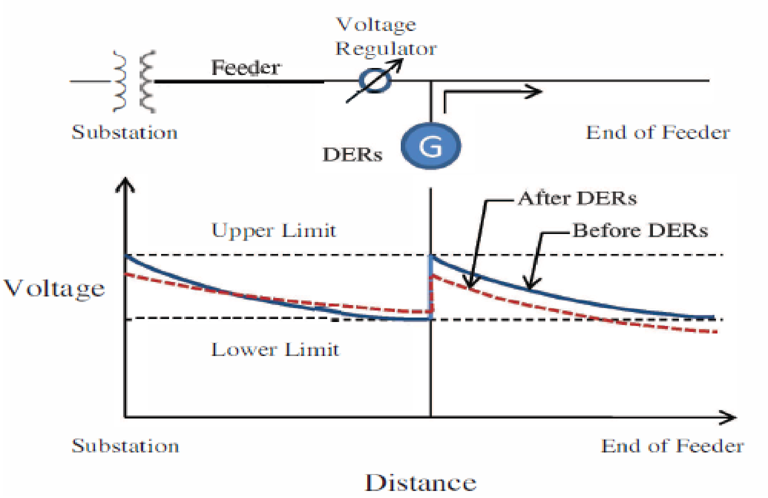

Fig. 2. Impact of DERs on the voltage regulation in smart grids [20]

2.1 Microgrid Model

The microgrid is a small-scale power network which can supply green energy to consumers. To mitigate the global warming at an acceptable level by reducing green house gas emissions and diversification of energy sources, the renewable microgrid is one of the prosing research topics in academia, environmentalist and utility operators [24]. The considered green micro-sources in this study are connected to the main grid through the IEEE-4 bus test feeder as shown in Figure 3 [25], [26].

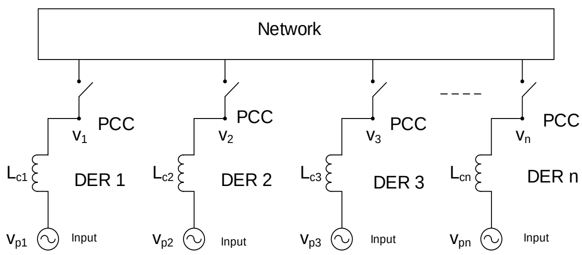

Fig. 3. Four micro-sources are connected to the IEEE 4-bus network.

Here the input voltages are denoted by the $\mathbf{v}_p = (v_{p1} v_{p2} v_{p3} v_{p4})^T$, where v_{pi} is the i-th DER input voltage. The four micro-sources are connected to the power network at the corresponding 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. Now by applying Laplace transformation, the nodal voltage equation can be obtained:

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

where $\mathbf{L}_c = \mathrm{diag}(L_{c1}, L_{c2}, L_{c3}, L_{c4})$ and $\mathbf{Y}(s)$ is admittance matrix [26]. Now we can convert the transfer function form into the linear state-space model [26]. The discrete-time linear dynamic system can be derived as follows:

$$\mathbf{x}(k+1) = \mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d\mathbf{u}(k) + \mathbf{n}_d(k), \qquad (2)$$

where $\mathbf{x}(k) = \mathbf{v}_s - \mathbf{v}_{ref}$ is the PCC state voltage deviation, $\mathbf{v}_{ref}$ is the PCC reference voltage, $\mathbf{u}(k) = \mathbf{v}_p - \mathbf{v}_{pref}$ is the DER control input deviation, $\mathbf{v}_{pref}$ is the reference control effort, $\mathbf{n}_d(k)$ is the zero mean process noise whose covariance matrix is $\mathbf{Q}_n$, the state matrix $\mathbf{A}_d = \mathbf{I} + \Delta_t\mathbf{A}$ and input matrix $\mathbf{B}_d = \Delta_t\mathbf{B}$ with

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

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

and Δ_t is the discretization parameter.

2.2 Observation and Proposed Communication Systems

The measurements of the microgrid states are obtained by a set of sensors and can be modelled as follows:

$$\mathbf{y}(k)=\mathbf{C}\mathbf{x}(k)+\mathbf{w}(k), \tag{3}$$

where $\mathbf{y}(k)$ is the measurements, $\mathbf{C}$ is the measurement matrix and $\mathbf{w}(k)$ is the zero mean sensor measurement noise whose covariance matrix is $\mathbf{R}_w$.

To secure the system states, in the signal processing research community, the channel code is used. Motivated by the convolutional coding concept [27], [28], the microgrid state-space and observation models are regarded as the outer code. Then the standard uniform quantizer performs quantization to get the sequence of bits $\mathbf{b}(k)$. $\mathbf{b}(k)$ is encoded by RSC channel code which is regarded as the inner code. In this work, an RSC encoder with two memories and the generator matrix [1, 5/7] is employed [27]. Therefore, RSC improves the system performance significantly due to the redundancy and preserving the microgrid state information. $\mathbf{b}(k)$ is then passed through the binary phase shift keying (BPSK), and $\mathbf{s}(k)$ is obtained. $\mathbf{s}(k)$ is passed through the channel with additive white Gaussian noisy (AWGN) noise. To illustrate, Figure 4 shows the proposed system model in the context of smart grids.

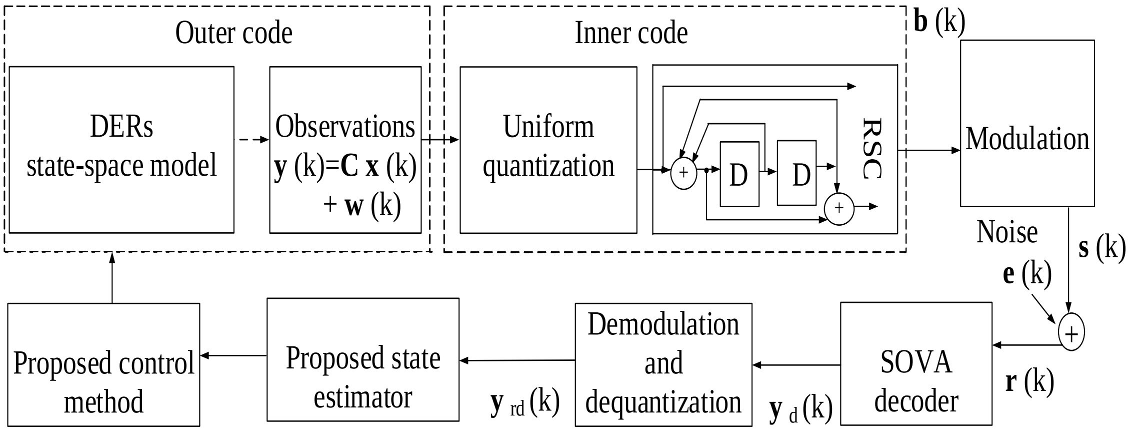

Fig. 4. An illustration of the proposed system model.

At the end, the received signal is:

$$\mathbf{r}(k)=\mathbf{s}(k)+\mathbf{e}(k), \tag{4}$$

where $\mathbf{e}(k)$ is the AWGN noise. The received signal $\mathbf{r}(k)$ is followed by the soft output Viterbi algorithm (SOVA) decoding for this dynamic system.

2.3 SOVA Decoding

The SOVA algorithm computes a maximum likelihood estimate on the code sequence from received signal. This algorithm traverses the entire trellis and traces back along the maximum likelihood path with noting all path metrics [27], [29]. The SOVA algorithm proceeds as follows:

Step 1. Initialize: k = 0, $V(M_{0,0})=0$ all other case $V(M_{\mathrm{s,k}})=\infty$. Here, $M_{\mathrm{s,k}}$ is the state in the trellis that corresponds to state M_s at time k and every state is assigned a value denoted $V(M_{\mathrm{s,k}})$. Moreover, y_d is the decoded bit sequence, n is the number of parallel output encoded bits at one time interval and L_r is the received signal length and D is the memory.

Step 2. Set k = k + 1 then compute the path metrics for all paths going to state M_s at time k. Firstly, compute the branch matric by $B[\mathrm{r}(k)|\mathrm{y}_d(\mathrm{k})]=\sum_{j=1}^{n}B[\mathrm{r}^j(k)|\mathrm{y}_d^j(\mathrm{k})]$. This is calculated from the squared Euclidean distance $\sum_{j=1}^{n}[\mathrm{r}^j(k)-\mathrm{y}^j(k)]^2$. Then compute path matric by $B^p[\mathrm{r}|\mathrm{y}_d]=\sum_{i=0}^{k}B[\mathrm{r}^i(k)|\mathrm{y}_d^i(\mathrm{k})]$. This is computed from $\mathrm{V(M}_{s,k-1})+\mathrm{B[r(k)}|\mathrm{y}_d\mathrm{(k)]}$.

Step 3. Set $V(M_{\mathrm{s,k}})$ to the best path matric (smallest value) going to state M_s at time k.

Step 4. Store the best path metric and its associated survivor bit and state paths.

Step 5. If $k = L_r + D - 1$, return to Step 2. The decoded output $y_{rd}(k)$ is sent to the demodulation and de-quantization module and then finally used for the state estimation purpose.

3. PROPOSED ESTIMATION AND OPTIMAL FEEDBACK CONTROL METHOD

The energy management system computes the following KF steps as follows [30]:

$$\hat{\mathbf{x}}^{-}(k) = \mathbf{A_d}\hat{\mathbf{x}}(k-1) + \mathbf{B_d}\hat{\mathbf{u}}(k-1), \tag{5}$$

where $\hat{\mathbf{x}}(k-1)$ is the estimated states of the last step. The predicted estimate error covariance matrix is given by:

$$\mathbf{P}^{-}(k) = \mathbf{A_d}\mathbf{P}(k-1)\mathbf{A}_d{}^{T} + \mathbf{Q}_n(k-1), \tag{6}$$

where $\mathbf{P}(k-1)$ is the estimated error covariance matrix of the last step. The measurement residual $\mathbf{d}$(k) is given by:

$$\mathbf{d}(k) = \mathbf{y}_{rd}(k) - \mathbf{C}\hat{\mathbf{x}}^{-}(k), \tag{7}$$

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

$$\mathbf{K}(k) = \mathbf{P}^{-}(k)\mathbf{C}^{T}[\mathbf{C}\mathbf{P}^{-}(k)\mathbf{C}^{T} + \mathbf{R}_w(\mathrm{k})]^{-1}. \tag{8}$$

The updated state estimation is given by:

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}^{-}(k) + \mathbf{K}(k)\mathbf{d}(k). \tag{9}$$

The updated estimate error covariance matrix $\mathbf{P}$(k) for the KF is given by:

$$\mathbf{P}(\mathrm{k}) = \mathbf{P}^{-}(\mathrm{k}) - \mathbf{K}(\mathrm{k})\mathbf{C}\mathbf{P}^{-}(k). \tag{10}$$

After estimating the system state, the proposed control method is applied for stabilizing the DER states. We first assume that the state information is available. Define the following state feedback control law:

$$\mathbf{u}(\mathrm{k}) = \mathbf{F}\mathbf{x}(\mathrm{k}), \tag{11}$$

where $\mathbf{F}$ is the state feedback gain matrix. The simulation result in the next section shows that the proposed estimation technique is able to estimate the system state properly. Therefore, according to the separation principle [31], we can implement the control law $\mathbf{u}(\mathrm{k}) = \mathbf{F}\hat{\mathbf{x}}(\mathrm{k})$ [12]. Consider the following Lyapunov function:

$$\mathrm{V}[\mathbf{x}(\mathrm{k})] = \mathbf{x}^{T}(k)\mathbf{P}\mathbf{x}(k). \tag{12}$$

The Lyapunov function increment is:

$$\begin{aligned}\Delta\mathrm{V} &= \mathrm{V}[\mathbf{x}(\mathrm{k+1})] - \mathrm{V}[\mathbf{x}(\mathrm{k})]\\ &= \mathbf{x}^{\mathrm{T}}(\mathrm{k+1})\mathbf{P}\mathbf{x}(\mathrm{k+1}) - \mathbf{x}^{\mathrm{T}}(\mathrm{k})\mathbf{P}\mathbf{x}(\mathrm{k})\\ &= \mathbf{x}^{T}(\mathrm{k})[(\mathbf{A}_d + \mathbf{B}_d\mathbf{F})^{T}\mathbf{P}(\mathbf{A}_d + \mathbf{B}_d\mathbf{F}) - \mathbf{P}]\,\mathbf{x}(\mathrm{k}).\end{aligned} \tag{13}$$

The system is stable if $\Delta\mathrm{V} \le 0$. This is achievable if the following condition holds:

$$(\mathbf{A}_d + \mathbf{B}_d\mathbf{F})^{T}\mathbf{P}(\mathbf{A}_d + \mathbf{B}_d\mathbf{F}) - \mathbf{P} \le \mathbf{0}. \tag{14}$$

In order to solve the above problem by using semidefinite programming technique, define $\tilde{\mathbf{P}} = \mathbf{P}^{-1}$, then (14) becomes:

$$\begin{aligned}&(\mathrm{A}_d + \mathrm{B}_d\mathrm{F})^{T}\tilde{\mathrm{P}}^{-1}(\mathrm{A}_d + \mathrm{B}_d\mathrm{F}) - \tilde{\mathrm{P}} \le 0\\ &\tilde{\mathrm{P}}(\mathrm{A}_d + \mathrm{B}_d\mathrm{F})^{T}\tilde{\mathrm{P}}^{-1}(\mathrm{A}_d + \mathrm{B}_d\mathrm{F})\tilde{\mathrm{P}} - \tilde{\mathrm{P}} \le 0.\end{aligned} \tag{15}$$

It can be observed that (15) is nonlinear because it involves the multiplication of variables $\tilde{\mathbf{P}}$ and $\mathbf{F}$. That is, (15) cannot be directly expressed in the form of linear matrix inequality. Fortunately, one can introduce a new variable $\mathbf{H} = \mathbf{F}\tilde{\mathbf{P}}$ and rewrite (14) as follows:

$$\begin{bmatrix} -\tilde{\mathbf{P}} & \tilde{\mathbf{P}}\mathbf{A}_d^{T} + \mathbf{H}^{T}\mathbf{B}_d^{T} \\ (\tilde{\mathbf{P}}\mathbf{A}_d^{T} + \mathbf{H}^{T}\mathbf{B}_d^{T})^{T} & -\tilde{\mathbf{P}} \end{bmatrix} \le \mathbf{0}. \tag{16}$$

The proposed optimization problem can be solved by the YALMIP toolbox [32]. Finally, the feedback gain matrix is computed as:

$$\mathbf{F} = \mathbf{H}\tilde{\mathbf{P}}^{-1}. \tag{17}$$

The performance of the proposed method is analysed in the next section.

4. PERFORMANCE ANALYSES

The simulation parameters are summarized in Table 1.

Table 1. The parameters for the simulation using Matlab.

Parameters	Values	Parameters	Values
Codes generator	5/7	Δ_t	0.0001
Quantization	Uniform	Decoding	SOVA
Code rate	1/2	Channel	AWGN
$\mathbf{Q}_n$	$0.005\mathrm{I}_4$	$\mathbf{R}_w$	$0.05\mathrm{I}_4$

The mean squared error (MSE) versus signal-to-noise ratio (SNR) is presented in Figure 5. It can be observed that the proposed method significantly outperforms the existing KF method [33]. In [33], KF is used for estimating the system states then it shows that the estimated state will deviate from the true state if there are attacks. If the deviation is larger than the threshold, an alarm will be issued for the detection of attacks. The main reason for improvement of system performance is that the RSC is used to protect messages by adding redundancy in the system states.

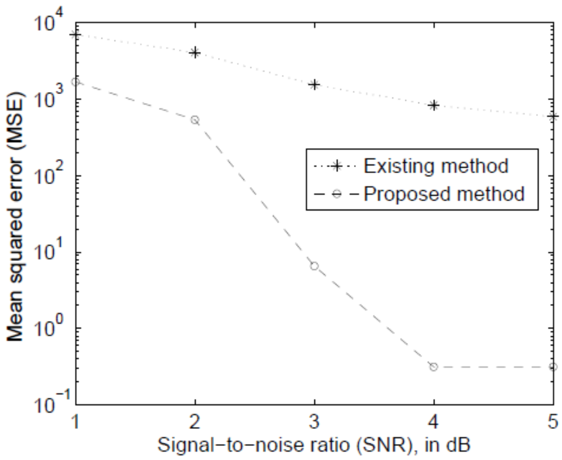

Fig. 5. MSE versus SNR performance comparison.

Furthermore, the SOVA decoding can also assist to extract the system information accurately. For better visualization, the states versus time step results are illustrated in Figures 6–9. It can be observed that the noise enormously affects the system states when KF filter is used to estimate system states [33]. In other words, there is a significant fluctuation due to the random noises. Interestingly, the proposed RSC based technique can regulate the system impairments by introducing redundancy and protection in the system states. As a result, the proposed method can estimate microgrid states accurately. Unfortunately, it is noticed that the true voltage deviations increase, which is very dangerous in terms of network stability and the operation of DERs. Therefore, it is necessary to apply a proper control method, so that the voltage deviations are driven to zero.

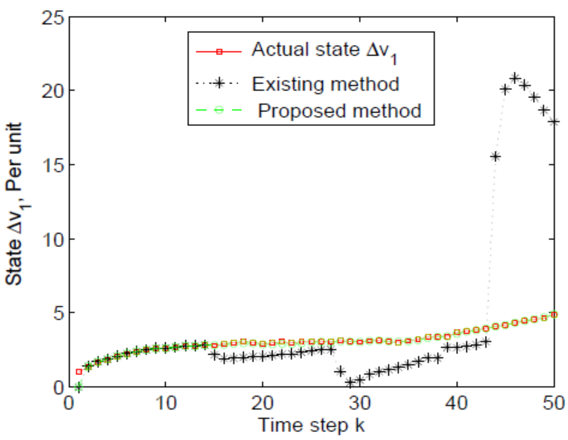

Fig. 6. State trajectory of ΔV_1 and its estimate.

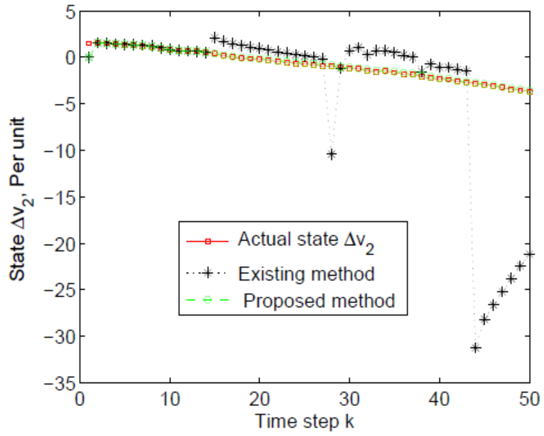

Fig. 7. State trajectory of ΔV_2 and its estimate.

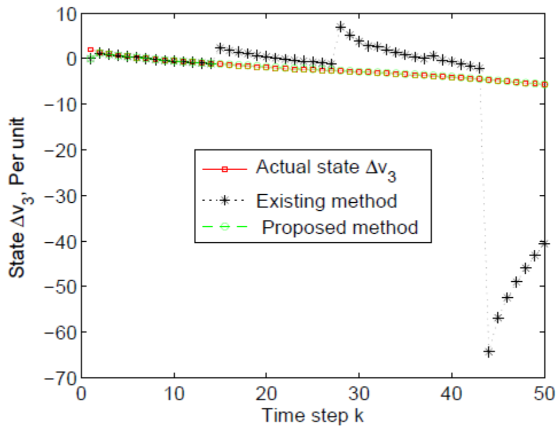

Fig. 8. State trajectory of ΔV_3 and its estimate.

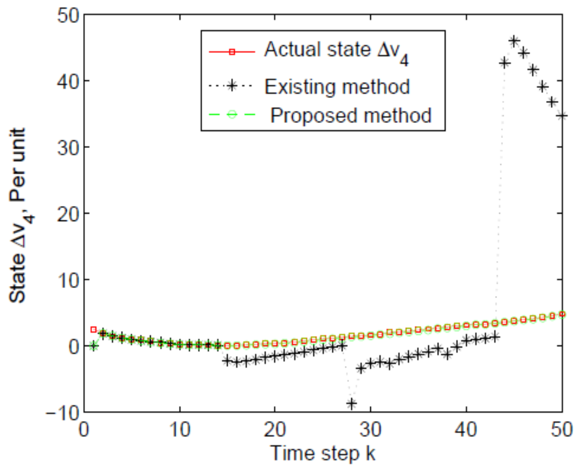

Fig. 9. State trajectory of ΔV_4 and its estimate.

After applying the proposed control method, it can also be seen in Figure 10 that the proposed controller is able to keep voltage deviations to zero by the time k=20, which acts as a precursor in terms of network stability and proper operation of DERs. Besides, the corresponding control input of each DER is shown in

Figure 11, which implies that it requires a small amount of the control input voltage.

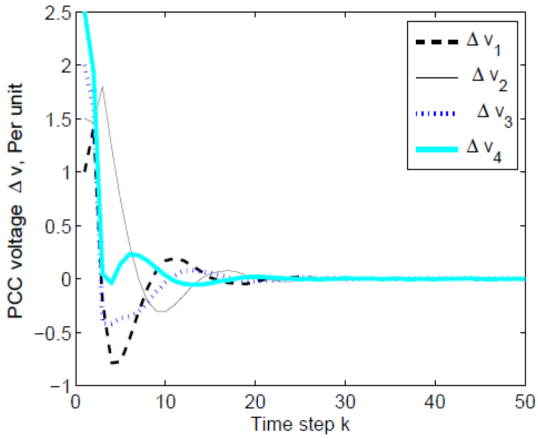

Fig. 10. Voltage control in the noise free case.

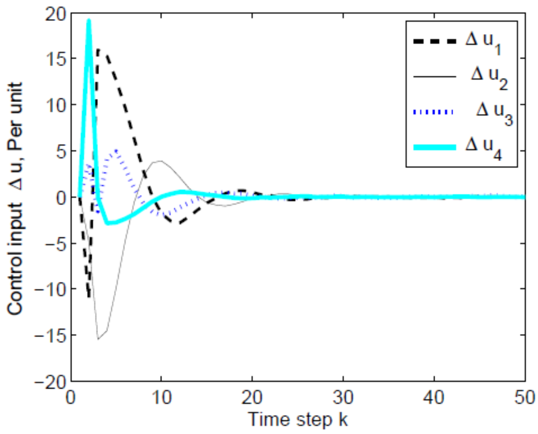

Fig. 11. Input voltage variations in the noise free case.

In practice, the control effort is affected by noise between the controller output and actuator. So, it can affect the estimation performance as well. It is assumed that the AWGN is added with the control effort $\mathbf{u}(k)$ between the controller output and actuator. The simulation results are presented in Figures 12-13. It can be seen that the proposed controller is also able to keep PCC voltage deviations within a small range of zero due to the AWGN noise between the controller output and the actuator.

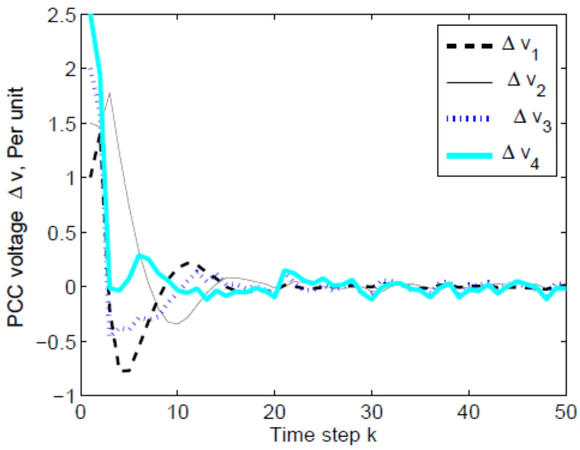

Fig. 12. Input voltage variations using random noise.

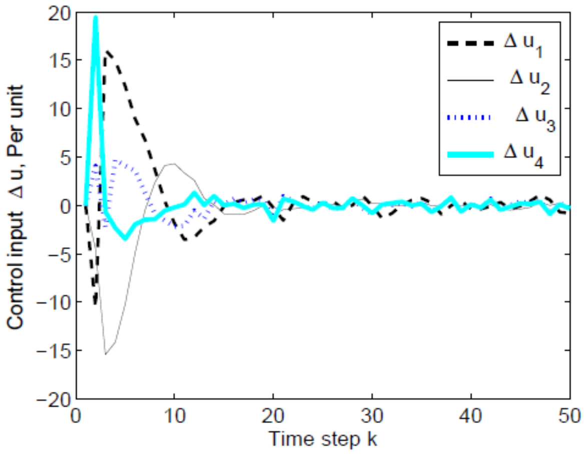

Fig. 13. Voltage control using random noise.

5. CONCLUSIONS

This paper proposes a KF algorithm for centralized microgrid state estimation. In order to regulate the voltage deviation, this study proposes an optimal control strategy based on semidefinite programming. The effectiveness of the developed approaches is verified by numerical simulations. The main limitation of this paper is that it needs more execution time as it involves encoder and decoder. To overcome this issue, one may use data compression or model reduction techniques. In order to improve the system performance, the low density parity check code, turbo decoder and machine learning algorithms may be use [34]. In the future, we will implement the communication networks in consideration of more realistic scenarios such as radio frequency disturbances, cyber attacks [35], noise spikes and fading, which is usually experienced by the wireless nodes.

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