Dual Extended Kalman Filter Reconstruction of Actuator and Sensor Faults in DC Microgrids with Constant Power Loads

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***Abstract*—This paper explores the problem of model-based detecting and reconstructing occurring actuator and sensor faults in direct current (DC) microgrids (MGs) connected to resistive and constant power loads (CPLs) and energy storage units. Both the actuator and sensor faults are modeled as an additive time-varying term in the state-space representation, which highly degrade the system response performance if they are not compensated. In this paper, a novel advanced extended Kalman filter (EKF), called dual-EKF (D-EKF) is proposed to estimate the system states as well as the accruing actuator and sensor faults. The main property of the developed approach is that it offers a systematic estimation procedure by dividing the estimating parameters into three parts and these parts are estimated in parallel. A first-order filter is utilized to turn the sensor faulty system into an auxiliary sensor faults-free representation. Thereby, the artificial output contains the filter states. The proposed D-EKF estimator does not require restrictive assumptions on the power system matrices and is highly robust against stochastic Gaussian noises. At the end, the proposed approach is applied on a practical faulty DC MG benchmark connected to a CPL, a resistive load, and an energy storage system and the obtained simulation results are analyzed form the accuracy and convergence speed viewpoints.**

***Keywords*—DC microgrid, Constant power load, Actuator Fault, Sensor Fault, Extended Kalman Filter, Dual-EKF.**

I. Introduction

Direct current (DC) and alternating current (AC) microgrids (MGs) are an effective solution to integrate distributed loads and renewable energy sources [1]. For recent power utilities involving DC wind turbine, fuel cells, and photovoltaics and DC electronic loads, it is wise to consider the DC MGs [1]. Thanks to power electronic advances, DC Mgs are now widely feeding tightly controlled loads that are inherently nonlinear and act as constant power loads (CPLs). The main issue associated with CPLs is that possess a destabilizing negative incremental resistance behaviour. The CPL stability issue has been attracting many attentions and different linear and nonlinear control strategies have been presented [2]–[4].

However, in none of those references the issue of fault detection and fault tolerant control is investigated. Indeed, reviewing the state-of-the-art methods reveals that the faulty operation of islanded DC MGs with CPLs has been rarely investigated. Nevertheless, occurring rigorous faults not only degrades the DC MG efficiency and reliability but also damages the MG connected elements if it is not detected and treated accordingly.

In [5], power management of generators and loads in a DC MG in the presence of grid faults is investigated. However, it is assumed that the faults are identified and no mechanism for that is not given. In [6], a fault tolerant passivity-based controller is developed for a faulty hybrid AC/DC MG. It is assumed that the fault occurs in the AC side and its corresponding voltage grid is measurable. Therefore, the actual fault is not detected and estimated and only its effects are tolerated.

In [7], the influence of several faults on a DC MG with multiple CPLs is investigated, and a fault-tolerant control (FTC) method was suggested to the closed-loop system robust against faults. However, that approach suggests the FTC for each CPL connected to the DC MG. By increasing the number of CPLs, that approach is not cost-effective.

In [8], the effect of sensor fault on a typical DC MG with different energy sources was investigated. However, the other classes of faults were ignored. A robust controller and monitoring technique was developed in [9] to alleviate the consequence of occurring faults. Though, the faults were not reconstructed. In [10], the actuator and sensor faults were detected by developing a robust linear observer was developed. However, the detected faults were not estimated.

In [11], both the actuator and sensor faults were detected and reconstructed. In that approach, a sliding mode observer was suggested. However, to design the observer gains, several assumptions on the ranks of the system were required. In parallel to the abovementioned attempts dealing with faults, several estimation methods have been presented in MGs to estimate the states, including estimating the' flux of rotor in motors [12], the state-of-charge in energy storage systems [13], and the currents in DC MGs [14]. However, in none of those approaches, the issue of occurring faults in the power system has been not investigated. This is the main motivation for this work.

This paper focuses on the problem of detecting and simultaneously estimating actuator and sensor faults and voltages and currents in a typical DC MG that connected to uncontrollable DC source, controllable energy storage units, and linear loads and CPLs. A model-based dual-extended Kalman filter (D-EKF) is presented through which the system states and actuator and sensor faults are evaluated and constructed in parallel. The developed approach extends the results of the conventional extended Kalman filter (EKF) and dual-EKF such that it not only capable of dealing with faulty systems but also requires almost the same computational time burden as the EKF. The main advantages of the proposed approach over the state-of-the-art method [11] are that I) it does not expose restrictive assumptions on the system matrices and II) is robust against stochastic Gaussian noises. To show the advantages of the developed dual-EKF approach, a numerical simulation is carried out on a DC MG benchmark with nonlinear dynamics and noises. The obtained results illustrate the accuracy and efficiency of the proposed approach in the presence of simultaneous faults.

This article is continued as follows: In Section II, the dynamics of the DC MG with an energy storage unit, CPLs, and linear loads are presented and additive actuator and sensor fault are then considered. In Section III, the developed dual-EKF is designed for the power system. In Section IV, the simulation and comparative results are provided and the obtained outcomes are discussed. Finally, in Section V, the achievements of this article are summarized and some future perspectives are drawn.

II. Faulty DC MG with CPLs

A typical DC MG involves some power generators, storage, and loads. These loads can be resistive or constant power, as shown in Fig. 1. The difference between the resistive loads and CPLs is appearing power electronic load converters. The CPLs are commonly integrated into DC MGs at the input point of the load converter by assuming the converters are ideal or consume constant power.

Since the goal of this paper is to address the FDI issue, only one DC source is considered. Nevertheless, the proposed approach is applicable to DC MGs with several sources. An overall state-space representation of the DC MG with one DC source, one energy storage system (ESS), and one CPL, shown in Fig. 1, is obtained as follows [15]:

$$\begin{aligned} \dot{x} &= Ax + B(u + f_a) + D(x) + B_s V_{dc} \\ y &= Hx + Ef_s + w \end{aligned} \tag{1}$$

where $x = [x_1 \;\; x_2 \;\; x_3 \;\; x_4]^T = [i_{L1} \;\; v_{C1} \;\; i_{L2} \;\; v_{C2}]^T$ the state vector comprising the current and voltage of CPL filter, i_{L1} and v_{C1}, and current and voltage of source filter, i_{L2} and v_{C2}. $u = i_{es}$ is the control input of system associated to the ESS, V_{dc} is the output voltage DC/DC converter in the DC source, E is the sensor fault matrix, and w is the measurement noise. Also,

$$A = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & 0 & 0 & 0 \\ 0 & 0 & -\frac{r_2}{L_2} & -\frac{1}{L_2} \\ -\frac{1}{C_2} & 0 & \frac{1}{C_2} & -\frac{R}{C_2} \end{bmatrix}; B = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -\frac{1}{C_2} \end{bmatrix}; \tag{2}$$

$$D(x) = \begin{bmatrix} 0 \\ \frac{-P}{C_1 v_{C1}} \\ 0 \\ 0 \end{bmatrix}; B_s = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L_2} \\ 0 \end{bmatrix};$$

$$H = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; \; E = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

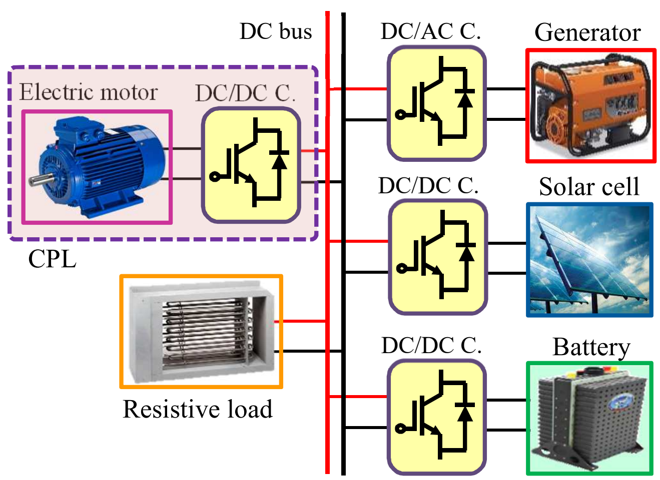

Fig. 1. Power system illustration of a DC MG.

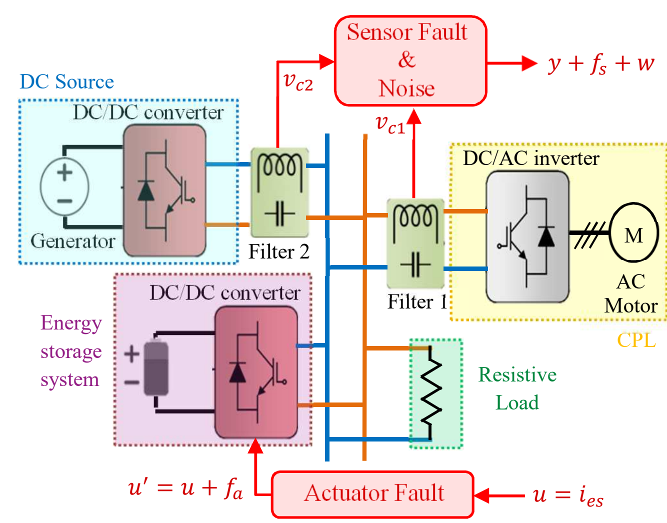

Fig. 2. A basic diagram of the DC MG with CPL, resistive loads, actuator fault, sensor fault and noise.

As can be seen in (1), the power system is subjected to the actuator and sensor faults f_a and f_s and white noise w. Also, the dynamics are nonlinear due to appearing $D(x)$.

The goal is to estimate the faults as well as the state vector based on the available voltage measurement in the presence of noise. This is done by presenting an improved nonlinear extended Kalman filter (EKF), which will be presented in the coming section.

III. Proposed Nonlinear State and Fault Estimator

a) Modifying the state-space representation

Estimating information of (1) has four main challenges due to appearing I) the actuator fault f_a, II) the sensor fault f_s, III) the nonlinear term $1/x_2$, and IV) the stochastic noise w. In order to tackle with the actuator and sensor faults f_a and f_s, they are considered as augmented states. On the other hand, since its time derivative is unknown, it is considered that

$$\dot{f}_a = 0, \qquad \dot{f}_s = 0 \tag{3}$$

It is worthy to note that, if there is any pre-knowledge of f_a and f_s, the dynamics (3) can be updated. Initially, the issue of appearing sensor fault in the output is handled by introducing the filtered output $\mu = [\mu_1 \ \ \mu_2]^T$ as follows [11]:

$$\dot{\mu} = -\gamma\mu + \gamma y = -\gamma\mu + \gamma Cx + \gamma E f_s + \gamma w \tag{4}$$

where $\gamma < 0$ is. The relation (4) illustrates a first-order filter on the measured output y. Considering (4), it is possible to introduce a fault-free output as follows:

$$y_f = \mu \tag{5}$$

This is the main feature of using the above first-order filter. The nonlinearity and white noise of (1) are also treated by using the EKF scheme. Now, by defining the augmented vector $X = [x^T \ \ \mu \ \ f_a \ \ f_s]^T = [x_1 \ \ x_2 \ \ x_3 \ \ x_4 \ x_5 \ x_6 \ \ x_7 \ \ x_8]^T$ and reminding (1), (3), (4), and (6) one has:

$$\begin{cases} \dot{X} = F(X) + \hat{B}u + \hat{B}_s V_{dc} \\ Y = \bar{H}X \end{cases} \tag{6}$$

where

$$F(X) = \begin{bmatrix} F_1(X) \\ F_2(X) \\ F_3(X) \\ F_4(X) \\ F_5(X) \\ F_6(X) \\ F_7(X) \\ F_8(X) \end{bmatrix} = \begin{bmatrix} -\frac{r_1}{L_1}x_1 - \frac{1}{L_1}x_2 + \frac{1}{L_1}x_4 \\ \frac{1}{C_1}x_1 - \frac{P_1}{C_1 x_2} \\ -\frac{r_2}{L_2}x_3 - \frac{1}{L_2}x_4 \\ \frac{1}{C_2}x_3 - \frac{1}{C_2}x_1 - \frac{x_4}{RC_2} - \frac{1}{C_2}x_7 \\ -\gamma x_5 + \gamma x_2 + \gamma x_8 \\ -\gamma x_6 + \gamma x_4 + \gamma x_8 \\ 0 \\ 0 \end{bmatrix}; \tag{7}$$

$$\hat{B} = \begin{bmatrix} 0 & 0 & 0 & -\frac{1}{C_2} & 0 & 0 & 0 & 0 \end{bmatrix}^T;$$

$$\hat{B}_s = \begin{bmatrix} 0 & 0 & \frac{1}{L_2} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T;$$

$$\bar{H} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Now, the continuous-time representation (6) is discretized by the Euler approach with the sample time T_s and subjected to system and measurement noises v and w. Thereby

$$\begin{cases} X(k+1) = \bar{F}\big(X(k)\big) + \bar{B}u(k) + \bar{B}_s V_{dc} + v(k) \\ Y(k) = \bar{H}X(k) + w(k) \end{cases} \tag{8}$$

where

$$\bar{F}\big(X(k)\big) = X(k) + T_s F\big(X(k)\big); \bar{B} = T_s\hat{B}; \ \bar{B}_s = T_s\hat{B}_s$$

b) Dual-Extended Kalman Filter

The main objective is to estimate the state vector X_k in the presence of noise. The conventional EKF is modified such that it estimates the actual system states and faults separately and simultaneously. In this regard, a dual-EKF (D-EKF) is proposed, which contains three modified EKFs each of which estimates the states, actuator fault, and sensor fault. To develop the D - EKF, the augmented state vector is split into two vectors as $X(k) = [e^T(k) \ \ f^T(k)]^T$, where $e(k) = [x_1(k) \ x_2(k) \ x_3(k) \ x_4(k) \ x_5(k) \ x_6(k)]^T$ and $f(k) = [f_a(k) \ \ f_s(k)]^T = [x_7(k) \ \ x_8(k)]^T$. Thereby, the nonlinear dynamics (8) are represented by their corresponding Jacobian matrix, as follows:

$$\begin{cases} \begin{bmatrix} e(k+1) \\ f(k+1) \end{bmatrix} = \begin{bmatrix} \Psi_{ee}(k) & \Psi_{ef}(k) \\ 0 & I \end{bmatrix} \begin{bmatrix} e(k) \\ f(k) \end{bmatrix} + \bar{B}u(k) \\ \qquad + \bar{B}_s V_{dc} + \begin{bmatrix} v_e(k) \\ v_f(k) \end{bmatrix} \\ y(k) = \bar{H}[e^T(k) \quad f(k)]^T + w(k) \end{cases} \tag{9}$$

where $v(k) = \left[v_e^T(k), v_f^T(k)\right]^T$, $\bar{H} = [H_e \ 0 \ 0]$, $\bar{B} = [B_e^T \ 0 \ 0]^T$, $\bar{B}_s = [B_{se}^T \ 0 \ 0]^T$, and

$$H_e = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}; B_e = \begin{bmatrix} 0 & 0 & 0 & -\frac{T}{C_2} \end{bmatrix}^T;$$

$$B_{se} = \begin{bmatrix} 0 & 0 & \frac{T}{L_2} & 0 \end{bmatrix}^T \tag{10}$$

Also, $v(k)$ are the system and measurement noise vectors, characterized by Gaussian function $\mathcal{g}$ with mean vector and variance matrix, as follows:

$$\begin{bmatrix} v_e(k) \\ v_f(k) \end{bmatrix} \sim \mathcal{g}\left(0, \begin{bmatrix} Q_e(k) & 0 \\ 0 & Q_f(k) \end{bmatrix}\right) \tag{11}$$

$$w(k) \sim \mathcal{g}(0, R(k)) \tag{12}$$

Also,

$$\Psi_{ee}(k) = \left[\frac{\partial \bar{F}_1(X)}{\partial s} \quad \dots \quad \frac{\partial \bar{F}_6(X)}{\partial s}\right]^T\Bigg|_{X=X(\boldsymbol{k})} \tag{13}$$

$$\Psi_{ef}(k) = \left[\frac{\partial \bar{F}_1(X)}{\partial f} \quad \dots \quad \frac{\partial \bar{F}_6(X)}{\partial f}\right]^T \Bigg|_{X=X(\boldsymbol{k})} \tag{14}$$

Inspired from the dual estimation idea [16]–[18], in the following, D-EKF is developed for the system (9):

- Initial conditions for the state EKF

$$\begin{cases} \hat{e}^+(0) = E\{e(0)\} \\ P_e^+(0) = E\{(e(0) - \hat{e}^+(0))(e(0) - \hat{e}^+(0))^T\} \end{cases} \tag{15}$$

- Initial conditions for the fault EKF

$$\begin{cases} \hat{f}(0) = E\{f(0)\} \\ P_f^+(0) = E\left\{\left(f(0) - \hat{f}(0)\right)\left(f(0) - \hat{f}(0)\right)^T\right\} \\ \Gamma_f^e(0) = \left.\dfrac{\partial \hat{e}^+}{\partial f}\right|_{f=\hat{f}(0)} \end{cases} \tag{16}$$

where $\hat{e}^+(.)$, and $\hat{f}(.)$ are the estimations of $e(.)$ and $f(.)$, respectively, $P_e^+(.)$, and $P_f^+(.)$ are the covariance matrices of the estimation errors. For $k = 1,2, \dots$ the following recursive algorithms are performed:

- Algorithm of the state EKF

$$\begin{cases} \hat{e}^-(k) = \Psi_{ee}(k)\hat{e}^+(k-1) + B_e u(k) + B_{se}V_{dc} \\ \qquad\quad +\Psi_{ef}(k)\hat{f}(k) \\ P_e^-(k) = \Psi_{ee}(k)P_e^+(k-1)\Psi_{ee}^T(k) + Q_e(k-1) \\ K_e(k) = P_e^-(k)H_e^T\left(H_e P_e^-(k)H_e^T + R(k)\right)^{-1} \\ \hat{e}^+(k) = \hat{e}^-(k) + K_e(k)\left(y(k) - C_e\hat{e}^-(k)\right) \\ P_e^+(k) = (I - K_e(k)H_e)P_e^-(k) \end{cases} \tag{17}$$

- Algorithm of the fault EKF

$$\begin{cases} P_f^-(k) = P_f^+(k-1) + Q_f(k-1) \\ K_f(k) = P_f^-(k)H_f^T\left(H_f P_f^-(k)H_f^T(k) + R(k)\right)^{-1} \\ \hat{f}(k) = \hat{f}(k-1) + K_e(k)\left(y(k) - H_e\hat{e}^-(k)\right) \\ P_f^+(k) = \left(I - K_f(k)H_f\right)P_f^-(k) \\ \Gamma_f^e(k) = (I - K_e(k)H_e)\left(\Gamma_f^e(k-1) + \Psi_{ef}(k)\right) \end{cases} \tag{18}$$

where $H_f = H_e\Gamma_f^e(k-1)$.

The flowchart of the D-EKF algorithm is summarized in Fig. 3. As can be seen in Fig. 3, the state EKF shares its estimation with the faults EKF and gets the faults information. If there is no occurring fault, the faults EKF stops and its corresponding information will be not needed in the state EKF and it operates independently. This can be done by setting $\hat{f}(k) = 0$ or $\hat{f}(k) = f^*$, where f^* is the last estimated constant value of the faults, in (17). The output of the D-EKF is system states and faults, which are needed for different actions such as online monitor, advanced control, as wells as repairing or replacing the converter.

IV. Simulation Results

The developed estimator is applied the DC MG dynamics (2) with the parameters $r_1 = 1.1\ (\Omega)$, $L_1 = 39.5\ (mH)$, $C_1 = 500\ (\mu F)$, $r_2 = 1\ (\Omega)$, $L_2 = 17\ (mH)$, $C_2 = 500\ (\mu F)$, $R = 100\ (\Omega)$, $P = 300\ (W)$, $V_{dc} = 200\ (V)$, and $i_{es} = 0$. Also, the sampling time is $T_s = 0.2\ (msec)$. Also, the actuator and sensor faults are chosen as follows:

$$f_a = \begin{cases} 0 & 0 \le t \le 1 \\ 1 & 1 < t \le 4 \\ -1 & 4 < t \end{cases}$$
$$f_s = \begin{cases} 0 & 0 \le t \le 4 \\ \sin\left(\dfrac{2\pi}{3}(t-4)\right) & 4 < t \end{cases} \tag{19}$$

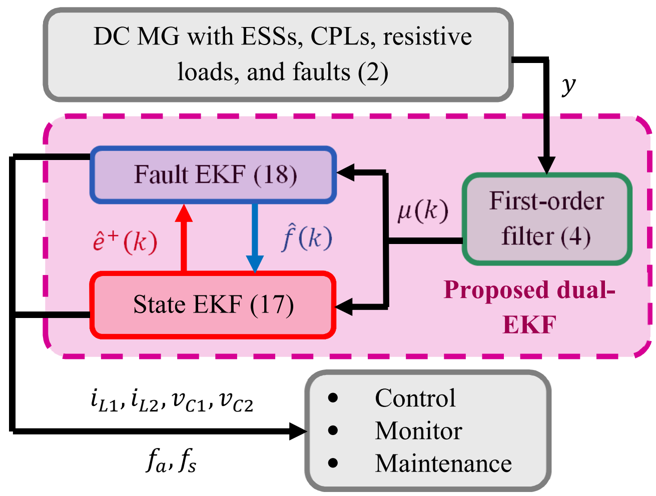

Fig. 3. Implementation of the proposed estimation method.

Also, it is considered that the voltage of the DC CPL is subjected to the sensor fault given in (19) and the voltage of the source connected convertor filter is measured accurately. The first-order filter parameter is set as $\gamma = 0.1$. The parameters of the D-EKF are selected as follows:

State EKF:

$$\hat{e}^+(0) = [1\,200\ \ 1\,200\ 0\ 0]^T; P_e^+(0) = 10^3 I_6;$$
$$Q_e = 10^{-5}I_6; R_e = 1^{-4}I_2$$

Fault EKF: (20)

$$f^+(0) = [0\ \ 0]^T; P_f^+(0) = 10^3 I_2;\ \Gamma_f^e(0) = 0_{6\times 2};$$
$$Q_f = diag\,\{10^2, 10\};$$
$$R_f = diag\{10^{-2}, 10^{-2}, 10^{-4}, 10^{-4}\};$$

The states of the system and their estimations are given in Fig. 4. From Fig. 4 one infers that the state D-EKF accurately estimates the states in a about 0.5 (sec).

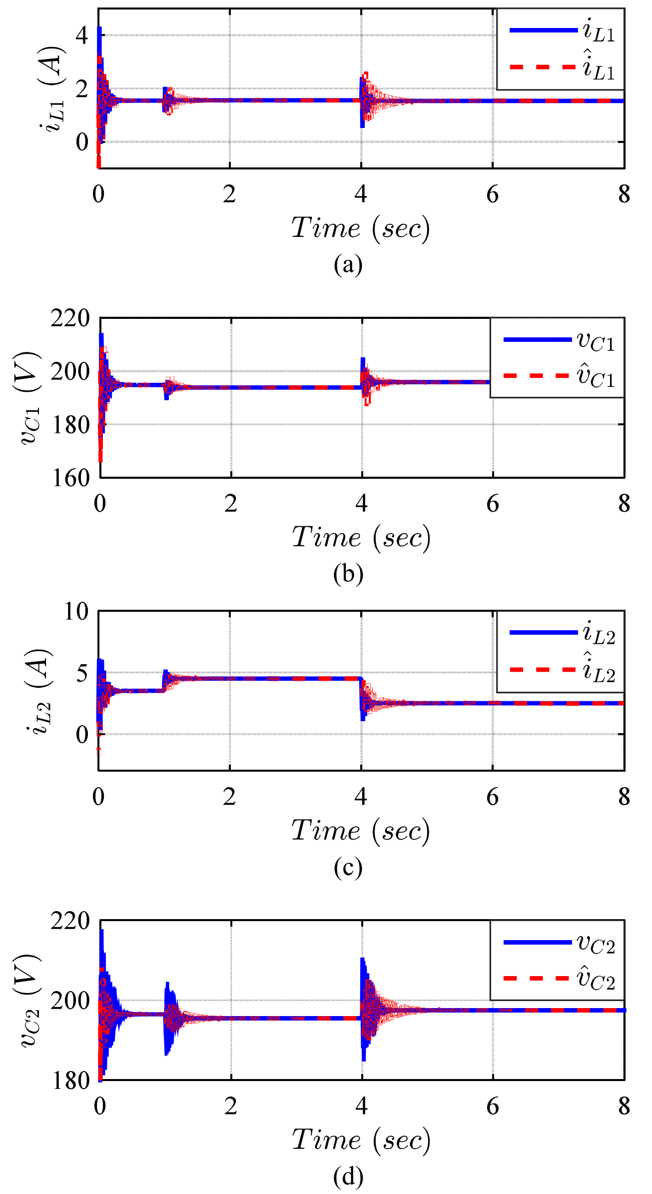

Fig. 4. The states and their estimations (Actual value by the blue line and the estimated value by the red line): (a). x_1, (b). x_2. (c). x_3, (d). x_4.

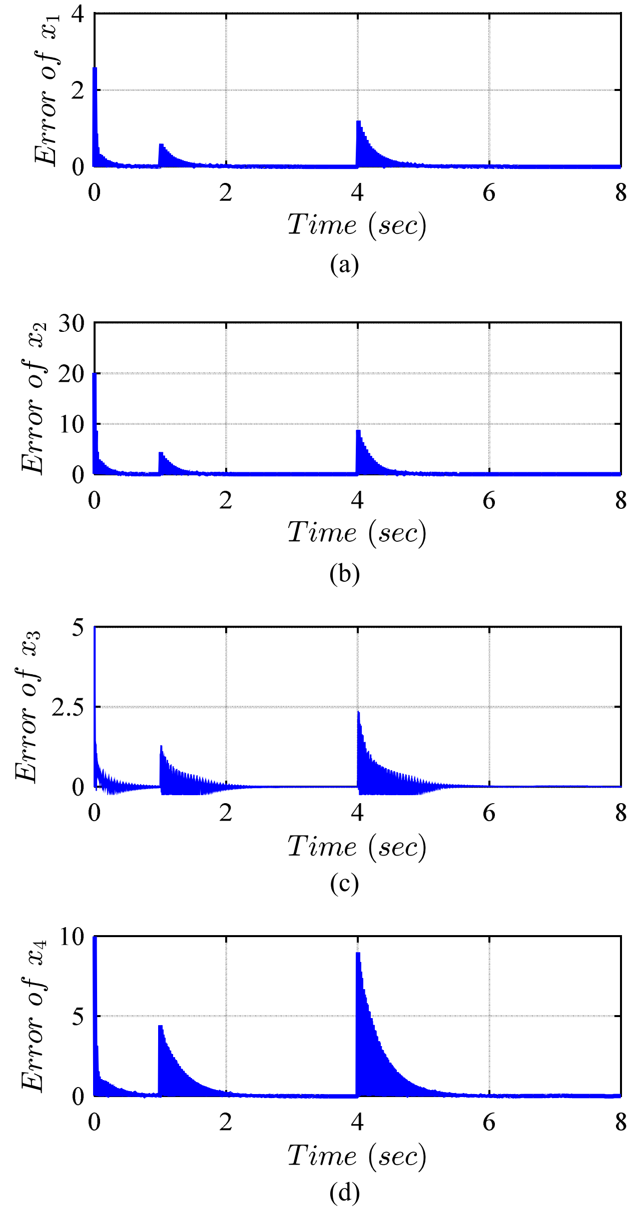

Fig. 5. The absolute values of the errors of the system states: (a). Error of x_1, (b). Error of x_2, (c). Error of x_3, (d). Error of x_4.

The absolute value of the estimation error for each of the states are given in Fig. 5. Compared to the amplitude of the currents and voltages of the DC MG system, the estimation error amplitudes are neglectable. More precisely, the amplitude error amplitudes divided by their associate state amplitudes are 0.2298, 0.0426, 0.3844, 0.0461, respectively.

Moreover, the estimation of the actuator and sensor faults are given in Fig. 6. As can be seen in Fig. 6, the proposed approach estimates the actuator fault faster than the sensor fault. This is an advantage especially for advanced control of power grid. The reason is that the system states and actuator fault are estimated fast and the control law is related to these quantities. Though, it is worthy to note that the converge speeds of the EKF estimations are influenced by the initial conditions of the EKFs.

Additionally, the actuator fault f_a changes promptly as can be seen in Fig. 6(a) and(19). On the other hand, the dual-EKF needs a transient time response to act and estimate the correct value. Consequently, at the moment of the step change in the faults, the overall estimator produces, a small estimation error to all states and faults.

However, if the fault changes smoothly like the sensor fault in Fig. 6(b), no estimation error will occur. As can be seen in Fig 6(b), the sensor fault oscillates after $t > 4$ (sec), but the estimation errors in Fig 5 and 6 are almost zero for $t > 5$ (sec).

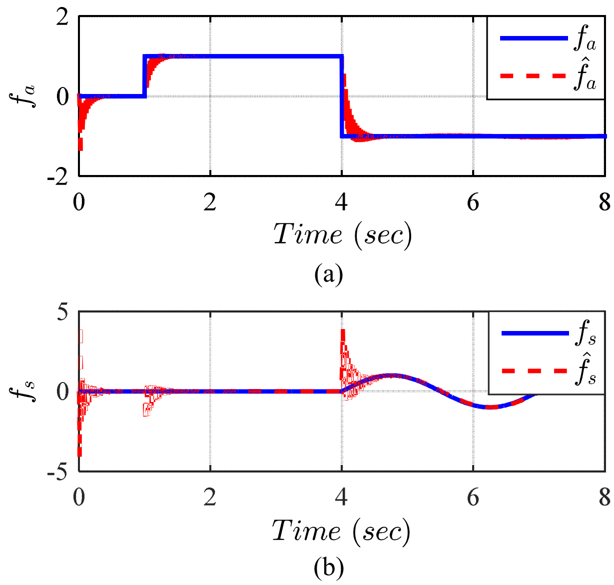

Fig. 6. The actuator and sensor faults and their estimations (Actual value by the blue line and the estimated value by the red line): (a). f_a, (b). f_s.

V. Conclusion

In this article, the issue of state and actuator and sensor faults estimation for DC MGs with nonlinear dynamics was studied. It was assumed that the considered DC MG feeds linear resistive loads and nonlinear CPLs. A novel dual-EKF approach, through which two EKFs were combined, was suggested for the power system. It was shown that the state EKF can work independent to the fault EKF. So, it is possible to use only one Kalman filter whenever the actuator fault does not happen. Or, each of the Kalman filters is implemented on a processor. Numerical results showed that in the presence of actuator and sensor faults, the dual-EKF accurately estimates the states and the faults. For future work, considering fault-tolerant control approach for the power system is suggested.

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