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Fault-Tolerant Energy Management in Renewable Microgrids using LPV MPC ⋆

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Abstract: In this paper, we formalise a fault-tolerant control and mitigation strategy for the energy management of renewable microgrids. The scheme is composed of a Model Predictive Control (MPC) algorithm based on a Linear Parameter Varying (LPV) model for the microgrid energy dispatch. The MPC uses fault diagnosis information in order to correctly update the LPV microgrid model, while adapting the process constraints in consonance with the level and location of faults. We show how closed-loop stability is ensured with simple quadratic terminal ingredients, provided through LMI-solvable remedies. Nonlinear simulation results of a real microgrid benchmark are included to demonstrate the effectiveness of the approach.

Keywords: Microgrids, Model Predictive Control, Linear Parameter Varying Systems, Reconfiguration, Fault-Tolerant Control.

1. INTRODUCTION

The search for a healthier future for nature and ecology has been topic of many international treaties and conventions over the last decades. More recently, the so-called "2030 agenda" has established concrete Sustainable Development Goals (SDGs) to act upon (Sachs, 2012). We highlight SDG 7 ("affordable and clean energy"), which discusses the key importance of transitioning to a renewable energy paradigm, enabled by the means of distributed generation.

Accordingly, the study of smart-grid/microgrid (MG) technologies has received considerable attention in recent years (Hu et al., 2021). MGs can be understood as systems with multiple local energy sources, demands, and storage units. In practice, MGs are able to efficiently benefit from renewable energy by "shifting" load demands to periods of greater availability (exceeding energy is stored at a given moment in order to compensate, later on, for lacking generation). There are many real examples of renewable MGs of interest: energy generation from sugarcane residuals in Brazil (Morato et al., 2018), hydrogen-based domestic generation systems (Valverde et al., 2013b), demand compliance in the off-grid islands of the Philippines (Morato et al., 2021), and so on. The main aspect that should be emphasised is that MG structures enable a distributed generation, thus being in consonance with SDG 7.

Model Predictive Control (MPC) has been shown as the standard method of choice for the energy management problem of MGs (Bordons et al., 2020), with many results published over the last years, e.g. (Valverde et al., 2013b; Parisio et al., 2014; Morato et al., 2019). Since MPC is based on the recursive solution of a constrained optimisation problem, it can conveniently incorporate the most used MG model structures (i.e. *energy hubs*, (Geidl et al., 2007)), consider generation/demand constraints of the components, while also taking into account the preview of future renewable generation (usually enabled via meteorological data).

Nevertheless, recent works have raised attention to the problem of faults in the operation of MGs (Freire et al., 2020). MG faults can occur when a specific subsystems stops working, or a storage unit is loosing loaded charge over time. In practice, the study of these faults is indeed a serious topic, since renewable generation is usually inconsistent, with many unpredictability-related issues, and thus not accounting for faults can lead to compromised performances (or even not complying with demands).

Some few works have addressed the topic of fault mitigation and fault-tolerant energy management of renewable MGs, i.e. (Morato et al., 2020a; Bernardi et al., 2021; Marquez et al., 2021), but concrete assessments with performance certificates are still lacking. Accordingly, we note that recent theoretical advances on the design of MPC algorithms for systems with Linear Parameter Varying (LPV) models have provided a well-suited set of tools to render such properties (Morato et al., 2020b). Moreover, LPV models can be used to represent microgrid dynamics under loss of effectiveness faults, as shown in (Morato et al., 2019).

Thus, benefiting from the LPV paradigm to model faulty renewable MGs, our contributions are:

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- We provide an unified methodology to represent renewable MGs subject to additive faults within an LPV representation, with corresponding faulty process constraints (Sec. 2).
- Then, we synthesise an LPV MPC algorithm for the fault-tolerant energy management of theses systems. This fault-tolerant control (FTC) scheme is able to directly encompass different multi-objective performance goals and process constraints (Sec. 3).
- Corresponding stability and recursive feasibility guarantees are enabled through quadratic terminal ingredients, generated by through sufficient Linear Matrix Inequality (LMI) constraints (Sec. 4).
- Finally, a high-fidelity nonlinear microgrid benchmark simulator is used to demonstrate the effectiveness of the proposed method (Sec. 6).

The main benefits of the proposed LPV MPC method for the energy management of faulty MGs is that fault information from diagnosis/estimation schemes, such as (Marquez et al., 2021), can be directly incorporated, while performance (demand compliance) is maintained, even in presence of faults, which was not assured in previous works, e.g. (Morato et al., 2020a; Freire et al., 2020; Bernardi et al., 2021).

Notation. The index set $\mathbb{N}_{[a,b]}$ gives $\{i \in \mathbb{N} \,|\, a \leq i \leq b\}$, with $0 \leq a \leq b$. The identity matrix of size j is denoted as I_j, with $I_{j,\{i\}}$ denoting its i-th row. The predicted value of a given variable $v(k)$ at time instant $k+i$, computed based on the information available at instant k, is denoted as $v(k+i|k)$. For a vector of n variables v, v_j denotes the j-th variable, while $\text{diag}\{v\} = \text{diag}\{[v_1, \ldots, v_n]\}$ gives the diagonal matrix generated with v. $\mathcal{K}$ refers to the class of positive and strictly increasing scalar functions that pass through the origin. $\|\cdot\|$ denotes the 2-norm. $(\star)$ denotes the corresponding symmetrical transpose within an LMI.

2. SETUP: RENEWABLE MICROGRID MODEL

2.1 Original Model

In this paper, we follow the *energy hubs* modelling approach to renewable microgrids (e.g. (Geidl et al., 2007)). Additionally, we complement it with the original additive fault framework description, as given in (Marquez et al., 2021). Thus, consider the following microgrid description:

$$x(k+1) = Ax(k) + B\left(u(k) + f(k)\right) + B_w w(k)\,, \quad (1)$$

where $x \in \mathbb{R}^{n_x}$ are the microgrid states (level of charge in energy storage units), $u \in \mathbb{R}^{n_u}$ are the corresponding control inputs, $w \in \mathbb{R}^{n_w}$ are the disturbances (such as solar irradiance, wind speed etc), and $f \in \mathbb{R}^{n_u}$ are the additive faults. In short notation, $x := \mathcal{G}(u, f, w)$ denotes the transfer function form of Eq. (1).

We stress that this model considers slow, tertiary-level dynamics; the discrete-time behaviour is in the order of hours. Therefore, it is implied that the control inputs u are, in fact, set-points to lower-level controllers, which ensure tracking within one sample (in less time than each sampling period T_s). Accordingly, each input $u_j, \forall j \in \mathbb{N}_{[1,n_u]}$ corresponds to a set-point value for the j-th subsystem of the renewable MG. Moreover, each fault term $f_j, \forall j \in \mathbb{N}_{[1,n_u]}$ is related to possible faults that occurs upon the corresponding j-th subsystem.

2.2 Fault Detection and Diagnosis

Throughout the sequel, we assume that there exists an operational Fault Detection and Diagnosis (FDD) scheme, similar to the one proposed in (Freire et al., 2020). Fig. 1 illustrates the overall setup, where the FDD provides online information regarding the occurrence of faults in the controlled microgrid. In this figure, κ denotes the proposed fault-tolerant LPV MPC scheme, detailed in Sec. 3.

There are many possible ways to formulate FDD schemes able to provide accurate fault information in the case of renewable microgrids. This topic has been addressed, for instance, with geometric residual-based approaches, as in (Marquez et al., 2021), and with observer-based techniques (Morato et al., 2019). We stress that the synthesis and design of modular FDD schemes for renewable microgrid deserve attention by their own, and thus are out of the scope of this paper.

Thus, for simplicity, we assume henceforth that the additive fault variable $f(k)$ is known [1] for all sampling instants $k \geq 0$. Moreover, we consider that there are known bounds imposed over each fault term, that is $f_j(k) \in [\underline{f}_j, \overline{f}_j], \forall j \in \mathbb{N}_{[1,n_u]}$. These bounds relate to the distinct situations that may happen in the microgrid subsystems. For instance, an Li-ion battery bank may fail due to electrical issues in its inverters, just as a hydrogen compressor may exhibit faults due to partial leakages of the gas.

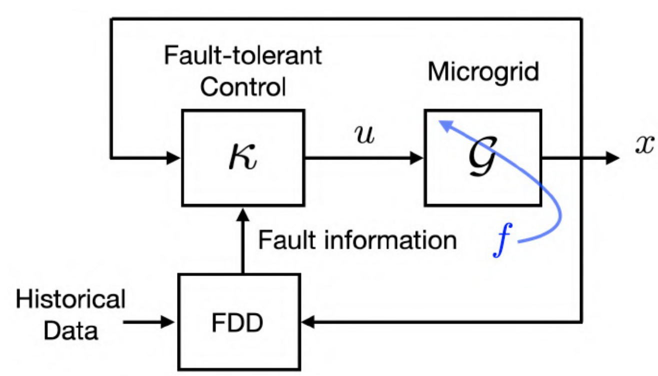

Fig. 1. Microgrid, FDD scheme, and FTC strategy.

2.3 LPV Representation

In order to apply the proposed fault-tolerant energy management strategy with stability and performance guarantees, we first adapt the model from Eq. (1) to suitable LPV coordinates.

For such, we re-write each fault and control input entry sum as follows: $u_j + f_j = \rho_j u_j, \forall j \in \mathbb{N}_{[1,n_u]}$. This implies that each introduced (scheduling) variable ρ_j satisfies the constraint: $\rho_j = \left(1 + \frac{f_j}{u_j}\right) \in [\underline{\rho}_j, 1], \forall j \in \mathbb{N}_{[1,n_u]}$. By using

[1] Again, note that, in practice, the fault signal is actually estimated/diagnosed by an FDD scheme, as gives Fig. 1. We assume, implicitly, that the estimation is precise. Robustness towards FDD estimation errors are out of the scope of this work.

such multiplicative representation, we obtain the following model, where $B(\rho) = B\text{diag}\{[\rho_1, \ldots, \rho_{n_u}]\}$:

$$x(k+1) = Ax(k) + B(\rho(k))u(k) + B_w w(k)\,. \tag{2}$$

Note that each scheduling variable ρ_j indicates the *loss of effectiveness* related to the j-th subsystem of the controlled microgrid. For instance, a scheduling variable $\rho_1 = 0.6$ indicates that the first subsystem of the MG (i.e., $j = 1$) exhibits a 40 % default on its behaviour. In terms of the original (additive) fault, this fault would be represented by a negative signal f_1, whose magnitude is 40 % of that from u_1.

Eq. (2) is considered for the fault-tolerant energy management control synthesis via MPC. For such, this model will be used to span the predictions of the faulty MG dynamics over a prediction horizon. Yet, the fault-related scheduling variables ρ_j are known for each sampling instant k, while unknown for any future sample. In practice, we assume that the fault levels will remain constant along the prediction horizon, i.e. $\rho(k+j|k) = \rho(k)$, since we are unable to preview future fault dynamics. In Sec. 3, we detail how this affects closed-loop stability.

2.4 Faulty Process Constraints

In order to correctly mitigate the effect of faults and maintain an adequate performance of the controlled microgrid, we consider operational constraints that are also subject to the effect of faults.

Under nominal, faultless conditions, we assume that the states and inputs should be bounded to nominal admissibility sets. Nonetheless, when faults occur, the input space should be further constrained. This is quite natural in practice: for instance, if a given system shows an energy conversion deficiency, it is reasonable to expect that its correlated control input space is smaller. If the input space is not further constrained when faults happen, the fault-tolerant controller could simply generate an input that compensates the loss of effectiveness by respectively magnifying the input, which is not coherent. A suitable FTC scheme would re-distribute inputs in order to maintain performances if a given subsystem fails, and not simply further exploit the faulty input.

Taking into account this discussion, we use the following fault-related constraints: $x(k) \in \mathcal{X}$ and $u(k) \in \mathcal{U}_{\rho(k)}, \forall k \geq 0$, as gives Eq. (3). We note that $U_{\rho(k)}$ is a time-varying set, whose bounds vary according to the level of faults measured through $\rho(k)$.

$$\begin{aligned} \mathcal{X} &:= \{x \in \mathbb{R}^{n_x} : |x_j| \leq \overline{x}_j,\ \forall j \in \mathbb{N}_{[1,n_x]}\}\,, \\ \mathcal{U}_{\rho(k)} &:= \{u \in \mathbb{R}^{n_u} : |\rho_j(k) u_j| \leq \overline{u}_j,\ \forall j \in \mathbb{N}_{[1,n_u]}\}\,. \end{aligned} \tag{3}$$

3. THE FAULT-TOLERANT LPV MPC APPROACH

Bearing in mind the previous discussion, we now detail the proposed fault-tolerant LPV MPC scheme. For such, denote $e_x(k+j|k) = x(k+j|k) - x_r(k+j)$ and $e_u(k+j|k) = u(k+j|k) - u_r(k+j)$ as error variables, where x_r and u_r are known state and input reference signals, respectively, which are assumed to be known. Thus, we consider the following multi-objective cost function $J := \sum_{j=0}^{N_p-1} \ell(e_x(k+i|k), e_u(k+j|k)) + V(e_x(k+N_p|k))$, where the stage cost $\ell(e_x, e_u) := \|e_x\|_Q + \|e_u\|_R$ has positive weights Q and R used to imply the envisioned trade-off between control effort and state regulation; $V(e_x)$ is a terminal cost and N_p is the prediction horizon.

Then, the proposed MPC scheme is based on the faulty LPV model from Eq. (2), using $\rho(k+j|k) = \rho(k), \forall j \in \mathbb{N}_{[0,N_p-1]}$ (assuming fixed faults for prediction), and on the fault-related set constraints from Eq. (3). Then, the control is retrieved from the solution of the following optimisation:

$$\begin{aligned} \min_{U_k} \sum_{j=0}^{N_p-1} & \ell\left(e_x(k+j|k), e_u(k+j|k)\right) + V(e_x(k+N_p|k))\,, \\ \text{s.t.}: \quad & x(k+j+1|k) = Ax(k+j|k) \\ & + B(\rho(k))u(k+j|k) + B_w w(k+j), \\ & u(k+j|k) \in \mathcal{U}_{\rho(k)}\,, \\ & x(k+j|k) \in \mathcal{X}\,, \\ & e_x(k+N_p|k) \in \mathbf{X}_f\,, \end{aligned} \tag{4}$$

where $\mathbf{X}_f$ is a terminal set. Assume that $J^\star(x(k), \rho(k))$ is the optimal solution of this problem, for which $U_k^\star$ is the minimiser. Then, the control input is retrieved by applying the first entry of the solution to the microgrid, i.e. $u^\star(k|k)$. Eq. (4) is a simple quadratic program at each sampling instant, since $U_{\rho(k)}$ is constant and the prediction model becomes Linear Time-Invariant (LTI). In the literature, this approach is widely referred to as frozen or gain-scheduled LPV MPC (Morato et al., 2020b).

4. STABILITY AND PERFORMANCE

In this section, we discuss how the proposed MPC is able to guarantee performances (demands compliance) and input-to-state stability [2], despite the presence of faults. For such, we give a simple remedy to compute the terminal ingredients of the corresponding optimisation ($V(\cdot)$ and $\mathbf{X}_f$). These ingredients also ensure that the MPC optimisation is continuously recursively feasible, even though the process model and constraints vary along iterations.

Theorem 1. Stability and Recursive Feasibility
Suppose the there exists a terminal control law $u = \kappa_t x$. Consider that the LPV system in Eq. (2) is controlled by the proposed state-feedback MPC, as rendered through Eq. (4). Then, asymptotic input-to-state stability is ensured if the following conditions hold $\forall \rho \in \mathcal{P}$:
(C1) The origin $x = 0$ lies in the interior of $\mathbf{X}_f$;
(C2) $\mathbf{X}_f$ is positively invariant under the terminal feedback controller $\kappa_t x$;
(C3) The discrete Lyapunov equation is verified within this invariant set, this is, $\forall x \in \mathbf{X}_f$ and $\forall \rho \in \mathcal{P}$: $V\left((A + B(\rho)\kappa_t)x\right) - V(x) \leq -\ell(x, \kappa_t x).$;
(C4) The image of the terminal control is admissible, i.e. $\kappa_t x \in \mathcal{U}_\rho, \forall \rho \in \mathcal{P}$;
(C5) The terminal set $\mathbf{X}_f$ is a subset of $\mathcal{X}$.

[2] Although the loss of effectiveness faults do not directly affect open-loop stability, we should verify closed-loop stability since the MPC is synthesised upon a biased model, which assumes frozen scheduling variables, whereas, in practice, these signals vary over time.

Assuming that the initial solution of the MPC problem $U_k^\star$ is feasible, then, the MPC is recursively feasible, steering $x(k)$ to the origin.

Proof 1. This proof is standard; refer to further details in (Mayne et al., 2000; Morato et al., 2020b). Note that x_r, u_r and w are considered null, for demonstration simplicity.

In order to satisfy the conditions required by Theorem 1, we use simple quadratic terminal ingredients, this is: $V(x) = x^T P x$, where $P = P^T \geq 0$ is a positive definite weight. The terminal set $\mathbf{X}_f$ is taken as a corresponding sub-level set to $V(x)$, i.e. $\mathbf{X}_f := \{x \in \mathbb{R}^{n_x} \,|\, x'Px \leq 1\}$. By definition, $\mathbf{X}_f$ is an ellipsoid, which should be positively invariant for the terminal feedback $\kappa_t x$ in order to satisfy the baseline conditions from Theorem 2. Accordingly, we give a numerically solvable sufficient solution that can be used to generate these terminal ingredients:

Theorem 2. Terminal Ingredients
Conditions (C1)-(C5) from Theorem 1 are satisfied if there exist a symmetric positive definite matrix $P \in \mathbb{R}^{n_x \times n_x}$ and a rectangular matrix $W \in \mathbb{R}^{n_u \times n_x}$ such that $Y = T^{-1} > 0$, $W = \kappa_t Y$ and that LMIs (5)-(7) hold under the minimisation of $\log\det\{Y\}$ for all $\rho \in \mathcal{P}$. Then, the terminal feedback is $u = \kappa_t x$.

$$\left[\begin{array}{cc|cc} Y & \star & \star & \star \\ (AY + B(\rho)W) & Y & \star & \star \\ Y & 0 & Q^{-1} & \star \\ W & 0 & 0 & R^{-1} \end{array}\right] \geq 0\,, \quad (5)$$

$$\left[\begin{array}{c|c} \rho_i \overline{u}_i^2 & I_{\{i\}} W \\ \hline \star & Y \end{array}\right] \geq 0,\; i \in \mathbb{N}_{[1,n_u]}\,, \quad (6)$$

$$\left[\begin{array}{c|c} \overline{x}_j^2 & I_{\{j\}} Y \\ \hline I_{\{j\}} Y' & Y \end{array}\right] \geq 0,\; j \in \mathbb{N}_{[1,n_x]}\,. \quad (7)$$

Proof 2. Apply two consecutive Schur complements to LMI (5), thus obtaining (C3), which suffices for (C1) and (C2) due to the ellipsoid form of the terminal set. (C4) and (C5) are obtained by Schur complements over LMIs (6) and (7), respectively. Note that LMI (6) implies a time-varying constraint over each control input, i.e. $\|u_j\|_2 \leq \rho_j \overline{u}_j, \forall j \in \mathbb{N}_{[1,n_u]}$. This concludes this brief proof. □

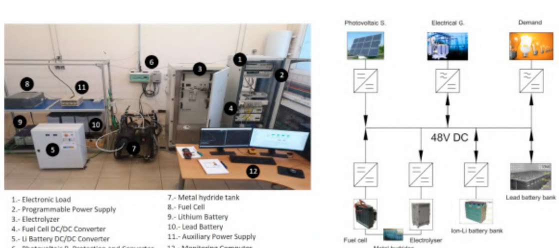

Fig. 2. Hylab Microgrid Setup.

Theo. 2 provides infinite-dimensional LMIs ((5) and (6)), which should hold for all $\rho \in \mathcal{P}$. Yet, since herein we consider LPV scheduling variables which stand for multiplicative fault terms such that $\rho_j \in [\underline{\rho}_j, 1], \forall j \in \mathbb{N}_{[1,n_u]}$, these LMIs can be simplified. In practice, their solution can be generated by enforcing these inequalities over a sufficiently dense grid of points over $\mathcal{P} := [\underline{\rho}_1, 1] \times [\underline{\rho}_2, 1] \times \dots [\underline{\rho}_{n_u}, 1]$. Then, they should be verified for a denser grid. Note that the worst-case complete breakdown condition of a given subsystem (implying that $\underline{\rho}_j = 0$) imposes a null terminal feedback, which is inherently infeasible. Thus, we use henceforth $\underline{\rho}_j > 0, \forall j \in \mathbb{N}_{[1,n_u]}$.

5. RESULTS: NUMERIC BENCHMARK

Next, we apply the proposed scheme for the fault-tolerant energy management of a realistic bechmark environment of the Hylab microgrid, from the University of Seville[3]. This MG, illustrated in Fig. 2 is composed of a lead–acid battery bank, a Li-ion battery bank, a photovoltaic field, an electrolyser, a fuel cell, an emulated solar photovoltaic (PV) system, an electronic load, DC/DC converters and metal hydride tanks. The model which describes this MG is in the likes of Eq. (2), where $x \in \mathbb{R}^3$ collects the state of charge of the lead-acid and Li-ion batteries, and the level of charge of the hydride tanks; the control inputs $u \in \mathbb{R}^4$ are the power outlet set-points of the electrolyser, of the fuell cell, of the Li-ion battery, of the lead-acid battery, and the total power that is consummated from the external grid (in order to comply with demands, when there occur shortages). The system disturbance w is the solar irradiance input, which generates PV energy.

Accordingly, we consider the same MPC costs and weights as in (Marquez et al., 2021), which is herein complemented with the terminal ingredients detailed in Sec. 4. The cost J is used to enforce that the total generated power follows a given demand profile (assumed to be known for all sampling instants). Moreover, the multi-objective cost J also weights the variation of the MG states x (level of charge in batteries and H_2 tank) to the target of 50 %, in order to avoid excessive fluctuation in these energy storage units. Note that all state and input variables are subject to hard box-type constraints (in the form of those given in Eq. (3)). We stress that the state-related constraints are quite direct: $x_j \in [0, 100]\,\%, \forall j \in \mathbb{N}_{[1,n_x]}$, since each state is related to a level of stored energy. The supervisory, energy management MPC operates each $T_s = 30$ s, with a prediction horizon of $N_p = 15$ discrete-time steps; the lower-level controllers, corresponding to each subsystem, are functional and well-posed. We consider scenarios of an approximate duration of 24 hours.

In the sequel, we evaluate the effectiveness of the proposed FTC under nominal (faultless) and faulty conditions. W.r.t. the latter, we consider the following situation: the Li-ion battery bank exhibits a sudden breakdown of 60 % in its effectiveness, i.e. $\rho_4(k) = 0.4, \forall k \geq k_{\text{fault}}$, being k_{fault} the sampling instant when the event occurs. In order to evaluate the mitigation actions of the proposed LPV MPC scheme, we compare the faulty situation under the action of the proposed scheme, but also under the action of a nominal MPC, which does not take into account the presence of faults (i.e. using the model and constraints in Eqs. (2) and (3) with $\rho_j(k) = 1, \forall k \geq 0, j \in \mathbb{N}_{[1,n_u]}$).

First, we show how the system operates in closed-loop when there are no faults. Accordingly, in Fig. 3, we present the power outlets of the Hylab microgrid, coordinated by the action of the LPV MPC. The most important aspect is that the MPC is able to successfully coordinate

[3] For further details, refer to (Valverde et al., 2013a). Parameters and specifications are given in (Marquez et al., 2021, Table 2).

all subsystems in order to obtain the envisioned goal: the total produced power is equal to the load demand requirements (null power balance). Moreover, the control system intelligently acts to benefit as best as possible from the PV generation, while maintaining the levels of charge (states) near the 50 % target, as shows Fig. 4.

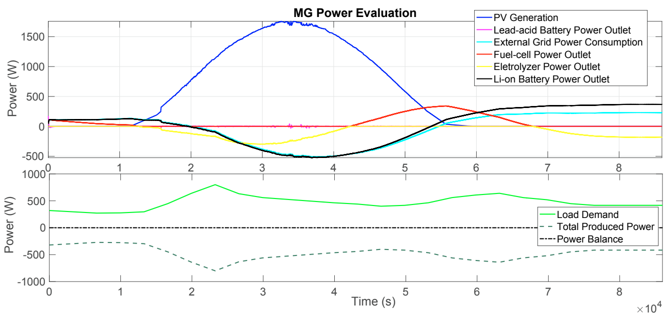

Fig. 3. Faultless scenario: MG Power Evaluation.

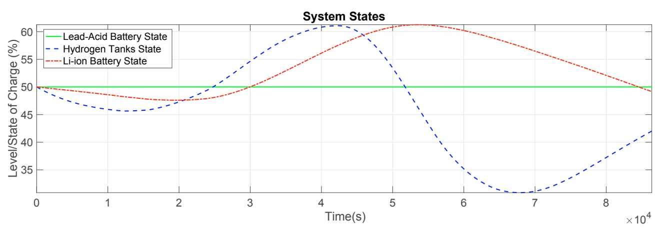

Fig. 4. Faultless scenario: MG States.

Next, we assess the performances obtained in the faulty situation, with and without fault mitigation (that is, with an MPC based on fixed model and constraints, and with an MPC with the LPV time-varying model and constraints, as well as the stability-related terminal ingredients). Regarding this context, we first show that the demand compliance goal is continuously guaranteed with the proposed FTC, as illustrated by Fig. 5. This is, the MPC is able to coordinate the MG in such a way that the dispatched energy meets the demand requirements (null power balance between the produced energy and load demand requirements). Nevertheless, we note that the fixed-model MPC, which has no inherent fault mitigation (named "no FTC"), is not able to ensure this goal. Thereby, a while after the occurrence of the Li-ion battery fault, the MG is not able to deliver sufficient energy and, thus, the corresponding MPC optimisation becomes infeasible. This nominal scheme ensured demand satisfaction whenever there where no faults, but, from the moment the fault occurs onward, it takes incorrect actions which soon lead the system to be unable to comply with demands (we demonstrate the incorrect coordination in the sequel). Anyhow, we stress that the proposed scheme has guaranteed stability and recursive feasibility, despite faults, due to the parameter ingredients detailed in Sec. 4. In a real-life condition, a total breakdown/stop of the MG, as happens with the "no FTC" approach, would be troublesome and certainly lead to economic losses.

In Fig. 6, we show in more details how the sudden fault affects the Li-ion battery subsystem. Specifically, this figure gives the corresponding control input, u_4 (set-point), together with the corresponding real actuation of the subsystem upon the MG, $\rho_4 u_4$. Evidently, the fault

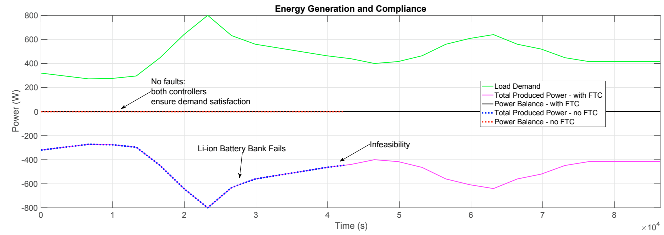

Fig. 5. Faulty case: MG Power Generation and Demand Compliance.

plays a significant role in decreasing the amount of power that is made available from these batteries to the MG, as well as in its capacity of absorb excessive energy and compensate fluctuations.

Complementary, Fig. 7 further illustrates how the proposed FTC scheme is able to mitigate faults, by compensating the lack of energy at one subsystem by the use of others. In this figure, we show the level of charge of the energy storage units of the MG (states), where we can see how the FTC approach tends to make a heavier use of the Lead-acid battery in order to handle the deficiencies of the Li-on battery under the faulty conditions. We stress that, when the fault occurs, the mitigation comes at the cost of a transient behaviour with some oscillations. Since the LPV model has parametric variations, the corresponding MPC issues slightly oscillatory inputs in order to overcome infeasibility (the "no FTC" approach tends to use the Lead-Acid battery in opposite fashion (issuing energy to the MG and not storing it), which causes the infeasibility issue. Anyhow, we recall that stability is ensured by design, and that these oscillations can be smoothed by the use of stronger slew-rate type constraints. We have not shown other tuning results due to lack of space, but we note that an interesting option is to further constraint the slew-rate of the systems that did not fail, in order to avoid abrupt usage, i.e. if $\rho_1(k) \neq 1, \forall k \geq k_{\text{fault}}$, for instance, we can take $|u_j(k+1) - u_j(k)| \leq \rho_1 \overline{\delta u_j}, \forall j \in \mathbb{N}_{[2,n_u]}, \forall k \geq k_{\text{fault}}$.

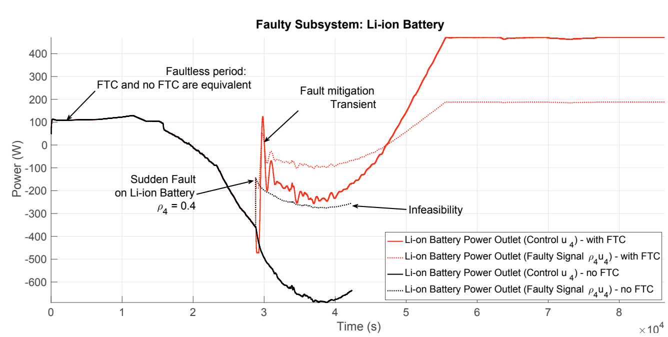

Fig. 6. Faulty case: Control Input and Fault.

Last, but not least, we show, in Fig. 8, the total power coordination of the considered MG, under the presence of faults in the Li-ion battery bank, with and without the fault-tolerant design. In this figure, it becomes clear how the FTC coordinates the remaining subsystem in order to ensure energy dispatch, with a transient behaviour related to fault mitigation. This intelligent coordination is not enabled by the nominal MPC, which fails to operate the system correctly.

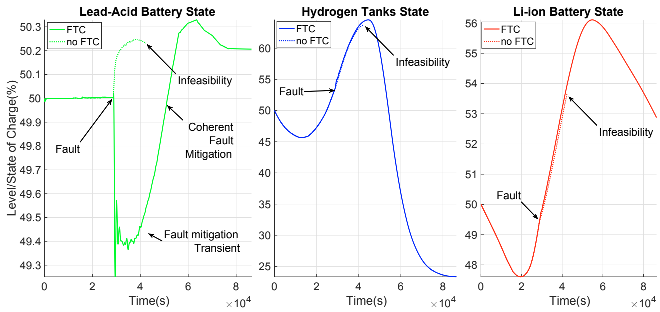

Fig. 7. Faulty case: MG States.

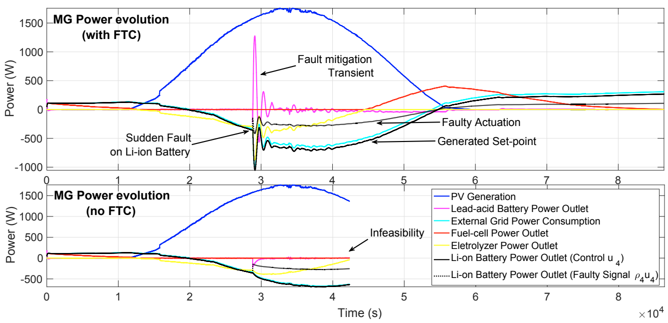

Fig. 8. Faulty case: MG Power Evaluation with no Mitigation.

6. CONCLUSIONS

In this paper, we studied how fault-tolerant energy management schemes for renewable microgrids can be synthesised using LPV MPC formulations. Accordingly, we provided a synthesis based on a fault-related LPV model, together with LPV constraints. The method is able to ensure closed-loop stability, as well as recursive feasibility of the optimisation, enabled through standard LMI synthesis. A realistic high-fidelity benchmark system is used to illustrate the features of the proposed method, which is compared against a nominal energy management MPC which has no fault-tolerant features, exhibiting enhanced performances. We recall the main features of our method:

(1) It does not require any ad-hoc re-tuning of the MPC parameters and weights, thus maintaining the same optimisation under both faultless and faulty environments.
(2) The LPV prediction model is able to automatically schedule the control,er action according to the level of faults.
(3) It ensures performance satisfaction and guarantees, even when abrupt faults happen.

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