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Dual-EKF-Based Fault Tolerant Predictive Control of Nonlinear DC Microgrids with Actuator and Sensor Faults

Navid Vafamand, Mohammad Mehdi Arefi, *Senior Member, IEEE*, Mohammad Hassan Asemani, Mohammad S. Javadi, *Senior Member, IEEE*, Fei Wang, *Senior Member, IEEE*, and João P. S. Catalão, *Fellow, IEEE*

***Abstract*—The issue of a state estimation-based fault-tolerant controller for direct current (DC) microgrids (MGs) is studied in this paper. It is considered that the DC MG contains nonlinear constant power load (CPL) and is subjected to actuator faults. Current sensors are not installed and the voltages of the DC MG are measured in the presence of noise and sensor faults. To estimate the system states, a novel dual-Extended Kalman filter (D-EKF) is proposed, which simultaneously estimates the states and faults. The fault- and noise-free estimations are then deployed in a nonlinear Takagi-Sugeno (TS) fuzzy predictive controller to regulate the DC MG. The proposed method outperforms the exiting results, being robust against faults and noise. Also, the predictive scheme makes it robust against system uncertainties and forces the system states to converge the desired values, precisely. The accuracy and robustness of the developed method are evaluated and compared to advanced state-of-the-art techniques for a typical DC MG with a resistive load, CPL, and energy storage unit.**

***Keywords*—DC microgrid, Constant power load, Actuator fault, Sensor fault, Dual-extended Kalman filter (Dual-EKF), Model predictive control (MPC), Fault-tolerant control.**

I. Introduction

a) Motivation and Background

Direct current (DC) microgrids (MGs) are small-scale power grids that include distributed generation units, energy storage devices, and flexible loads. The DC MGs have been gaining popularity, because of robustness, simple control, and high efficiency of integrating DC sources such as wind turbines, fuel cells, and photovoltaics [1]. In spite of their advantages, the DC MGs have some challenging issues. They should feed nonlinear loads, such as constant power loads (CPLs). The key challenging issue of CPLs is that they destabilize a power system by inserting a negative incremental resistance [2], [3].

Corresponding authors: F. Wang and J.P.S. Catalão.

N. Vafamand, M.M. Arefi and M.H. Asemani are with the Shiraz University, Shiraz, Iran (e-mails: {n.vafamand, arefi, asemani}@shirazu.ac.ir).

M.S. Javadi is with INESC TEC, Porto, Portugal (e-mail: msjavadi@gmail.com).

F. Wang is with the Department of Electrical Engineering, North China Electric Power University, Baoding 071003, China, also with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (North China Electric Power University), Beijing 102206, China, and also with the Hebei Key Laboratory of Distributed Energy Storage and Microgrid (North China Electric Power University), Baoding 071003, China (e-mail: feiwang@ncepu.edu.cn).

J.P.S. Catalão is with the Faculty of Engineering of University of Porto, and INESC TEC, Porto, Portugal (e-mail: catalao@fe.up.pt).

The voltage and current sensors are not ideal and subject to faults and noise. Therefore, the measures of a DC MG are not completely reliable. The controllable power electronic devices in a power system may work with faults, which degrade the control performance. These issues affect the DC MG operation and should be treated in monitoring and controlling actions. These challenges have been investigated in the literature and several control and estimation methods have been suggested.

b) Related Literature

The related works are classified into three groups:
i) CPL destabilizing effect and its stabilizing methods,
ii) fault detection,
iii) fault reconstruction and tolerant control.
In the following, these groups are reviewed.

The undesired effect of nonlinear CPLs is avoided and the DC MG is stabilized by active stabilizing techniques and different linear and nonlinear control strategies, as presented in [4]–[6]. Compared with linear proportional-integral (PI) methods, nonlinear ones, such as backstepping [7], [8], predictive [9], [10], and sliding mode [11], [12] assure the global stabilization of the DC MG. However, those nonlinear controllers deploy the power system state vector information and therefore, require the installation of several current and voltage sensors. This makes them fragile to sensor faults and noisy measurements.

In parallel to stabilizing controllers, recently, few sensor fault detections have been deployed for DC MGs [13]. They can be classified into data-driven and model-based methods. Compared to the data-driven approaches, model-based methods sensor fault detectors require a low computational burden and are more robust against noise. In [14], a linear high-gain Luenberger observer is suggested for DC MGs with CPL. In that approach, the nonlinear CPLs are linearized and system states are estimated near the operating point. Based on an error between the actual output and estimated output, the sensor fault is detected. But it is not reconstructed and the system states estimations are not accurate.

In [15], a fusion Kalman filter is used to detect attacks and estimate states accurately. In that approach, measurements are grouped and each group is deployed to estimate the states. By evaluating the estimations of each group, the faulty sensor is found and localized. Therefore, an accurate estimation is achieved. Since Kalman filter is used [15], estimations are robust against noise. However, sensor fault is not reconstructed.

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Although detecting sensor faults and estimating states are useful for monitoring of a power system, they are unsuited for dealing with actuator faults and control actions, since an effective control mechanism should contemplate actuator faults.

In [16], the actuator and sensor faults were detected by developing a robust linear observer. However, the detected faults were not estimated. In [17], a Takagi-Sugeno (TS) fuzzy-based sliding mode observer ~was deployed to detect both sensor and actuator faults. However, that approach mandates some matrix rank conditions and transformations and is not applicable to complicated DC MGs. Additionally, the fault-tolerant control (FTC) issue of DC MG based on the estimated information was not investigated.

In [1], a noise resilient nonlinear filter was developed to estimate both sensor and actuator faults. However, the optimal and fault-tolerant control of DC MG was not studied.

A robust controller and monitoring technique was presented in [18] to alleviate the consequence of occurring faults. In [19], a faulty hybrid AC/DC MG was stabilized by a fault-tolerant passivity-based controller. System fault occurred at the AC side and AC bus voltage was measured. However, in [18] and [19], the actual fault is not reconstructed and is only tolerated.

In [20], the influence of several faults on a typical DC MG with CPLs was evaluated, and an FTC method was developed. In that approach, for each CPL, an FTC was deployed. However, for complicated DC MGs with a high number of CPLs, several controllers should be considered, which is not cost-effective.

Reviewing the state-of-the-art methods reveal that the control methods are not robust against faults, or only estimate sensor faults, or require a complicated implementation.

c) *Paper Innovation and Contribution*

This work develops a novel fault-tolerant predictive controller for the class of DC MGs with nonlinearities, sensor and actuator faults, and noisy measurements. The main novelty of this work is presenting a novel dual-EKF (D-EKF) based on which the system's noise-free states and sensor and actuator faults are estimated.

Since in the estimation procedure the effect of faults is involved, an accurate state estimation is achieved. Moreover, the D-EKF uses two parallel EKFs, which reduces the overall computation burden by implementing them on different processors. An improved adaptive fault-tolerant predictive controller is proposed, which acquires the faults and states estimations to precisely regulate the DC bus voltage.

To deal with the nonlinear CPL load, the prediction mechanism in the predictive controller is equipped with a nonlinear TS fuzzy representation, which improves the prediction. The considered DC MG connects a DC source and energy storage unit to linear and nonlinear loads. The controlled energy storage unit and the voltage sensors are assumed to be faulty. The proposed approach is applied to the DC MG and its estimation and control action results are compared with state-of-the-art methods.

d) *Paper Organization*

In Section II, the state space presentation of the DC MG with an energy storage unit and a CPL is presented and additive actuator and sensor faults are thoroughly explained. In Section III, the developed fault-tolerant controller, including the dual-EKF and TS fuzzy-based predictive controller, is designed. In Section IV, numerical comparative results are provided and the obtained outcomes are discussed. Finally, in Section V, the achievements of this paper are summarized and some future perspectives are drawn.

II. Faulty Nonlinear DC MG Representation

An islanded DC MG, as shown in Fig. 1, comprises a DC source, an energy storage unit, a nonlinear constant power load (CPL), a resistive load, and passive RLC filters.

It is assumed that the voltage of the DC source is fixed by a DC/DC converter and it is not controllable. On the other hand, the current of the energy storage unit can be manipulated to regulate the DC bus voltage. The voltages of the capacitors are measured and current sensors are not deployed [21].

Additionally, the power DC MG is subjected to sensor and actuator faults. The main source of sensor faults is the mis-functionality of the sensors, which produces a bias term in the outputs. Also, the power electronic converters of the energy storage units may perform improperly, which results in actuator faults. The nonlinear CPLs are generated by precise control of the load side power electronic devices.

The dynamics of the typical system of Fig. 1 are as follows [22]:

$$\begin{aligned} \dot{x} &= Ax + B_1(u + f_a) + D(x) + B_2 V_{dc} \\ y &= C_1 x + C_2 f_s \end{aligned}, \tag{1}$$

where $x = [x_1 \ \ x_2 \ \ x_3 \ \ x_4]^T = [i_{L1} \ \ v_{C1} \ \ i_{L2} \ \ v_{C2}]^T$ is the state vector. It contains the inductor current and capacitor voltage of the filter connected to the CPL(source), i.e. i_{L1} (i_{L2}) and $v_{C1}(v_{C2})$, respectively; the control input is the current of the energy storage unit and can be both positive or negative to inject or absorb power to the DC MG, respectively; V_{dc} is the voltage of the DC source; $f_a(f_s)$ stands for the actuator(sensor) fault; y is the output measurement. The actuator and sensor faults are modeled by additive terms [17], [23].

Also, the constant matrices, A, B_1, B_2, C_1, and C_2 and nonlinear functional matrix $D(x)$ are defined as follows:

$$A = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & 0 & 0 & 0 \\ 0 & 0 & -\frac{r_2}{L_2} & -\frac{1}{L_2} \\ -\frac{1}{C_2} & 0 & \frac{1}{C_2} & -\frac{1}{RC_2} \end{bmatrix}; B_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -\frac{1}{C_2} \end{bmatrix};$$

$$D(x) = \begin{bmatrix} 0 \\ \frac{-P}{C_1 v_{C1}} \\ 0 \\ 0 \end{bmatrix}; B_2 = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L_2} \\ 0 \end{bmatrix}; \tag{2}$$

$$C_1 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; \ C_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

where $r_1(r_2)$, $L_1(L_2)$, and $C_1(C_2)$ are the resistive, inductive, and capacitance values of the CPL(source) filter, R and P stand for the resistive and constant power loads, respectively.

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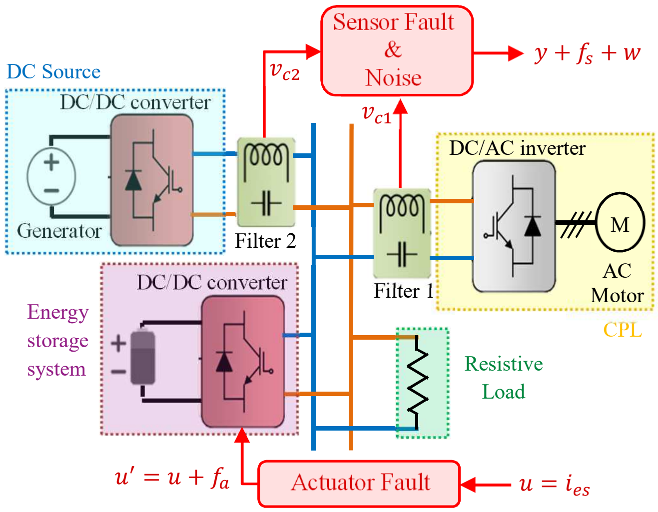

Fig. 1. The DC MG with CPL, resistive loads, actuator fault, sensor fault, and noise.

The goal of this work is to propose a fault-tolerant controller to adaptively regulate the DC bus voltage of the DC MG. Since only some states (i.e. x_2 and x_4) are measurable, it is desired that the state vector is estimated. This facilitates deploying the estimated state vector as the feedback in the controller. Appearing the faults degrades the estimation and control actions. To solve this issue, the state estimator should be enhanced so that it can estimate the faults as well. The CPL in the DC MG makes the dynamics nonlinear. Thereby, the estimator and the controller should be applicable to nonlinear systems to stabilize the power system, effectively. These challenges will be responded in the following parts.

III. Proposed Nonlinear Fault-Tolerant Controller

The proposed fault-tolerant controller involves two parts of the states and faults estimator and model predictive controller. These parts will be discussed in the following.

a) Dual-Extended Kalman Filter

The D-EKF algorithm is an improved version of the conventional EKF and can estimate the state and the called parameters of a nonlinear system, simultaneously.

To deploy the D-EKF, the faults can be treated as parameters and estimated. Although the faults can be time-varying, their dynamics are not known. Therefore, the following consideration is considered:

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

It is worth noting that although (3) indicates that the faults are constant, it is applicable for time-varying parameters [24], [25]. Also, to make the dynamics more accurate, system noise can be added to (3). The D-EKF mandates that the output is parameter-free, which is not the case of (1).

Therefore, the measurement equation of the faulty DC MG should be modified by introducing a filtered output $\mu = [\mu_1 \;\; \mu_2]^T$ as follows [17]:

$$\dot{\mu} = -\gamma\mu + \gamma y = -\gamma\mu + \gamma C_1 x + \gamma C_2 f_s, \tag{4}$$

where $\gamma < 0$.

Considering (4), it is possible to introduce a fault-free output as follows:

$$Y = \mu(t). \tag{5}$$

By defining the two vectors $X_1 = [x^T \;\; \mu]^T = [x_1 \;\; x_2 \;\; x_3 \;\; x_4 \;\; x_5 \;\; x_6]^T$ and $X_2 = [f_a \;\; f_s]^T = [x_7 \;\; x_8]^T$, reminding (1), (3), and (4), and using the Euler discretization method, one has

$$\begin{cases} \begin{bmatrix} X_1(k+1) \\ X_2(k+1) \end{bmatrix} = \begin{bmatrix} \Psi_{11}(k) & \Psi_{12}(k) \\ 0 & I \end{bmatrix} \begin{bmatrix} X_1(k) \\ X_2(k) \end{bmatrix} + T_s \bar{B}_1 u(k) \\ \qquad + T_s \bar{B}_2 V_{dc} + v(k) \\ Y(k) = \bar{C}_1 X_1(k) + w(k) \end{cases} \tag{6}$$

where T_s is the discretizing sample and

$$\bar{B}_1 = [B_1^T \;\; 0 \;\; 0]^T, \bar{B}_2 = [B_2^T \;\; 0 \;\; 0]^T,$$
$$\bar{C}_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$
$$\Psi_{11}(k) = I + T_s \left[\frac{\partial F_1(X)}{\partial X_1} \;\; \cdots \;\; \frac{\partial F_6(X)}{\partial X_1} \right]^T \Bigg|_{X_1 = X_1(k)}, \tag{7}$$
$$\Psi_{12}(k) = T_s \left[\frac{\partial F_1(X)}{\partial X_2} \;\; \cdots \;\; \frac{\partial F_6(X)}{\partial X_2} \right]^T \Bigg|_{X_1 = X_1(k)},$$

and

$$\begin{bmatrix} F_1(X) \\ F_2(X) \\ F_3(X) \\ F_4(X) \\ F_5(X) \\ F_6(X) \end{bmatrix} = \begin{bmatrix} -\frac{r_1}{L_1} x_1 - \frac{1}{L_1} x_2 + \frac{1}{L_1} x_4 \\ \frac{1}{C_1} x_1 - \frac{P_1}{C_1 x_2} \\ -\frac{r_2}{L_2} x_3 - \frac{1}{L_2} x_4 \\ \frac{1}{C_2} x_3 - \frac{1}{C_2} x_1 - \frac{x_4}{R C_2} - \frac{1}{C_2} x_7 \\ -\gamma x_5 + \gamma x_2 + \gamma x_8 \\ -\gamma x_6 + \gamma x_4 + \gamma x_8 \end{bmatrix}.$$

Also, $v(k)$ and $w(k)$ are system and measurement noises characterized by Gaussian function $\mathcal{g}$, respectively as follows:

$$v(k) \sim \mathcal{g}\left(0, \begin{bmatrix} Q_1 & 0 \\ 0 & Q_2 \end{bmatrix}\right), \quad w(k) \sim \mathcal{g}(0, Q_3). \tag{8}$$

These noises can represent the system uncertainties such as the discretizing error, and un-modeled dynamics such as energy storage dynamics.

Inspired from the dual estimation idea [24], [26], [27], in the following, D-EKF is developed for system (1):

- Initialize the state EKF by $\hat{X}_1^+(0)$ and $P_1^+(0)$.
- Initialize the fault EKF by $\hat{X}_2^+(0)$, $P_2^+(0)$, and $\Gamma_{X_2}^{X_1}(0)$.

where $\hat{X}_i^+(.)$ is the estimation of $X_i(.)$, $P_i^+(.)$ is the covariance matrix of the estimation error of $X_i(.)$, and $\Gamma_{X_2}^{X_1}(.)$ is an auxiliary state vector showing the interaction of the states and faults in the D-EKF. For $k \geq 1$, the following recursive algorithms should be performed:

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- Algorithm of the state-EKF

$$\begin{cases} \hat{X}_1^-(k) = \Psi_{11}(k)\hat{X}_1^+(k-1) + T_s B_1 u(k) + T_s B_2 V_{dc} \\ \qquad +\Psi_{12}(k)\hat{X}_2^+(k-1) \\ P_1^-(k) = \Psi_{11}(k)P_1^+(k-1)\Psi_{11}^T(k) + Q_1 \\ K_1(k) = P_1^-(k)\bar{C}_1^T(\bar{C}_1 P_1^-(k)\bar{C}_1^T + Q_3)^{-1} \\ \hat{X}_1^+(k) = \hat{X}_1^-(k) + K_1(k)\left(Y(k) - \bar{C}_1\hat{X}_1^-(k)\right) \\ P_1^+(k) = (I - K_1(k)\bar{C}_1)P_1^-(k) \end{cases} \tag{9}$$

- Algorithm of the fault-EKF

$$\begin{cases} P_2^-(k) = P_2^+(k-1) + Q_2 \\ K_2(k) = P_2^-(k)H_2^T(H_2 P_2^-(k)H_2^T(k) + Q_3)^{-1} \\ \hat{X}_2^+(k) = \hat{X}_2^+(k-1) + K_2(k)\left(Y(k) - \bar{C}_1\hat{X}_1^-(k)\right) \\ P_2^+(k) = (I - K_2(k)H_2)P_2^-(k) \\ \Gamma_{X_2}^{X_1}(k) = \Psi_{11}(k)(I - K_1(k)\bar{C}_1)\Gamma_{X_2}^{X_1}(k-1) \\ \qquad +\Psi_{12}(k) \end{cases} \tag{10}$$

where $H_2 = \bar{C}_1\Gamma_{X_2}^{X_1}(k-1)$.

Since the state-EKF and fault-EKF operate in parallel, if no fault occurs or a constant fault occurs, the fault-EKF can be stopped, and in the state-EKF $\hat{X}_2^+(k) = 0$ or $\hat{X}_2^+(k) = \hat{X}_2^*$, where $\hat{X}_2^*$ is the last estimated constant value of the faults, in (9). The output of the D-EKF corresponds to system states and faults, which will be deployed in the fault-tolerant controller.

b) *Nonlinear TS-based MPC Controller*

Since the system dynamics are nonlinear, a nonlinear MPC based on a Takagi-Sugeno (TS) fuzzy model is deployed. Also, to deal with faults, future system behavior in the presence of faults should be calculated. After that, the control law is designed. In the following, these issues are studied.

For the desired reference for the DC MG bus x_2^* and letting $\dot{x} = 0$ in (1), the desired references for the other states and control input can be obtained as follows:

$$x_1^* = \frac{P}{x_2^*}; x_4^* = x_2^* + \frac{r_1 P}{x_2^*}; x_3^* = \frac{x_4^* - V_{dc}}{r_2}; \\ u^* = x_3^* - x_1^* - \frac{x_4^*}{R} - f_a \tag{11}$$

Defining $\bar{x} = x - x^*$ where $x^* = [x_1^*, x_2^*, x_3^*, x_1^*]^T$ and $\bar{u} = u - u^*$, the dynamics (1) are re-written as follows:

$$\dot{\bar{x}} = A\bar{x} + B_1\bar{u} + D(x) - D(x_d). \tag{12}$$

To deal with the nonlinearity term $D(x) - D(x_d)$, TS fuzzy modeling is deployed. TS fuzzy representation of a nonlinear system is a fuzzy aggregation of linear subsystems. This fuzzy model facilitates computing the future behavior of the system by formulating the nonlinear dynamics in a quasi-linear form. For the region $\mho = \{x_2 | \, \theta_1 \le x_2 \le \theta_2\}$, where $\theta_1 \le x_2^* \le \theta_2$, the term $\frac{1}{x_2} - \frac{1}{x_2^*}$ is within lower and upper sectors $\sigma_1 x_2$ and $\sigma_2 x_2$, as shown in Fig. 2. Therefore,

$$\sigma_1 x_2 \le \frac{1}{x_2} - \frac{1}{x_2^*} \le \sigma_2 x_2, \tag{13}$$

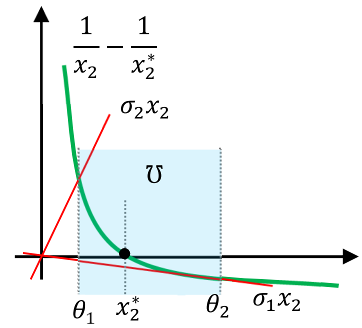

Fig. 2. Sector region of the nonlinear term $1/x_2 - 1/x_2^*$.

where

$$\sigma_1 = \frac{x_2^* - \theta_2}{\theta_2^2 x_2^*}; \sigma_2 = \frac{x_2^* - \theta_1}{\theta_1^2 x_2^*}, \tag{14}$$

and $\sigma_1 = 1/\theta_2^2$ and $\sigma_2 = 1/\theta_1^2$. Inspired from the sector nonlinearity, consider the following equalities:

$$\begin{cases} \frac{1}{x_2} - \frac{1}{x_2^*} = \beta_1\sigma_1 x_2 + \beta_2\sigma_1 x_2 \\ \beta_1 + \beta_2 = 1 \end{cases}. \tag{15}$$

Solving (15) to calculate the fuzzy membership functions β_i for $i = 1,2$, results into

$$\beta_1 = \frac{\sigma_2 x_2 + 1/x_2^* - 1/x_2}{(\sigma_2 - \sigma_1)x_2}; \\ \beta_2 = \frac{1/x_2 - 1/x_2^* - \sigma_1 x_2}{(\sigma_2 - \sigma_1)x_2}. \tag{16}$$

Substituting (15) into (1) results a 2-rule TS fuzzy system, as follows:

$$\left\{ \dot{\bar{x}} = \sum_{i=1}^{2} \beta_i \{A_i\bar{x} + B_1\bar{u}\}. \right. \tag{17}$$

where

$$A_1 = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & -\frac{P_1}{C_1}\sigma_1 & 0 & 0 \\ 0 & 0 & -\frac{r_2}{L_2} & -\frac{1}{L_2} \\ -\frac{1}{C_2} & 0 & \frac{1}{C_2} & \frac{1}{RC_2} \end{bmatrix},$$

and

$$A_2 = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & -\frac{P_1}{C_1}\sigma_2 & 0 & 0 \\ 0 & 0 & -\frac{r_2}{L_2} & -\frac{1}{L_2} \\ -\frac{1}{C_2} & 0 & \frac{1}{C_2} & \frac{1}{RC_2} \end{bmatrix}.$$

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The TS fuzzy system (17) is discretized by the Euler discretizing method with the sampling time T_s, as follows:

$$\{\bar{x}(k+1) = \Psi(k)\bar{x}(k) + T_s B_1 \bar{u}(k), \tag{18}$$

where $\Psi(k) = I + T_s \sum_{i=1}^{2} \beta_i(x(k))A_i$.

Based on (18), the future behavior of the system is formulated. To do this, the freezing method [21], [28] is utilized in which $\Psi(k+s) = \Psi(k)$ for $s > 0$. Therefore, one gets:

$$\bar{X} = \begin{bmatrix} \Psi(k) \\ \Psi(k)^2 \\ \vdots \\ \Psi(k)^{N_p} \end{bmatrix} \bar{x}(k) + \begin{bmatrix} T_s B_1 & \dots & 0 \\ T_s\Psi(k)B_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ T_s\Psi(k)^{N_p-1}B_1 & \dots & T_s\Psi(k)^{N_p-N_u+1}B_1 \end{bmatrix} \bar{U}, \tag{19}$$

where $\bar{X} = [\hat{x}(k+1|k)\ \hat{x}(k+2|k)\ \dots\ \hat{x}(k+N_p|k)]^T$, $\hat{x}(k+j|k)$ is the j-step ahead prediction of the state $\bar{x}$ and $\bar{U} = [\bar{u}(k)\ \bar{u}(k+1) \dots\ \bar{u}(k+N_u-1)]^T$. Equation (19) can be expressed in a vector form as

$$\bar{X} = \bar{\Upsilon} + \bar{\Theta}\bar{U}, \tag{20}$$

where

$$\bar{\Upsilon} = \begin{bmatrix} \Psi(k) \\ \Psi(k)^2 \\ \vdots \\ \Psi(k)^{N_p} \end{bmatrix} x(k),$$

$$\bar{\Theta} = \begin{bmatrix} T_s B_1 & \dots & 0 \\ T_s\Psi(k)B_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ T_s\Psi(k)^{N_p-1}B_1 & \dots & T_s\Psi(k)^{N_p-N_u+1}B_1 \end{bmatrix}.$$

To design the control input vector $\bar{U}$, a minimization problem with the following cost function is considered:

$$J(N_p, N_u) = (\bar{X} - \bar{W})^T \bar{\Delta}(\bar{X} - \bar{W}) + \bar{U}^T \bar{\Lambda}\bar{U}. \tag{21}$$

where $\bar{W} = [w(t+1)\ \ w(t+2)\ \dots\ w(t+N_p)]^T$ is the vector of future references, $\bar{\Delta} = \mathrm{diag}\{\delta(1), \delta(2), \dots \delta(N_p)\}$ and $\bar{\Lambda} = \mathrm{diag}\{\lambda(1), \lambda(2), \dots, \lambda(N_p)\}$ are cost function weight vectors, diag{.} stands for a diagonal matrix. By substituting (20) into (21), one gets

$$J(N_p, N_u) = \bar{U}^T \bar{H}\bar{U} + \bar{K}\bar{U} + \bar{U}^T\bar{K}^T + \bar{G}, \tag{22}$$

where

$$\bar{H} = \bar{\Theta}^T\bar{\Delta}\bar{\Theta} + \bar{\Lambda} > 0,\ \ \bar{K} = (\bar{\Upsilon} - \bar{W})^T\bar{\Delta}\bar{\Theta},$$
$$\bar{G} = (\bar{\Upsilon} - \bar{W})^T\bar{\Delta}(\bar{\Upsilon} - \bar{W}).$$

The analytic solution of minimizing the cost function J given in (22) with respect to U is as follows:

$$\bar{U} = -\bar{H}^{-1}\bar{K}^T. \tag{23}$$

The first array of the $\bar{U}$, i.e. $\bar{u}(k)$, is the control input law for (12). Using the change of variables based on (11), the control input law for the DC MG is obtained as $u(k) = \bar{u}(k) + u^*$. Also, since the desired value of the control input u^* is a function of f_a, it is constructed based on the estimation of actuator fault.

The closed-loop system based on the stable filter (4), D-EKF (9) and (10), and the control law (23) are given in Fig. 3. The measurements of the system are applied to the stable filter to construct artificial outputs. Then, the D-EKF is utilized to estimate the state and faults vectors. Based on the desired reference and the estimations, the controllable energy storage current is designed.

IV. Simulation Results

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

It is worth noting that the parameters of the filter are chosen similarly to [21]. Inspired from [1], the sensor and actuator faults are selected to cover real behaviors, including time-varying or constant and prompt or smooth changing. Two scenarios are considered. In the first one, the performance of the developed D-EKF in estimating the faults and states is evaluated. Then, the performance of the fault-tolerant MPC is studied in the second scenario. For both scenarios, comparative results are also given to illustrate the advantages of the proposed methods.

To have a fair comparison, the same initial conditions for the filters and the same weights for the cost functions for the proposed approach and state-of-the-art methods are considered.

Scenario 1: In this scenario, the energy storage current is set as $i_{es} = 0$, although the system is subjected to actuator fault, which highly affects the power system. Also, the voltage measurement of the CPL, i.e. x_2, is subjected to the sensor fault and the convertor voltage of the source, i.e. x_4, is measured correctly. To evaluate the applicability of the D-EKF, two stepwise and smooth time-varying functions are considered for the actuator and sensor faults as follows:

$$f_a = \begin{cases} 0 & 0 \le t \le 1 \\ 1 & 1 < t \le 4 \\ -1 & 4 < t \end{cases}$$
$$f_s = \begin{cases} 0 & 0 \le t \le 4 \\ \sin\left(\dfrac{2\pi(t-4)}{3}\right) & 4 < t \end{cases} \tag{24}$$

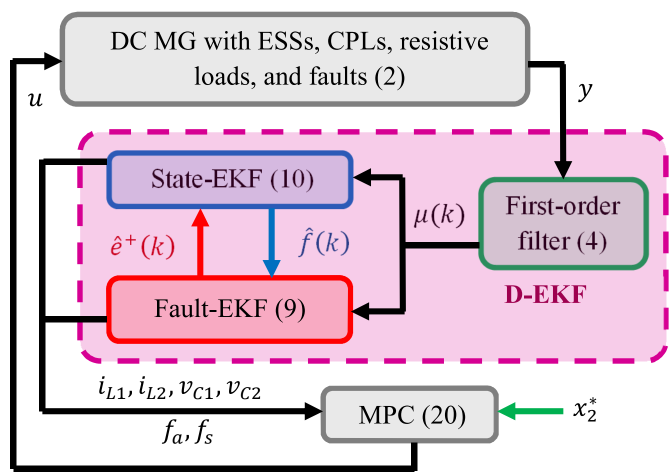

Fig. 3. Implementation of the proposed estimation method.

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To implement the D-EKF, the parameter of first-order (4) is $\gamma = 0.1$. The parameters of the D-EKF initials are given in Table 1.

The actual value and estimation of the DC MG states are provided in Fig. 4. As can be seen in Fig. 4, when the actuator fault value changes, the system states react and experience oscillations. However, the D-EKF accurately estimates the states in about $0.5\,(sec)$. Reminding the amplitude of the currents and voltages of the DC MG system, Fig. 4 reveals that the estimation error amplitudes are neglectable. Also, the estimation error converges to zero.

TABLE 1. D-EKF INITIALS FOR SCENARIO 1.

State-EKF
$\hat{X}_1^+(0) = [1\ 200\ \ 1\ 200\ 0\ 0]^T$; $P_1^+(0) = 10^3 I_6$; $Q_e = 10^{-5} I_6$; $R_e = 1^{-4} I_2$
Fault-EKF
$\hat{X}_2^+(0) = [0\ \ 0]^T$; $P_2^+(0) = 10^3 I_2$; $\Gamma_{X_2}^{X_1}(0) = 0_{6\times 2}$; $Q_f = diag\,\{10^2, 10\}$; $R_f = diag\{10^{-2}, 10^{-2}, 10^{-4}, 10^{-4}\}$

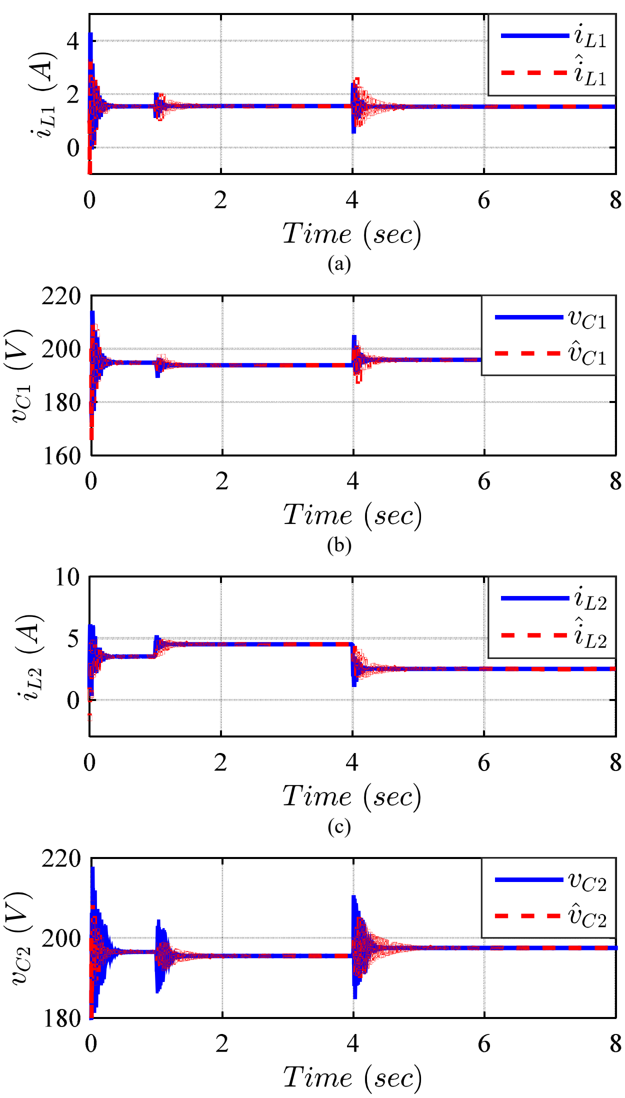

Fig. 4. The states and their estimations (Actual value by the blue line and the estimated value by the red line): (a). x_1, (b). x_2. (c). x_3, (d). x_4.

The actual and estimation of the faults are provided in Fig. 5. The results illustrate that the D-EKF algorithm estimates the actuator fault about 1.3 times faster than the sensor fault. Since D-EKF needs a transient time response to estimate the correct values of faults. Therefore, for the case of a fast actuator fault, the overall estimator produces a small estimation error to all states and faults. However, for the case of slowly varying sensor fault the D-EKF tracks the faults.

To illustrate the performance improvement and online computational reduction of the D-EKF, it is compared with conventional EKF [25] and augmented joint-EKF [24]. The estimation error indices and computational burden per iteration of all approaches are given in Table 2.

The estimation errors are calculated based on norm 1 (sum of the absolute value of a signal) and bias error (the absolute value of the last quantity of a signal). It is worth noting that to better provide the results, the error indices are normalized by multiplying by 10^{-3} and 10^3, respectively.

Table 2 affirms less computational burden belongs to the conventional EKF [25], but it fails to estimate the faults and provide accurate state estimation. More especially, the norm 1 and bias value of the estimations based on conventional EKF are about 16 and 113 times bigger than those of the D-EKF and augmented joint-EKF, respectively.

Contrary to the conventional EKF, the augmented joint-EKF [24] and the proposed D-EKF estimate the faults and states, precisely. Meanwhile, the proposed approach has less computational burden than the augmented joint-EKF and performs about 2 times faster than the augmented joint-EKF.

Scenario 2: The performance of the fault-tolerant MPC is studied in this scenario. As discussed in Scenario 1, stepwise varying faults are more challenging than the slowly varying ones. Therefore, the following actuator and sensor faults are considered:

$$f_a = \begin{cases} 0 & 0 \le t \le 1 \\ 1 & 1 < t \le 4 \\ -1 & 4 < t \end{cases};\quad f_s = \begin{cases} 0 & 0 \le t \le 4 \\ 1 & 4 < t \end{cases} \tag{25}$$

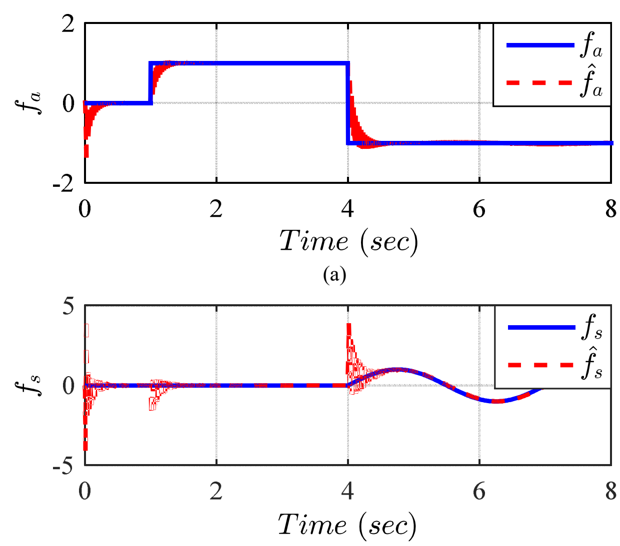

Fig. 5. The actuator and sensor faults and their estimations (Actual value by the blue line and the estimated value by the red line): (a). f_a, (b). f_s.

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TABLE 2. PERFORMANCE COMPARISONS OF KALMAN FILTERS.

Results \ Approach		Proposed approach	Conventional EKF [25]	Augmented joint-EKF [24]
Computational burden × 10^4		3.0621	2.0412	6.2534
Norm 1 of estimation error × 10^{-3}	x_1	1.3263	4.6983	1.1528
	x_2	8.0585	37.6723	8.1391
	x_3	2.4762	35.1053	2.4514
	x_4	4.5437	37.0002	4.9072
	f_a	1.5525	Not estimated	1.5991
	f_s	2.9492	Not estimated	3.0288
Bias value of estimation error × 10^3	x_1	0.0498	7.9476	0.0478
	x_2	8.8966	1006.737	9.2525
	x_3	7.9661	997.9626	7.8625
	x_4	8.7304	997.9687	8.9923
	f_a	1.4521	Not estimated	1.4666
	f_s	2.4973	Not estimated	2.9864

Applying the proposed D-EKF fault-tolerant MPC with the desired bus voltage $x_2^* = 200\ V$ is used to stabilize the DC MG power system. The initial voltage of the DC bus is set as $190\ V$. This can occur if the desired voltage level changes because of different operating modes. The results of the proposed control method and [21] are given in Fig. 6.

The approach of [21] uses a method to deal with the system state estimation and predictive control similar to this paper. However, in that approach, the effect of faults on the estimation and control is not mitigated.

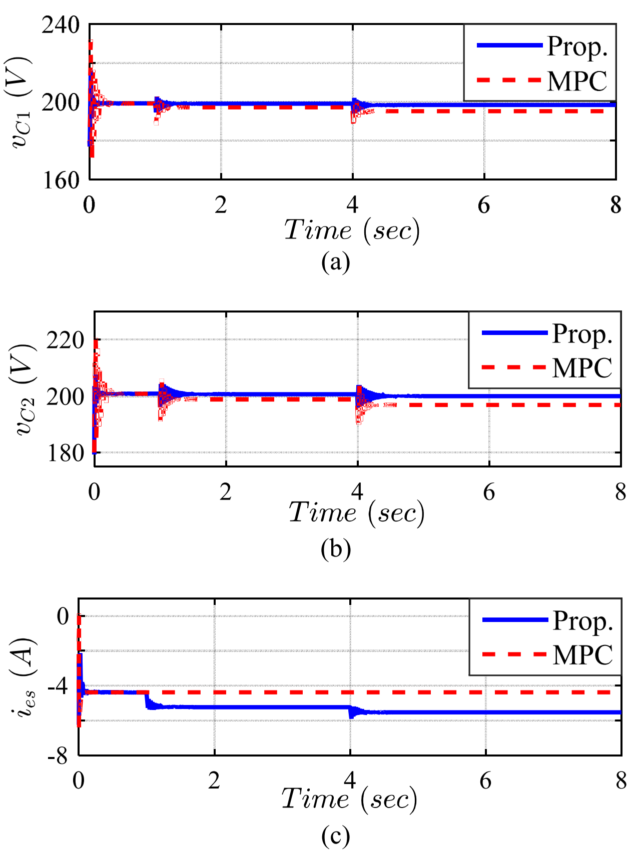

Fig. 6. The states and their estimations (Proposed approach the blue line and the MPC [21] by the red line): (a). x_2, (b). x_4. (c). u.

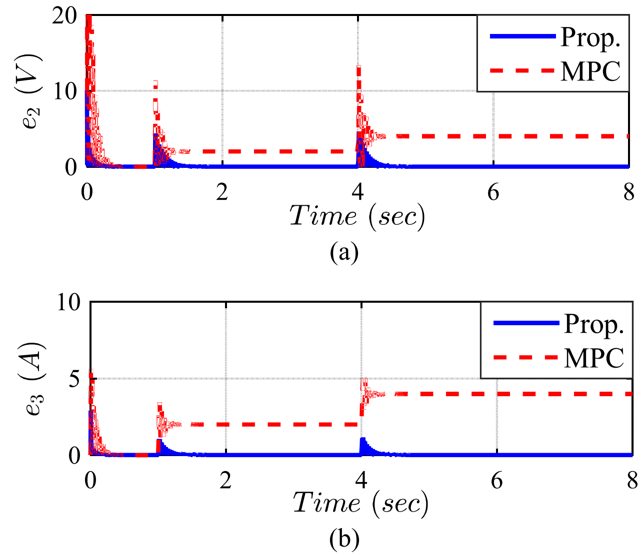

Fig. 7. The absolute value of the estimation error states (Proposed approach the blue line and the MPC [21] by the red line): (a). x_2, (b). x_3.

The reason that the approach [21] is used for comparison is that that approach uses a similar control strategy as the proposed work. More specifically, both methods use a nonlinear Kalman filter to estimate the system states and a state-feedback nonlinear fuzzy controller to manipulate the DC/DC converter. The results show that although both approaches stabilize the DC MG, the developed fault-tolerant controller rejects the effects of faults on the DC bus voltage.

Fig. 7 shows two estimation errors of the DC MG system. Since the actual values of the closed-loop system based on the proposed approach and the MPC [21] differs, the estimation error is presented to study the effect of faults on the estimation. The estimation errors of the second and third states are given as samples and the others are not provided to save space. Fig. 7 reveals that the proposed D-EKF outperforms the conventional estimator of [21].

V. CONCLUSION

This work focused on the issue of stabilizing a typical nonlinear DC MG in the presence of sensor and actuator faults. It was considered that some states of the system are measurable subject to faults and noise. Based on a D-EKF, the DC MG states were estimated such that the effect of faults was eliminated. The estimated information was then used in a nonlinear TS fuzzy fault-tolerant predictive controller, which was suggested to regulate the DC bus voltage. Since the faults were avoided in the estimation and control process, the DC voltage was precisely regulated. Simulation results showed that the proposed approach outperforms the state-of-the-art estimators and predictive controllers in which faults were not treated. More precisely, the estimation and tracking errors based on the proposed approach are zero. On the other hand, the proposed approach is not robust against parameter uncertainty and the state-space representation of the power system should be given in prior. For future work, considering unknown CPLs and loads and multi-area DC MG power systems, and extending the results of this work to cyber-attacks in more-electric transportation systems are suggested.

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Navid Vafamand received his B.Sc. degree in electrical engineering and M.Sc. degree in control engineering form Shiraz University of Technology, Iran, in 2012 and 2014, respectively, and Ph. D. in control engineering at Shiraz University, Shiraz, Iran, in 2019. Currently, he serves as a research assistant at Shiraz University. He was a Ph.D. Visiting student with the Department of Energy Technology, Aalborg University, Denmark, from 2017 to 2018. Dr. Vafamand is the co-author of more than 100 international conference and journal papers and two chapter-books and an active reviewer in several journals. He is among the top 2% of scientists in the world based on the Scopus database for the 2020 single year. His main research interests include Takagi-Sugeno (TS) fuzzy systems, linear parameter varying (LPV) models, predictive control, and DC microgrids.

Mohammad Mehdi Arefi (Senior Member, IEEE) was born in 1982. He received the B.Sc. degree from the Department of Electrical Engineering, Shiraz University, Shiraz, Iran, in 2004, and the M.Sc. and Ph.D. degrees from the Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran, in 2007 and 2011, respectively. He is an Associate Professor with the Department of Power and Control Engineering, School of Electrical and Computer Engineering, Shiraz University. His current research interests include adaptive robust control, nonlinear control, system identification, and application of control methods in power systems.

Mohammad Hassan Asemani received his B.Sc. degree in 2006 from the electrical engineering department of the Shiraz University, Shiraz, Iran. He then received his M.Sc. and Ph.D. degrees in Control Engineering from the electrical and computer engineering department of Tarbiat Modares University, Tehran, Iran in 2008 and 2012, respectively. He received a one-year scholarship award of the Ministry of Science, Research and Technology of Iran in 2012. He is now an associate professor in the power & control department of Shiraz University, Shiraz, Iran. His areas of interest include T-S fuzzy control, Linear Parameter Varying (LPV) systems, fractional-order systems, Observer-based control, Linear Matrix Inequalities in Control.

Mohammad Sadegh Javadi (Senior Member, IEEE) received the B.Sc. degree from Shahid Chamran University of Ahwaz, Iran in 2007, M.S.c in Power System from University of Tehran in 2009 and the Ph.D. degree in the field of Electrical Power Engineering from Shahid Chamran University of Ahwaz, Iran in 2014. He is an Associate Professor at IAU, Shiraz, Iran and currently is a Researcher at INESC TEC, Porto, Portugal. He is serving as an Associate Editor of E-Prime Journal from 2021 and he received the Best Reviewer Awards from IEEE TRANSACTIONS ON SMART GRID and IEEE TRANSACTIONS ON POWER SYSTEM in 2019. His research interests include Power System Operations and Planning, Multi-Carrier Energy Systems, Islanding Operation of Active Distribution Networks, Distributed Renewable Generation, Demand Response and Smart Grid.

Fei Wang (Senior Member, IEEE) received the B.Sc. degree from Hebei University, Baoding, China in 1993, the M.Sc. and Ph.D. degree in Electrical Engineering from North China Electric Power University (NCEPU), Baoding, China, in 2005 and 2013, respectively. He is currently a Professor with the Department of Electrical Engineering, NCEPU and the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, Baoding and Beijing, China. He is the Director of Smart Energy Network Integrated Operation Research Center (SENIOR) and the Leader of "Double First-Class" research team project at NCEPU. He was a Visiting Professor with the Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, USA, from 2016 to 2017. He was a Researcher with the Department of Electrical Engineering, Tsinghua University, Beijing, China, from 2014 to 2016.

He is an Associate Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, the IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS, the IEEE POWER ENGINEERING LETTERS, the IEEE OPEN ACCESS JOURNAL OF POWER AND ENERGY, the IET RENEWABLE POWER GENERATION, the FRONTIERS IN ENERGY RESEARCH, the PROTECTION AND CONTROL OF MODERN POWER SYSTEMS (Springer), and the E-PRIME JOURNAL (Elsevier). He was the *Guest Editor-in-Chief* for the Research Topic "*Source-Grid-Load-Storage Collaborative and Interactive Optimization Control Technology of New Types of Active Distribution Network*" of the FRONTIERS IN ENERGY RESEARCH, and the *Guest Editor* for the special issue "*Demand Side Management and Market Design for Renewable Energy Support and Integration*" of the IET RENEWABLE POWER GENERATION. He is an IEEE Senior Member and the Expert Member of *IEC SC8A/WG2*. He supervised more than 80 Postdocs, Ph.D. and M.Sc. students. He has authored or coauthored more than 260 publications, including 100 international journal papers.

He was the recipient of the 2021 Elsevier China Highly Cited Scholar, the *2020 Science and Technology Progress First Award* of Hebei Province, *2018 Technical Invention First Award* of Hebei Province, the *2018 Patent Third Award* of Hebei Province, the *2014 Natural Sciences Academic Innovation Achievement Award* of Hebei Province, the *2018 China Electric Power Science and Technology Progress Third Award*, and the *2014 Outstanding Doctoral Dissertation Award* of NCEPU. He was the General Chair of the 2017 International Seminar of Renewable Energy Power Forecasting and Absorption Technology and 2018 International Seminar of Integrated Energy and Smart Microgrid Technology. He was the member of Series Steering Committee and Program Committee of 1st to 5th *International Conference on Smart Energy Systems and Technologies* (SEST) from 2018 to 2022. He was also the member of Scientific Advisory Board of 14th to 17th *International Conference on Sustainable Development of Energy, Water and Environment Systems* (SDEWES) from 2019 to 2022.

His research interests include renewable energy power/electricity price/electricity load forecasting, electricity market, demand response, smart grid, microgrid and integrated energy system.

João P. S. Catalão (Fellow, IEEE) received the M.Sc. degree from the Instituto Superior Técnico (IST), Lisbon, Portugal, in 2003, and the Ph.D. degree and Habilitation for Full Professor ("Agregação") from the University of Beira Interior (UBI), Covilha, Portugal, in 2007 and 2013, respectively. Currently, he is a Professor at the Faculty of Engineering of the University of Porto (FEUP), Porto, Portugal, and Research Coordinator at INESC TEC. He was also appointed as Visiting Professor by North China Electric Power University (NCEPU), Beijing, China.

He was the Primary Coordinator of the EU-funded FP7 project SiNGULAR ("Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration"), a 5.2-million-euro project involving 11 industry partners. He was also the Principal Investigator of 3 funded projects by FCT (Portuguese National Funding Agency for Science, Research and Technology) and FEDER (European Regional Development Fund). Moreover, he has authored or coauthored more than 975 publications, including 485 international journal papers (more than 165 IEEE TRANSACTIONS/JOURNAL papers, 218 Elsevier and 22 IET journal papers), 443 international conference proceedings papers (vast majority co-sponsored by IEEE), 4 books and 43 book chapters, with an h-index of 77, an i10-index of 419, and more than 23,000 citations (according to Google Scholar), having supervised more than 110 post-docs, Ph.D. and M.Sc. students, and other students with project grants.

He was the inaugural Technical Chair of SEST 2018 — 1st International Conference on Smart Energy Systems and Technologies (technically co-sponsored by IEEE IES), the General Chair of SEST 2019 (technically co-sponsored by IEEE PES and IEEE IES), the General Co-Chair of SEST 2020 (technically co-sponsored by IEEE PES, IEEE IES and IEEE IAS), and the Honorary Chair of SEST 2021 (technically co-sponsored by IEEE PES, IEEE IES, IEEE IAS and IEEE PELS). He was also the Editor of the books entitled "Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling" and "Smart and Sustainable Power Systems: Operations, Planning and Economics of Insular Electricity Grids" (Boca Raton, FL, USA: CRC Press, 2012 and 2015, respectively).

He is an Associate Editor of the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS: SYSTEMS, the IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS, the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, the IEEE TRANSACTIONS ON CLOUD COMPUTING, and the IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS. He was the Senior Editor of the IEEE TRANSACTIONS ON SMART GRID and the Promotion and Outreach (Senior) Editor of the IEEE OPEN ACCESS JOURNAL OF POWER AND ENERGY, 2020-2021, being also a member of the IEEE PES Publications Board. Furthermore, he was an Associate Editor of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, 2011-2018, an Associate Editor of the IEEE TRANSACTIONS ON SMART GRID, 2013-2020, an Associate Editor of both the IEEE TRANSACTIONS ON POWER SYSTEMS and the IEEE POWER ENGINEERING LETTERS, 2017-2021, and an Associate Editor of both the IEEE SYSTEMS JOURNAL and the IEEE ACCESS, 2020-2022.

He was the Guest Editor-in-Chief for the Special Section on "Real-Time Demand Response" of the IEEE TRANSACTIONS ON SMART GRID, published in December 2012, the Guest Editor-in-Chief for the Special Section on "Reserve and Flexibility for Handling Variability and Uncertainty of Renewable Generation" of the IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, published in April 2016, the Corresponding/Lead Guest Editor (*Guest Editor-in-Chief*) for the Special Section on "Industrial and Commercial Demand Response" of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, published in November 2018, the *Guest Co-Lead Editor* for the Special Section on "Invited Papers on Emerging Topics in the Power and Energy Society" of the IEEE OPEN ACCESS JOURNAL OF POWER AND ENERGY, published in October 2020, the Guest Co-Lead Editor for the Special Section on "Invited Papers in 2021 on Emerging Topics in the Power and Energy Society" of the IEEE OPEN ACCESS JOURNAL OF POWER AND ENERGY, published in November 2021, and the *Guest Editor-in-Chief* for the Special Section on "Demand Response Applications of Cloud Computing Technologies" of the IEEE TRANSACTIONS ON CLOUD COMPUTING, published in March 2022.

He was the recipient of the 2011 Scientific Merit Award UBI-FE/Santander Universities, the 2012 Scientific Award UTL/Santander Totta, the 2016-2020 (five years in a row) FEUP Diplomas of Scientific Recognition, the 2017 Best INESC-ID Researcher Award, and the 2018 Scientific Award ULisboa/Santander Universities (with an Honorable Mention in 2017). He was recognized as one of the Outstanding Associate Editors 2020 of the IEEE TRANSACTIONS ON SMART GRID, and also one of the Outstanding Associate Editors 2021 of the IEEE TRANSACTIONS ON POWER SYSTEMS. He has multiple Highly Cited Papers in Web of Science. He is a Top Scientist in Research.com, which lists only scientists having h-index equal or greater than 30. He is also among the 0.5% Top Scientists, according to a study published by a team at Stanford University. Furthermore, he has won 5 Best Paper Awards at IEEE Conferences (MELECON, POWERENG, SEGE, EDST, SCEMS) and the MPCE Best Paper Award 2019. Moreover, his former M.Sc. and Ph.D. students have won the National Engineering Award in 2011, the 1st Prize in the REN (Portuguese TSO) Award in 2019, and the 1st Prize in the Young Engineer Innovation Award in 2020.

His research interests include power system operations and planning, power system economics and electricity markets, distributed renewable generation, demand response, smart grid, and multi-energy carriers.