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Fault Reconstruction of Islanded Nonlinear DC Microgrids: An LPV-based Sliding Mode Observer Approach

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Abstract—This paper investigates the problem of fault detection and reconstruction in direct current microgrids (DC MGs) with nonlinear loads. First, a state-space representation of the DC MG with nonlinear constant power loads (CPLs) is obtained. The faults in components, actuators, and sensors in a DC MG system are modeled by using additive terms in the state-space and measurement equations. A novel robust nonlinear detector is then proposed to estimate and reconstruct the faults. The proposed detector deploys a sliding mode technique and a polytopic linear parameter varying (LPV) approach. The proposed approach utilizes the robustness and simplicity offered by the sliding mode and polytopic LPV approaches to provide a simple, but effective, detector. By employing the Lyapunov stability theory, sufficient detector design conditions are derived in terms of linear matrix inequalities (LMIs) which are numerically solved by convex optimization techniques. The proposed approach is experimentally tested on a practical DC MG benchmark connected to a CPL. Furthermore, the results are compared with other state-of-the-art methods.

Index Terms — DC microgrid, fault detection and reconstruction, constant power load, polytopic linear parameter varying (LPV) model, sliding mode detector, linear matrix inequality (LMI).

I. INTRODUCTION

Microgrids (MGs) have been introduced to provide an effective way of integrating various distributed renewable energy sources [1]. The MGs are classified into DC and AC ones. There has been a great deal of research on AC MGs, mainly due to its compatibility with traditional AC electrical power systems. On the other hand, in applications involving renewable DC sources (e.g., wind and photovoltaics) and DC electronic loads, the DC MGs are more suitable and cost-effective than conventional AC MGs [1]. Due to avoiding frequency control, regulation of the DC MGs is simpler than AC MGs. However, there is a growing share of loads which are tightly controlled by power converters in DC MGs. Such loads are nonlinear since they act as CPLs. In the small-signal sense, they exhibit negative incremental resistance which may destabilize the overall system. In recent years, the stability issue of the CPLs in the DC MGs has been widely investigated with

several control methods proposed such as backstepping [2], robust linear [3], fuzzy-model-based [4], (linear parameter varying) LPV-based reset [5], and model predictive control [6]. However, in these control approaches, it is assumed that the overall system operates without any faults. Indeed, a literature search indicates that the fault operation of islanded DC MGs that feed CPLs has been rarely investigated. On the other hand, rigorous faults may damage the MG's components if they are not identified and compensated properly [7]. The faults can originate either from the dysfunctionality of individual components or connections of the conductors to ground and/or each other. These faults can also be categorized as *steady-state* and *transient*. In [8], different faults were considered and applied to a DC MG with multiple CPLs, and a robust fault-tolerant control (FTC) method was suggested. However, the aforementioned approach uses a fault-tolerant controller for each of the CPLs, which is not cost-effective. In [9], [10], the effect of sensor fault on a typical DC MG was investigated. In [8]–[10], a robust controller or monitoring technique was presented to mitigate the effect of the occurring faults; however, the faults were not reconstructed. In [11], the above methods were classified as passive FTC methods, in which the controller can guarantee the reliability of systems in the presence of weak faults with limited amplitudes. In the active FTC techniques, the information about faults is required. Such information is then exploited in the controller to actively mitigate faults. The fault information is obtained by a fault detection and isolation (FDI) scheme. This fact illustrates the importance of applying FDI techniques to practical systems [9]. The main objectives of the FDI are to initially produce an alarm when a fault is detected, followed by diagnosing the faults by determining their location and structure [13].

Among the existing FDI methods, observer-based ones have attracted a great deal of attention due to their effectiveness and theoretical merits [14]. The rationale behind observer-based FDI is to estimate both the states and faults of a system based on the available measurements [13]. Sliding mode observer (SMO) is one of the most effective and robust observer-based FDI methods, which aims at estimating the actuator and sensor faults. The superiority of the SMOs is their resiliency against uncertainties and external perturbations [12]. In [15], a linear

state-space representation was obtained and an SMO was developed for AC and DC MGs. However, CPLs in MGs would introduce significant nonlinearities. Thereby, a nonlinear SMO (NSMO) is required. Since NSMOs have a complex design procedure in nonlinear systems, the combination of conventional NSMOs and polytopic LPV models is presented in this paper as a solution that can offer a systematic scheme for the FDI issue.

Recently, several papers have exploited the LPV-based NSMOs as a tool for the detection and isolation of faults in continuous-time systems, in which the time-varying parameters are assumed to be measurable [16]–[19]. Other works extend the results to the systems with unmeasurable time-varying parameters [20], [21]. In [16]–[20], a quadratic Lyapunov function (QLF) was proposed to investigate the stability of the system. These approaches escalate the conservative nature of FDI methods and thereby degrade the FDI transient and steady-state performances, or may lead to unfeasible results. In this paper, a systematic and highly effective approach for FDI of DC MGs with nonlinear CPLs is proposed. The presented approach is based on the NSMO, the polytopic LPV model, and a parameter-dependent Lyapunov function (PDLF). The main contributions of this paper are as follows. First, the proposed approach can reconstruct additive actuator and sensor faults. To the best knowledge of the authors, this paper is the first attempt to study and reconstruct the occurring faults of nonlinear stand-alone DC MGs feeding CPLs, which is one of the major contributions of this paper. Furthermore, utilizing the PDLF method provides less conservative LMI conditions and brings about faster and more accurate fault reconstructions. The proposed approach is applicable to a wide range of nonlinear systems which can be represented by a polytopic LPV representation with unmeasurable premise variables. The polytopic LPV approach has certain advantages over other nonlinear methods. First, its design procedure is simple and mainly based on the linear systems theory. Secondly, it offers a systematic approach to design an observer. Moreover, the observer gains are computed via LMI techniques. Finally, an experimental DC MG with one CPL is considered as a case study. The merits of the proposed FDI method over existing methods are illustrated by applying them to the case study and comparing the obtained results.

This paper is organized as follows: Section II presents the class of DC MG with CPLs. Section III presents the derivation of the polytopic-LPV model of DC MG. In Section IV, the proposed NSMO approach is discussed. Section V presents experimental results and conclusions are presented in Section VI.

II. DC MICROGRID DYNAMICS

A simplified circuit diagram of the DC MG considered in this paper comprises of AC and/or DC sources, constant power loads (CPLs), energy storage units, and RLC filters. This structure of DC MGs is shown in Fig. 1, which is widely utilized in several applications including more electric aircraft, ships, and automotive systems [3], [22].

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 Q CPLs, as shown in Fig. 2, is obtained as follows [3]

$$\dot{x} = Ax + DH + B_{es}i_{es} + B_sV_{dc} \quad (1)$$

where $x = [x_1^T \ x_2^T \ \dots \ x_Q^T \ x_s^T]^T$, $x_j = [i_{L,j} \ v_{C,j}]^T$ is the state vector of the j -th CPL filter comprises the current of the j -th inductor and the voltage of the j -th capacitor, respectively, $x_s = [i_{L,s} \ v_{C,s}]^T$, i_{es} is the control input of system associated with the ESS, and V_{dc} is the voltage of the DC source. Also, $H = [h_1, \dots, h_Q]^T$ with $h_j = \frac{1}{v_{C,j}}$ and

$$A = \begin{bmatrix} A_1 & 0 & \dots & 0 & A_{1s} \\ 0 & A_2 & \dots & 0 & A_{2s} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & A_Q & A_{Qs} \\ A_{cn} & A_{cn} & \dots & A_{cn} & A_s \end{bmatrix}, B_{es} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ b_{es} \end{bmatrix},$$

$$D = \begin{bmatrix} d_1 & 0 & \dots & 0 \\ 0 & d_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & d_Q \\ 0 & 0 & \dots & 0 \end{bmatrix}, B_s = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ b_s \end{bmatrix}, d_j = \begin{bmatrix} 0 \\ \frac{P_j}{C_j} \end{bmatrix}, \quad (2)$$

$$A_j = \begin{bmatrix} -\frac{r_j}{L_j} & -\frac{1}{L_j} \\ \frac{1}{C_j} & 0 \end{bmatrix}, A_{js} = \begin{bmatrix} 0 & \frac{1}{L_j} \\ 0 & 0 \end{bmatrix}, b_{es} = \begin{bmatrix} 0 \\ -\frac{1}{C_s} \end{bmatrix},$$

$$A_s = \begin{bmatrix} -\frac{r_s}{L_s} & -\frac{1}{L_s} \\ \frac{1}{C_s} & 0 \end{bmatrix}, b_s = \begin{bmatrix} \frac{1}{L_s} \\ 0 \end{bmatrix}, A_{cn} = \begin{bmatrix} 0 & 0 \\ -\frac{1}{C_s} & 0 \end{bmatrix},$$

Fig. 1. Detailed block diagram of a DC MG.

The state-space representation (1) contains both linear (i.e. $Ax + B_{es}i_{es} + B_sV_{dc}$) and nonlinear (i.e. DH) terms. Thereby, the overall dynamics are nonlinear. In the following sections, the goal is to design an LPV-based SMO for the nonlinear DC MG system (1).

III. POLYTOPIC LPV MODELING

A polytopic quasi-LPV model is a precise nonlinear convex aggregation of some local linear representations of the nonlinear plant [5], [20]. The convex theory facilitates deploying the well-known linear control theories to stabilize nonlinear smooth systems. To derive a polytopic quasi-LPV system, it is necessary to model the nonlinearities of (1) by its corresponding polytopic LPV representation [23]. As can be seen in (1) and (2), the overall DC MG system has Q nonlinear terms (i.e. h_j). Without loss of generality, the equivalent polytopic quasi-LPV model for a DC MG with one CPL is obtained as [6]

$$\dot{\tilde{x}} = \sum_{i=1}^2 \rho_i \{A_i \tilde{x} + B_{es} \tilde{i}_{es} + B_s \tilde{V}_{dc}\} \quad (3)$$

Fig. 2. Electrical schematic of the considered DC MG case study.

where $\tilde{x}$, $\tilde{i}_{es}$, and $\tilde{V}_{dc}$ are the changes of coordinates of x , i_{es} , and V_{dc} , respectively [6], and

$$\rho_1 = \frac{U_{max} \tilde{v}_{C,1} - h_1}{(U_{max} - U_{min}) \tilde{v}_{C,1}}, \rho_2 = \frac{h_1 - U_{min} \tilde{v}_{C,1}}{(U_{max} - U_{min}) \tilde{v}_{C,1}}$$

$$U_{min} = \frac{1}{v_{C0,1}(v_{C0,1} + \tilde{v}_{C,1})}, U_{max} = \frac{1}{v_{C0,1}(v_{C0,1} - \tilde{v}_{C,1})}$$

$$A_1 = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & \frac{P_1}{C_1} U_{min} & 0 & 0 \\ 0 & 0 & -\frac{r_s}{L_s} & -\frac{1}{L_s} \\ -\frac{1}{C_s} & 0 & \frac{1}{C_s} & 0 \end{bmatrix}, B_{es} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -\frac{1}{C_s} \end{bmatrix},$$

$$A_2 = \begin{bmatrix} -\frac{r_1}{L_1} & -\frac{1}{L_1} & 0 & \frac{1}{L_1} \\ \frac{1}{C_1} & \frac{P_1}{C_1} U_{max} & 0 & 0 \\ 0 & 0 & -\frac{r_s}{L_s} & -\frac{1}{L_s} \\ -\frac{1}{C_s} & 0 & \frac{1}{C_s} & 0 \end{bmatrix}, B_s = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L_s} \\ 0 \end{bmatrix} \quad (4)$$

where the time-varying parameters ρ_1 and ρ_2 are functions of system states and assure the convexity constraint. Thereby, the LPV model (3) is called the polytopic quasi-LPV. Besides, the obtained polytopic LPV model is valid for the given region $-\tilde{w}_{2,1} \leq \tilde{v}_{C,1} \leq \tilde{w}_{2,1}$. The details of polytopic LPV modeling of DC MGs with CPLs can be found in [5]. The goal is to

reconstruct the occurring faults in (3). Therefore, such a system is merged with actuator and sensor faults and disturbance as

$$\begin{cases} \dot{\tilde{x}} = \sum_{i=1}^r \rho_i \{A_i \tilde{x} + B_{es} \tilde{i}_{es} + B_s \tilde{V}_{dc} + M_i f_a + D_i \xi\} \\ y = C \tilde{x} + N f_s \end{cases} \quad (5)$$

where $f_a \in R^q$, $f_s \in R^h$, $\xi \in R^l$, $\tilde{x} \in R^n$, and $y \in R^p$ are unknown actuator and sensor faults, the system disturbance, the measured outputs and the state vector, respectively. Also, $M_i \in R^{n \times q}$, $D_i \in R^{n \times l}$, $C \in R^{p \times n}$, and $N \in R^{p \times h}$ are constant real matrices.

IV. MAIN RESULT

First, the system dynamics (5) is re-written in a way that all faults appear in the dynamics and the new output vector does not contain any faults. To perform this, a proper orthogonal matrix $T_r \in R^{p \times p}$ is derived by using the QR reduction of matrix N [12], and the new state vector is constructed as $X = [x^T \ \mu^T]^T \in R^{n+h}$ where $\mu \in R^h$ is defined as follows:

$$\dot{\mu} = -A_f \mu + A_f C_2 x + A_f N_2 f_s \quad (6)$$

Thus, the new polytopic-LPV system of order $n + h$ is given by

$$\begin{cases} \dot{X} = \sum_{i=1}^r \hat{\rho}_i \{A_i X + B_{es} \tilde{i}_{es} + B_s \tilde{V}_{dc} + M_i f + D_i \xi + \phi\} \\ Y = C X \end{cases} \quad (7)$$

$$\begin{aligned} A_i &= \begin{bmatrix} A_i & 0 \\ A_f C_2 & -A_f \end{bmatrix}, B_{es} = \begin{bmatrix} B_{es} \\ 0 \end{bmatrix}, B_s = \begin{bmatrix} B_s \\ 0 \end{bmatrix}, \\ D_i &= \begin{bmatrix} D_i \\ 0 \end{bmatrix}, M_i = \begin{bmatrix} M_i & 0 \\ 0 & A_f N_2 \end{bmatrix}, C = \begin{bmatrix} C_1 & 0 \\ 0 & I_h \end{bmatrix} \end{aligned} \quad (8)$$

$$\phi := \sum_{i=1}^r (\rho_i - \hat{\rho}_i) \{A_i X + M_i f + D_i \xi\}$$

$f = [f_a^T \ f_s^T]^T \in R^{q+h}$, $N_2 \in R^{h \times h}$ is a nonsingular matrix and $A_f > 0 \in R^{h \times h}$ is a user-defined matrix with positive eigenvalues. The time-varying parameters $\hat{\rho}_i$ are based on the state estimation vector $\hat{x}$. Also, ϕ satisfies the Lipschitz condition with a positive scalar γ , as follows:

$$\|\phi\| \leq \gamma \|x - \hat{x}\|, \quad \forall x, \hat{x} \in R^n \quad (9)$$

Some assumptions and lemmas are presented below to propose an NSMO for the system modeled in (7).

Assumptions:

$$\text{rank}(C[M_i \ D_i]) = q + h + l \quad (10)$$

$$\text{rank} \begin{bmatrix} sI - A_i & M_i & D_i \\ C & 0 & 0 \end{bmatrix} = n + 2h + q + l \text{ for } \quad (11)$$

$$\text{Re}(s) \geq 0 \quad n + h > p \geq q + h + l \quad (12)$$

$$\|f\| \leq \rho_f; \quad \|\xi\| \leq \rho_d; \quad \|\dot{\rho}_k\| \leq \rho_{mk} \quad (13)$$

Lemma 1 [12]: If (10) holds, changes of coordinates $\bar{T}_i$ can be found so that the triples $(A_i, [M_i \ D_i], C)$ are of the following format:

$$\begin{aligned} A_i &= \begin{bmatrix} A_{11,i} & A_{12,i} \\ A_{21,i} & A_{22,i} \end{bmatrix}, A_{21,i} = \begin{bmatrix} A_{211,i} \\ A_{212,i} \end{bmatrix}, \\ [M_i \ D_i] &= \begin{bmatrix} 0 & 0 \\ M_{2,i} & D_{2,i} \end{bmatrix}, C = [0 \ T_0] \end{aligned} \quad (14)$$

where $\mathcal{A}_{11,i} \in R^{(n+h-p) \times (n+h-p)}$, $\mathcal{A}_{21,i} \in R^{(p-q-h-l) \times (n+h-p)}$, $T_0 \in R^{p \times p}$ is an orthogonal matrix, and $\mathcal{M}_{2,i} \in R^{p \times (q+h)}$ and $\mathcal{D}_{2,i} \in R^{p \times l}$ have the following format:

$$[\mathcal{M}_{2,i} \quad \mathcal{D}_{2,i}] = \begin{bmatrix} 0 & 0 \\ \mathcal{M}_{0,i} & \mathcal{D}_{0,i} \end{bmatrix} \quad (15)$$

Note that $[\mathcal{M}_{0,i} \quad \mathcal{D}_{0,i}] \in R^{(q+h+l) \times (q+h+l)}$ is nonsingular.

Lemma 2 [24]: The parameter-dependent inequality $\sum_{i=1}^r \sum_{j=1}^r \rho_{ij} \rho_{ij} Q_{ij} < 0$ holds if the following parameter-independent inequalities hold:

$$\begin{cases} Q_{ii} < 0 & \text{for } i = 1, \dots, r \\ \frac{2}{1-r} Q_{ii} + Q_{ij} + Q_{ji} < 0 & \text{for } i \neq j = 1, \dots, r \end{cases} \quad (16)$$

The proposed NSMO is defined based on the coordinate transformation $\bar{T}_i$ given in Lemma 1, as follows

$$\begin{cases} \dot{\hat{X}} = \sum_{i=1}^r \hat{\rho}_i \left\{ \mathcal{A}_i \hat{X} + \mathcal{B}_{es} \tilde{e}_s + \mathcal{B}_s \tilde{V}_{dc} + G_{l,i} e_y + \right. \\ \left. \eta_{f,i} G_{n,i} \text{sign}(e_y) + \eta_{d,i} G_{d,i} \text{sign}(e_y) \right\} \\ \hat{Y} = \mathcal{C} \hat{X} \end{cases} \quad (17)$$

where $e_y := Y - \hat{Y}$ is the output error estimation and is considered as the sliding surface, in this paper. Thereby, the estimation vector X of the NSMO is modified by the terms $\eta_{f,i} G_{n,i} \text{sign}(e_y) + \eta_{d,i} G_{d,i} \text{sign}(e_y)$. The scalars $\eta_{f,i}$ and $\eta_{d,i}$ satisfy the following inequalities

$$\begin{aligned} \eta_{f,i} &\geq \rho_f \|T_0 \mathcal{M}_{2,i}\| \max_j \left(\frac{\|P_{2,j}\|}{\lambda_{\min}(P_{2,j})} \right) + w_{f,i} \\ \eta_{d,i} &\geq \rho_d \|T_0 \mathcal{N}\| \max_j \left(\frac{\|P_{2,j}\|}{\lambda_{\min}(P_{2,j})} \right) + w_{d,i} \end{aligned} \quad (18)$$

$1, \dots, r$

with $w_{f,i}$ and $w_{d,i}$ are arbitrary positive constants. Also, the sign function operator is defined as follows:

$$\text{sign}(e_y) = \begin{cases} \frac{e_y}{\|e_y\|} & e_y \neq 0 \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

Moreover, the design matrices $G_{n,i}$ and $G_{l,i}$ should be chosen to assure the stability of the tracking error dynamics. This issue will be discussed in Theorem 1. Before presenting Theorem 1, the state estimation error $e := X - \hat{X}$, and its dynamics are derived by considering (7) and (17), as follows

$$\dot{e} = \sum_{i=1}^r \hat{\rho}_i \left\{ (\mathcal{A}_i - G_{l,i} \mathcal{C}) e + \mathcal{M}_i f + \mathcal{D}_i \xi - \eta_{f,i} G_{n,i} \text{sign}(e_y) - \eta_{d,i} G_{d,i} \text{sign}(e_y) + \phi \right\} \quad (20)$$

Now define another change of coordinates as follows

$$T_{L,i} = \begin{bmatrix} I_{n+h-p} & L_i \\ 0 & T_0 \end{bmatrix}, \quad L_i = [\bar{L}_i \quad 0] \in R^{(n+h-p) \times p} \quad (21)$$

where $\bar{L}_i \in R^{(n+h-p) \times (p-q-h-l)}$ is the stabilizing gain matrix, the system (20) can be re-written as

$$\dot{\tilde{e}} = \begin{bmatrix} \dot{\tilde{e}}_1 \\ \dot{\tilde{e}}_2 \end{bmatrix} = \sum_{i=1}^r \hat{\rho}_i \left\{ \begin{bmatrix} \mathcal{A}_{t,i} \tilde{e} + T_{L,i} \phi + \tilde{\mathcal{M}}_i f - \\ \eta_{f,i} \tilde{G}_{n,i} \text{sign}(e_y) + \\ \tilde{\mathcal{D}}_i \xi - \eta_{d,i} \tilde{G}_{n,i} \text{sign}(e_y) \end{bmatrix} \right\} \quad (22)$$

where

$$\mathcal{A}_{t,i} = \begin{bmatrix} \mathcal{A}_{11,i} + L_i \mathcal{A}_{21,i} & 0 \\ T_0 \mathcal{A}_{21,i} & \mathcal{A}_{s,i} \end{bmatrix} \quad (23)$$

in which $\mathcal{A}_{s,i}$ is a user-defined matrix with negative eigenvalues. Moreover, the matrix L_i (21) is selected such that $\mathcal{A}_{11,i} + L_i \mathcal{A}_{21,i} < 0$. Since $\mathcal{A}_{t,i}$ has a zero off-diagonal matrix, its eigenvalues are the same as its diagonal matrix elements. As a

consequence, since $\mathcal{A}_{11,i} + L_i \mathcal{A}_{21,i}$ and $\mathcal{A}_{s,i}$ have negative eigenvalues, the matrix $\mathcal{A}_{t,i}$ (23) is asymptotically stable.

In the following Theorem 1, the sufficient LMI conditions, which guarantee the asymptotic stability of (22) with a maximized admissible Lipschitz constant γ^* for the ϕ in (9), will be derived.

Theorem 1. If for the given scalars $\varepsilon > 0$, and $\sigma > 0$, there exist matrices $P_{1,i}$ and $P_{2,i}$ such that the following LMI optimization problem has a solution

$$\min (\sigma + \varepsilon) \quad (24)$$

Subject to

$$P_{1,i} = P_{1,i}^T > 0 \quad (25)$$

$$P_{2,i} = P_{2,i}^T > 0 \quad (26)$$

$$\begin{cases} Q_{ii} < 0 & \text{for } i = 1, \dots, r \\ \frac{2}{1-r} Q_{ii} + Q_{ij} + Q_{ji} < 0 & \text{for } i \neq j = 1, \dots, r \end{cases} \quad (27)$$

$$\begin{cases} Q_{ii}' < 0 & \text{for } i = 1, \dots, r \\ \frac{2}{1-r} Q_{ii}' + Q_{ij}' + Q_{ji}' < 0 & \text{for } i \neq j = 1, \dots, r \end{cases} \quad (28)$$

where

$$Q_{ij} = \begin{bmatrix} \Delta_{1,ij} & \mathcal{A}_{21,i}^T T_0^T P_{2,j} & P_{1,j} & 0 & I & 0 & \mathcal{A}_{21,i}^T \\ * & \Delta_{2,ij} & 0 & P_{2,j} & 0 & I & 0 \\ * & * & -\varepsilon I & 0 & 0 & 0 & 0 \\ * & * & * & -\varepsilon I & 0 & 0 & 0 \\ * & * & * & * & -\sigma I & 0 & 0 \\ * & * & * & * & * & -\sigma I & 0 \\ * & * & * & * & * & * & -\beta I \end{bmatrix}$$

$$Q_{ij}' = \begin{bmatrix} \Delta_{1,ij} & \mathcal{A}_{21,i}^T T_0^T P_{2,j} & P_{1,j} & 0 & I & 0 & P_{1,j} \\ * & \Delta_{2,ij} & 0 & P_{2,j} & 0 & I & 0 \\ * & * & -\varepsilon I & 0 & 0 & 0 & 0 \\ * & * & * & -\varepsilon I & 0 & 0 & 0 \\ * & * & * & * & -\sigma I & 0 & 0 \\ * & * & * & * & * & -\sigma I & 0 \\ * & * & * & * & * & * & -\beta I \end{bmatrix}$$

$$\Delta_{1,ij} = \mathcal{A}_{11,i}^T P_{1,j} + P_{1,j} \mathcal{A}_{11,i} + \sum_{k=1}^r \rho_{mk} P_{1,k}$$

$$\Delta_{2,ij} = \mathcal{A}_{s,i}^T P_{2,j} + P_{2,j} \mathcal{A}_{s,i} + \sum_{k=1}^r \rho_{mk} P_{2,k}$$

with ρ_{mk} defined in (13). Finally, the estimation error is bounded and the maximized admissible Lipschitz constant is $\gamma^* = \max(\gamma) = \frac{1}{\|T_L\| \|T_L^{-1}\| \sqrt{\varepsilon \sigma}}$.

Proof: See the proof in Appendix A.

Remark 1- Lipchitz constraint: In this paper, the Lipchitz constraint (9) is utilized to deal with the nonlinearity term ϕ . The Lipchitz condition is a simple but effective way to convert nonlinear terms into quasi-linear ones and facilitate deriving the controller/observer design conditions in terms of LMIs [25], [26]. As can be seen in (39) of Appendix A, the asymptotic stability of error dynamics is achieved regardless the value of the Lipchitz constant γ . However, the value of γ affects the local region of attraction (ROA). In [27], the effect of the Lipchitz constraint on the ROA for DC MGs systems with CPLs is studied. furthermore, a robust stabilizing controller is suggested and its sufficient design conditions are derived in

terms of LMIs. Also, in [28] a Kalman-based robust linear controller for the same power system is developed.

Since the sliding surface reaches zero, on the sliding surface e_Y one concludes $e_Y = \dot{e}_Y = 0$. Consequently, the actuator fault, sensor fault, and the disturbance input are reconstructed as follows

$$\begin{aligned} \begin{bmatrix} \hat{f}_a \\ \hat{f}_s \end{bmatrix} &= \left(\sum_{k=1}^r \hat{\rho}_i \{ \mathcal{M}_{2,i} \} \right)^\dagger T_0^{-1} \sum_{k=1}^r \hat{\rho}_i \{ \eta_{f,i} \text{sign}(e_Y) \}, \\ \hat{\xi} &= \left(\sum_{k=1}^r \hat{\rho}_i \{ [\mathcal{D}_{2,i}] \} \right)^\dagger T_0^{-1} \sum_{k=1}^r \hat{\rho}_i \{ \eta_{d,i} \text{sign}(e_Y) \} \end{aligned} \quad (29)$$

To reduce the chattering of the constructed signals, the sign function is replaced by the saturation one, as follows

$$\begin{aligned} \begin{bmatrix} \hat{f}_a \\ \hat{f}_s \end{bmatrix} &= \left(\sum_{k=1}^r \hat{\rho}_i \{ \mathcal{M}_{2,i} \} \right)^\dagger T_0^{-1} \sum_{k=1}^r \hat{\rho}_i \{ \eta_{f,i} \text{sat}(e_Y) \}, \\ \hat{\xi} &= \left(\sum_{k=1}^r \hat{\rho}_i \{ [\mathcal{D}_{2,i}] \} \right)^\dagger T_0^{-1} \sum_{k=1}^r \hat{\rho}_i \{ \eta_{d,i} \text{sat}(e_Y) \} \end{aligned} \quad (30)$$

where $\dagger$ represents the pseudo-inverse of a matrix and

$$\text{sat}(e_Y) = \frac{e_Y}{\|e_Y\| + \delta_s} \quad (31)$$

with δ_a and δ_s are small positive user-defined constants.

Remark 2- Overall design procedure: The main steps to numerically solve Theorem 1 can be summarized as follows:

Step 1. Find the transfer matrix $T_r \in R^{p \times p}$ by using the QR reduction of matrix N and obtain the transformed system (7).

Step 2. Check the assumptions (10)-(13).

Step 3. Find the changes of coordinates $\bar{T}_i$ such that the triples $(\mathcal{A}_i, [\mathcal{M}_i \mathcal{D}_i], \mathcal{C})$ are in the format (14).

Step 4. Compute the scalars σ and ε and the matrices L_i from the LMIs (24)-(28).

Step 5. Compute the matrices $T_{L,i}$ from the obtained matrices L_i based on (21).

Step 6. Compute the maximized admissible Lipschitz constant which is $\gamma^* = \max(\gamma) = \frac{1}{\|T_L\| \|T_L^{-1}\| \sqrt{\varepsilon \sigma}}$.

Step 7. Reconstruct the faults and disturbance by using equations (30) and (31).

Remark 3- Merits of the proposed approach and its design challenges: Almost all prior researches on fault detection in nonlinear systems, represented by polytopic LPV systems through SMOs, have deployed a QLF (Quadratic Lyapunov function) [16]–[20]. The novelty of the proposed fault detection approach is reducing the conservativeness of the state-of-the-art methods by employing a PDLF (Parameter-Dependent Lyapunov Function), which reduces the conservativeness of LMI conditions. The proposed approach is established based on LPV systems. So, it detects and constructs sensor and actuator faults of nonlinear systems. Since, LPV model and PDLF are utilized, conventional change of variables presented in [16]–[20] are not useful. Thereby, the Finsler's lemma is utilized. Also, since the PDLF comprises several Lyapunov matrices, the structure of the sliding mode fault observer is adopted. On the other hand, this paper focuses on the issue of fault detection and reconstruction for DC MGs with CPLs for the first time. In this paper, a proper approach is presented to effectively detect and reconstruct the DC MGs with CPLs plant faults, simultaneously.

V. REAL-TIME SIMULATION AND EXPERIMENTAL RESULTS

To evaluate the performance advantages including fast transient response and robustness characteristics, the developed NSMO is tested on a DC MG characterized in Table I, and the results are compared with [29]–[31]. The parameters in Table I are chosen such that the DC MG is stable and, thereby, no power from the ESS to the DC MG is injected (i.e. $\tilde{i}_{es} = 0$). Moreover, the matrices are chosen as follows to meet the conditions (10)-(12).

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}, D_1 = D_2 = [0 \ 1 \ 1 \ 0]^T, \\ M_1 = M_2 = [1 \ 1 \ 1 \ -1]^T, N = [1 \ 0 \ 1]^T$$

Using Theorem 1, the feasible results are obtained as $\varepsilon = 0.3651$, $\sigma = 0.3653$, $\gamma^* = 2.7379$.

Scenario 1. Real-time software-in-the-loop simulations:

In the first scenario, the proposed approach is compared with the EKF method of [29] and the TS fuzzy approach [30]. Although in [29], the issue of fault detection is not investigated, the presented approach is used to estimate unknown CPL powers. Utilizing the above approach, it is possible to detect actuator faults by augmenting them (instead of CPL power) in the system states and estimating them via the joint-EKF of [29]. The initial covariance matrices of the joint-EKF are set as $R = 10^{-4}I^3$ and $Q = 10^{-4}I^5$, where I^b is a b -dimensional identity matrix. Also, in the TS fuzzy approach [30], the actuator fault and disturbance are estimated. To have a fair comparison, only the actuator fault is considered in this scenario. To perform the real-time simulations, all proposed NSMO, joint-EKF algorithm [29], and TS fuzzy approach [30] are implemented by the OPAL-RT hardware, connected to a personal computer with the DK60 board. Figs. 3(a)-(e) represent the estimation errors of the states and actuator fault. As can be seen in Fig. 3, although the proposed approach estimates the system states with a small ultimate bound, the actuator fault is constructed more accurately than the joint-EKF algorithm [29] and TS fuzzy approach [30]. Note that the steady-state estimation error is due to using the saturation function, instead of the sign function, in (30). On the other hand, the joint-EKF algorithm [29] and the TS fuzzy approach [30] are not able to estimate the actuator and sensor faults and disturbance, simultaneously.

Fig. 3. Faults and disturbance introduced in the DC MG: (a) Estimation error of $i_{L,1}$, (b) Estimation error of $v_{C,1}$, (c) Estimation error of $i_{L,s}$, (d) Estimation error of $v_{C,s}$, (e) Actuator fault.

Table I: Parameters for DC MG with one CPL

$r_1 = 1.1 \Omega$	$P_1 = 300 W$	$C_s = 500 \mu F$
$L_1 = 4 mH$	$\tilde{x}_{2N} = 130.4$	$L_s = 4 mH$
$C_1 = 500 \mu F$	$r_s = 1.1 \Omega$	$V_{dc} = 200 V$

Furthermore, the re-construction error specifications of the actuator fault are given in Table II. As can be seen in Table II, one observes that the fault estimation accuracy of the proposed approach remarkable outperforms the other approaches in the sense of norms 2 and ∞ , mean absolute error (MAE) and mean square error (MSE).

Table II: Error specifications of the actuator fault for all approaches

Criteria \ Approach	Proposed Approach	EKF [29]	Fuzzy [30]
Error L_2 norm	63.6023	152.6336	128.5209
Error L_∞ norm	0.2457	0.5912	0.3943
MAE	0.1340	0.3231	0.2756
MSE	0.0253	0.1456	0.1032

Scenario 2. Experimental results: The proposed NSMO approach [31] is verified for an experimental set-up equivalent to the dynamics (1). The OPAL-RT is used as a real-time Simulator (RTS) which monitors the DC MG and estimates the faults. The experimental DC MG setup and its simplified schematic are drawn in Fig. 4. Moreover, the QLF-based approach [31] is considered for the comparison. The FDI method [31] can construct actuator and sensor faults for a disturbed system.

Fig. 4. Experimental setup of the DC MG: (a) Overall setup, (b) Simplified schematic.

Figs. 5(a)-(c) demonstrate that the proposed LPV-based NSMO approach is able to reconstruct the disturbance input and the occurring faults more efficiently in comparison with the QLF method presented in [31].

Fig. 5. Faults and disturbances introduced in the DC MG: (a) Actuator fault, (b) Sensor fault, (c) Disturbance.

Fig. 6 shows the estimation error of the system states. As it can be observed, the state estimation errors converge to zero in finite-time. Moreover, both the proposed approach and QLF-based approach [31] lead to a small state estimation error because they use NSMO with saturation functions.

Fig. 6. State estimation errors.

VI. CONCLUSION

In this paper, the problem of fault detection and reconstruction in DC MGs with nonlinear loads was investigated. A novel robust gain-scheduling detector was established based on a sliding mode technique and a polytopic quasi-LPV approach was proposed to estimate and construct the occurring faults of a DC MG. The proposed approach was tested for robustness in face of disturbances. The results indicate that the proposed method can effectively estimate the system states and construct the system faults. Experimental results on a DC MG with one CPL demonstrate that the proposed approach was able to estimate the constant and time-varying faults very fast with small oscillations. Also, the estimated faults and disturbances are more accurate than other methods in the literature. For future work, further analysis of the effects of the faults on the DC system to locate the faults is of great importance.

APPENDIX A

The following parameter-dependent Lyapunov function (PDLF) is employed to verify the asymptotic stability of (22) and the performance of the observer (17), as follows

$$V = \tilde{e}^T \left(\sum_{j=1}^r \hat{\rho}_j P_j \right) \tilde{e} \quad (32)$$

where $P_j = \text{diag}(P_{1,j}, P_{2,j})$ with $P_{1,j} = P_{1,j}^T > 0 \in R^{(n+h-p) \times (n+h-p)}$ and $P_{2,j} = P_{2,j}^T > 0 \in R^{p \times p}$ are Lyapunov candidate matrices. The Lyapunov function (32) is called (PDLF) because it comprises the time-varying scheduling parameters. The time derivative of the PDLF along with the dynamics (22) is given by

$$\begin{aligned} \dot{V} = & \sum_{i=1}^r \sum_{j=1}^r \hat{\rho}_i \hat{\rho}_j \left\{ \tilde{e}^T \left(\mathcal{A}_{t,i}^T P_j + P_j \mathcal{A}_{t,i} + \sum_{k=1}^r \hat{\rho}_k P_k \right) \tilde{e} \right. \\ & \left. + 2\tilde{e}^T P_j (\tilde{\mathcal{M}}_i f - \eta_{f,i} \tilde{G}_{n,i} \text{sign}(e_Y) + \tilde{\mathcal{D}}_i \xi \right. \\ & \left. - \eta_{d,i} \tilde{G}_{n,i} \text{sign}(e_Y) + T_L \phi) \right\} \end{aligned} \quad (33)$$

By using (9) and considering the fact that $2\psi^T \vartheta \leq \frac{1}{\varepsilon} \psi^T \psi + \varepsilon \vartheta^T \vartheta$ with $\varepsilon > 0$, it follows that

$$2\tilde{e}^T P_j T_L \phi \leq \frac{1}{\varepsilon} \tilde{e}^T P_j P_j \tilde{e} + \varepsilon \alpha^2 \|\tilde{e}\|^2 \quad (34)$$

where $\alpha = \|T_L\| \|T_L^{-1}\| \gamma$. From (13), we obtain

$$\begin{aligned} \tilde{e}^T P_j (\tilde{\mathcal{M}}_i f - \eta_{f,i} \tilde{G}_{n,i} \text{sign}(e_Y)) \\ \leq -w_{f,i} \lambda_{\min}(P_{2,j}) \|e_Y\| \leq 0 \end{aligned} \quad (35)$$

and

$$\begin{aligned} \tilde{e}^T P_j (\tilde{\mathcal{D}}_i \xi - \eta_{d,i} \tilde{G}_{n,i} \text{sign}(e_Y)) \\ \leq -w_{d,i} \lambda_{\min}(P_{2,j}) \|e_Y\| \leq 0 \end{aligned} \quad (36)$$

Using (34)-(36), the (33) can be written as

$$\begin{aligned} \dot{V} \leq & \sum_{i=1}^r \sum_{j=1}^r \hat{\rho}_i \hat{\rho}_j \left\{ \tilde{e}^T \left(\mathcal{A}_{t,i}^T P_j + P_j \mathcal{A}_{t,i} + \varepsilon^{-1} P_j P_j \right. \right. \\ & \left. \left. + \sigma^{-1} I_{n+h} + \sum_{k=1}^r \hat{\rho}_k P_k \right) \tilde{e} \right\} \end{aligned} \quad (37)$$

where $\sigma := (\varepsilon \alpha^2)^{-1}$. From (13), we obtain

$$\tilde{e}^T \sum_{k=1}^r \hat{\rho}_k P_k \tilde{e} \leq \tilde{e}^T \sum_{k=1}^r \rho_{mk} P_k \tilde{e} \quad (38)$$

Thereby, (37) takes the following form

$$\begin{aligned} \dot{V} \leq & \sum_{i=1}^r \sum_{j=1}^r \hat{\rho}_i \hat{\rho}_j \times \\ & \left\{ \begin{bmatrix} e_1 \\ e_Y \end{bmatrix}^T \begin{bmatrix} \Phi_1 & \mathcal{A}_{21,i}^T T_0^T P_{2,j} \\ P_{2,j} T_0 \mathcal{A}_{21,i} & \Phi_2 \end{bmatrix} \begin{bmatrix} e_1 \\ e_Y \end{bmatrix} \right\} < 0 \end{aligned} \quad (39)$$

where $\Phi_1 = P_{1,j} \mathcal{A}_{11,i} + P_{1,j} L_i \mathcal{A}_{21,i} + \mathcal{A}_{11,i}^T P_{1,j} + \mathcal{A}_{21,i}^T L_i^T P_{1,j} + \varepsilon^{-1} P_{1,j} P_{1,j} + \sigma^{-1} I_{n+h-p} + \sum_{k=1}^r \rho_{mk} P_{1,k}$, $\Phi_2 = P_{2,j} \mathcal{A}_{s,i} + \mathcal{A}_{s,i}^T P_{2,j} + \varepsilon^{-1} P_{2,j} P_{2,j} + \sigma^{-1} I_p + \sum_{k=1}^r \rho_{mk} P_{2,k}$

Exploiting the Congruence lemma [25], (39) is satisfied by

$$\sum_{i=1}^r \sum_{j=1}^r \hat{\rho}_i \hat{\rho}_j \left\{ \begin{bmatrix} \Phi_1 & \mathcal{A}_{21,i}^T T_0^T P_{2,j} \\ P_{2,j} T_0 \mathcal{A}_{21,i} & \Phi_2 \end{bmatrix} \right\} < 0 \quad (40)$$

Whereas the bilinear terms $P_{1,j} L_i \mathcal{A}_{21,i}$ and $\mathcal{A}_{21,i}^T L_i^T P_{1,j}$ appear in Φ_1 , the constraint (40) is not in the form of LMIs. To turn (40) into LMIs, the Finsler's Lemma [24] is applied on (40). Therefore, we have

$$\begin{bmatrix} \Delta_1 + \beta^{-1} \mathcal{A}_{21,i}^T \mathcal{A}_{21,i} & \mathcal{A}_{21,i}^T T_0^T P_{2,j} \\ P_{2,j} T_0 \mathcal{A}_{21,i} & \Phi_2 \end{bmatrix} < 0 \quad (41)$$

and

$$\begin{bmatrix} \Delta_1 + \beta^{-1} P_{1,j} P_{1,j} & \mathcal{A}_{21,i}^T T_0^T P_{2,j} \\ P_{2,j} T_0 \mathcal{A}_{21,i} & \Phi_2 \end{bmatrix} < 0 \quad (42)$$

where $\Delta_1 = P_{1,j} \mathcal{A}_{11,i} + \mathcal{A}_{11,i}^T P_{1,j} + \varepsilon^{-1} P_{1,j} P_{1,j} + \sigma^{-1} I_{n+h-p} + \sum_{k=1}^r \rho_{mk} P_{1,k}$. In the final stage, deploying the Schur complement [24] and employing Lemma 2, the (41) and (42) lead to LMIs (27) and (28), respectively. To compute the maximum admissible Lipchitz constant, remind the definitions of α and σ (i.e. $\sigma := (\varepsilon \alpha^2)^{-1}$). Thus, we have $\gamma = \frac{\alpha}{\|T_L\| \|T_L^{-1}\|} = \frac{1}{\|T_L\| \|T_L^{-1}\| \sqrt{\sigma \varepsilon}}$. Minimizing the sum of σ and ε (i.e. $\min(\sigma + \varepsilon)$), maximizes the Lipchitz constant γ . Thereby, (24) is added.

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