Adaptive Control Approach of Microgrids

Juan S. Velez-Ramirez, Maximiliano Bueno-Lopez, Eduardo Giraldo

***Abstract*—In this article a novel adaptive control approach of microgrids is presented, where a robust estimation is performed based on a linear ARMAX model. In addition, an adaptive Linear Quadratic Regulator is used for optimal control based on an extended state space approach to compute the control signal. It is noticeable that the dynamical models of the microgrids are presented in state space. In addition, in order to validate the results, two microgrids are evaluated under noise and noise free condition for regulation by using the same structure of the adaptive control in state space. As a result, a general methodology of multivariable adaptive control in state space is presented which effectively estimate and control any of the evaluated microgrids.**

***Index Terms*—Multivariable adaptive control, microgrids, state space.**

I. Introduction

THE adaptive control strategies allow continuous update of the system parameters and also the variability of the design in terms of the identified model [1]. The control of systems with non-linearities around an operational point also can be performed by adaptive linear control techniques [2], [3] or by intelligent neural networks based control [4]. In [5], an ARMAX based methodology for identification and control of multivariable time-varying systems is proposed, which is based in a pole placement technique. It can be seen, that the multivariable system can effectively track any set point under noise conditions. However, the model is designed only for systems with equal number of inputs and outputs.

In the discussion about the new distribution systems topologies, the integration of the non-conventional energy resources, and the standardization of the so called *smart grid*, the microgrid concept has won special attention due to the flexibility, reliability and benefits that these network topologies will add to the distribution lines in the near future [6]. Several definitions have been established for a microgrid but each country has a legislation for the topic, the grid features, and its operation capabilities, but in general, all definitions agree that a microgrid is a cluster of distributed generators and loads, with clearly defined electrical boundaries and the capacity of operate in connection with the grid or autonomously (island mode) [7], [8], [9]. According with these definition, Fig. 1 shows an arbitrary microgrid architecture, with distributed generators and loads.

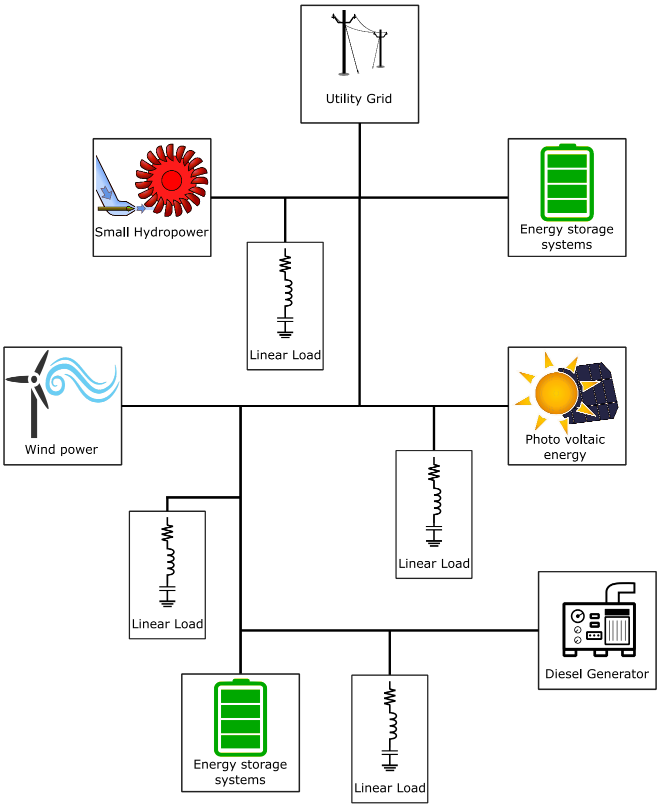

Fig. 1. Example of a microgrid with distributed energy resources

Due to the changing structure, and the different kind of disturbances that a microgrid have to deal in normal operation conditions, the control of a microgrid requires the design of techniques with adaptive capabilities in order to track any system variability. Usually the control of microgrids is designed according to the structure depicted in Fig. 2, in which each layer seeks to meet specific control objectives, determined by the system's operational needs. The primary layer (field level) takes care of the internal control of each distributed generator and loads, regulating the power production and and loads consumption; the secondary layer (management level) seeks to maintain a stable operation of the grid, exchanging information with the tertiary layer with the aim of setting the appropriate references to the first layer, at the end, the tertiary layer (Grid Level) regulates the economic dispatch, determining the times to sell or buy energy from the utility grid [10], [11], [12].

Since the primary control is embedded at the site of the distributed generators, and the tertiary control usually is implemented in a centralised way, located in the point of common coupling (PCC) of the microgrid with the distribution line, the main control objectives of the microgrid rest in the secondary layer, that define the turn on, turn down,

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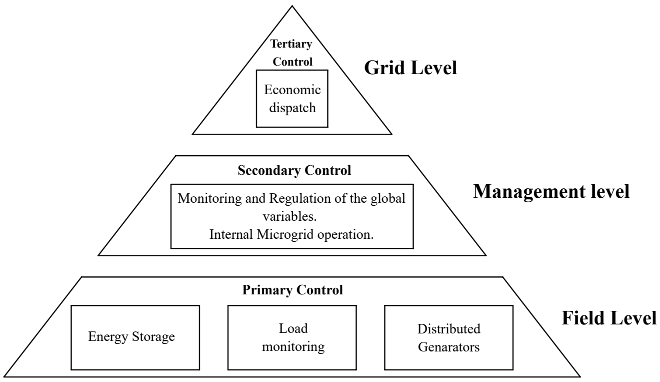

Fig. 2. General structure of microgrids control

isolation, and re-connection protocols, besides the regulation of the internal power production and consumption [13], [14]. The control architecture in this layer does not have a consensus due the different topologies proposed in the literature, these include the centralized, distributed, and decentralised methods, each one with its advantages and drawbacks [15], [11], [16]

Due to the better performance and efficiency, the centralized control have lead to important developments in optimization and robustness, as is shown in [17], [18], and the coordination of different renewable sources power dispatch, shown in [19]. Notwithstanding, as demonstrated in [20], [15], the great issue that centralized architecture have, is the single point failure, since all the microgrid operation is carried out by the central controller, a control failure will lead to a generalized collapse of the system.

Examples of decentralized controllers whit significant improvements could be seen in [21], [22], with a robust drop control strategies in [21], and a sliding mode control in [22]. However, this investigations only develop algorithms for stand alone microgrids, avoiding the grid connection. Another well known drawback of the decentralized control, also developed by [20] is the poorer energy, and frequency quality (compared with centralized structures), owing to the time delays among the controllers response.

Between this methods, the distributed strategies seek to obtain the best features of both architectures: the improved variable management of the centralized, and the flexibility and plug and play service of the decentralized. The literature in distributed topologies include complex methodologies like H_∞ norm, Model Predictive Control, Intelligent Control, among others, all have in common, model based math techniques and complex implementation due to the algorithms computational cost. In [23] an MPC technique is applied to a renewable based microgrid with satisfactory results, that need to be adapted to arbitrary microgirds configurations. In [24] a novel *broadcast gossip technique* with applicability in real-world scenarios is presented, but still dependent on the mathematical model. In [25] a resilient distributed control with the capability of avoid certain sensor faults is shown, however it is developed to work only in stand alone microgrids. Note that most of the aforementioned works have in common the dependence of an existing mathematical model to be implemented.

A useful approach to model any multivariable system, like a microgrid, is by using state space equations, where a set of first order differential equations are presented to describe the system dynamics. Several attempts to model microgrids in state space have been presented [26], [27], [28], [29], [30]. For example, in [29] a state space equation of a composite microgrid model based on IEEE 14 bus standard mode is presented, where the microgrid includes diesel generators, PV model, battery energy storage system, nonlinear loads such as arc. In [28] a microgrid based on IEEE 4 bus network is presented, where an analysis of communications delays is also performed. An also, in [30] a smartgrid with decentralized control is proposed in state space. However, the control design of these approaches are model dependant and require a detailed knowledge of the system to be controlled.

In this work a novel adaptive control approach of microgrids is presented, where a robust estimation is performed based on a linear ARMAX model where the an extended state space representation of system is estimated. In addition, an adaptive Linear Quadratic Regulator is used for optimal control based on the extended state space approach to compute the control signals. It is noticeable that the dynamical models of the microgrids are presented in state space. In order to validate the results, two microgrids are evaluated under noise and noise free condition for regulation by using the same methodology of the state space model. In addition for the second microgrid, an analysis in steady state is presented under noise conditions. It is remarkable, that the same estimation structure is used for both microgrids for estimation and control tasks. As a result, a multivariable control in state space is obtained which effectively estimate and control the microgrid. This paper is organized as follows: in section II a mathematical modeling of the microgrid is presented in state space, in section III the adaptive control approach of microgrids is presented, and in section IV the results for the two microgrid cases described in section II are presented.

II. Mathematical modeling of microgrids

In this work, a general state space modeling of microgrids is used by including the disturbance inputs, as follows:

$$\dot{x} = Ax(t) + Bu(t) + H\omega(t) \tag{1}$$

being x the state vector, u the input vector, and ω the disturbance vector, A the feedback matrix, B the input matrix, and H the disturbance matrix, and where (1) is used to describe the dynamic behaviour of the microgrid.

In this framework, according to (1), two cases are presented: the first case considers a four states microgrid and the second case that uses 11 states microgrid.

A. Case 1: 4 states microgrid

The first case of a microgrid is based on the model described in [27] and [28], where four micro-sources are connected to the IEEE 4-bus network [31]. An schematic diagram of the microgrid is presented in Fig. 3.

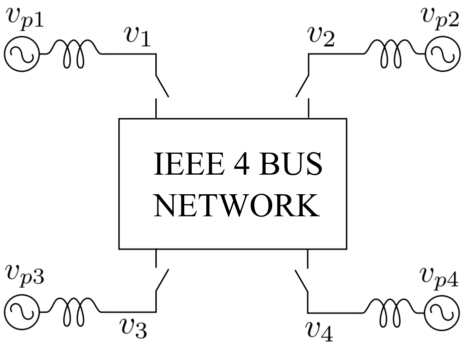

Fig. 3. Schematic of the 4 states microgrid where four micro-sources are connected to the IEEE 4-bus network

According to (1), the matrix A, B, and H of the state space model can be described as:

$$A = \begin{bmatrix} 175.9 & 176.8 & 511 & 103.6 \\ -350 & 0 & 0 & 0 \\ -544.2 & -474.8 & -408.8 & -828.8 \\ -119.7 & -554.6 & -968.8 & -1077.5 \end{bmatrix} \tag{2}$$

and

$$B = \begin{bmatrix} 0.8 & 334.2 & 525.1 & -103.6 \\ -350 & 0 & 0 & 0 \\ -69.3 & -66.1 & -420.1 & -828.8 \\ -434.9 & -414.2 & -108.7 & -1077.5 \end{bmatrix} \tag{3}$$

and $H = I$ being I the identity matrix.

In this case, the disturbance input (1) is related to the zero mean process noise, $x(t)$ is the state voltage deviation defined as $x(t) = v_s(t) - v_{ref}(t)$, being v_{ref} the point of common coupling (PCC) reference voltage and $v_s(t)$ the PCC voltages. In addition, the control signal $u(t)$ is the distributed energy generation resources (DER) control signal deviation, and is defined as the $u(t) = v_p(t) - v_{pref}(t)$, being v_{pref} the reference control effort, and $v_p(t)$ the input voltages, being v_s and v_p defined as

$$v_s(t) = \begin{bmatrix} v_1(t) \\ v_2(t) \\ v_3(t) \\ v_4(t) \end{bmatrix}, v_p(t) = \begin{bmatrix} v_{p1}(t) \\ v_{p2}(t) \\ v_{p3}(t) \\ v_{p4}(t) \end{bmatrix} \tag{4}$$

where v_i is the i-th PCC voltage. It can be seen that the four micro-sources are connected to the power network at the corresponding PCCs whose voltages are denoted by $v_s(t)$.

B. Case 2: 11 states microgrid

In [30] a state space model of a smartgrid is presented, where the model considers an electric power network composed of two subsystems which are: a thermal power plant and a wind power plant in Area 1 and a battery system and micro gas turbine generators in Area 2. The structure of the microgrid is described in Fig.4.

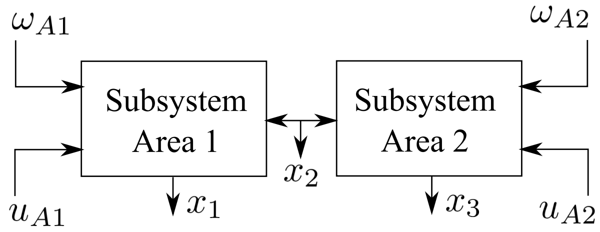

Fig. 4. Structure of the microgrid composed by subsystems which include a thermal power plant and a wind power plant in Area 1 and a battery system and micro gas turbine generators in Area 2

According to (1) the state space matrices are defined as follows:

$$A = \begin{bmatrix} -0.1 & 0.1 & 0 & 0 & 0.03 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.1 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -80 & 0 & -4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -5 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -2 & 0 & 0 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -0.1 & -0.2 & 0.1 & 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.9 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & -1 & -5 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

and

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 4 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0.8182 \\ 0 & 0 \\ 0 & 0.1818 \\ 0 & 0 \end{bmatrix}, H = \begin{bmatrix} 0.1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0.1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

with centralized control inputs for area A_1 and A_2 defined as

$$u = \begin{bmatrix} u_{A1} \\ u_{A2} \end{bmatrix}, \omega = \begin{bmatrix} \omega_{A1} \\ \omega_{A2} \end{bmatrix} \tag{5}$$

and the state space vector defined as

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{6}$$

being

$$x_1 = \begin{bmatrix} \Delta f_{A1} \\ \Delta P_T \\ \Delta x_{gA1} \\ U_{A1} \end{bmatrix}, x_2 = \Delta P_{tie}, x_3 = \begin{bmatrix} \Delta f_{A2} \\ \Delta P_G \\ \Delta x_{gA2} \\ x_B \\ \Delta P_B \\ U_{A2} \end{bmatrix} \tag{7}$$

The state space models of case 1 and case 2 described by using (1) can be represented as a difference equation by using backward difference approach, resulting in the following discrete state space equation

$$x[k+1] = A_d x[k] + B_d u[k] + H_d n_d[k] \tag{8}$$

where $A_d = A + It_s$, $B_d = Bt_s$, $H_d = Ht_s$ being t_s the sample time, $t_k = kt_s$, being k the sample. It can be noticed that (8) is the representation needed in order to apply the adaptive control approach proposed in this work.

III. Adaptive control of microgrids

In order to perform adaptive control of microgrids based on an estimated modeling it is necessary to estimate the parameters of the system through an Auto Regressive Moving Average with eXogenous inputs (ARMAX) model. The approach is divided in two stages: robust estimation of parameters considering disturbances or noise and adaptive linear quadratic regulator for control vector computing.

A. Robust estimation of parameters

A model defined by the following equation is proposed to identify the model [5]:

$$\begin{aligned}\mathbf{y}(k) &= \mathbf{B}_1\mathbf{u}(k-1)+\cdots+\mathbf{B}_{n_2}\mathbf{u}(k-n_2)\\ &\quad -\mathbf{A}_1\mathbf{y}(k-1)-\cdots-\mathbf{A}_{n_1}\mathbf{y}(k-n_1)\\ &\quad +\mathbf{C}_0\mathbf{w}(k)+\mathbf{C}_1\mathbf{w}(k-1)+\cdots+\mathbf{C}_{n_3}\mathbf{w}(k-n_3)\end{aligned} \tag{9}$$

where

$$\hat{\mathbf{w}}(k)=\mathbf{y}(k)-\hat{\mathbf{y}}(k)=\mathbf{y}(k)-\boldsymbol{\theta}^T\boldsymbol{\phi}(k-1) \tag{10}$$

being $\boldsymbol{\theta}^T$ the transpose of $\boldsymbol{\theta}$, and with $\boldsymbol{\theta}$ a matrix of dimension $(mn_1+pn_2+rn_3)\times m$ that holds the matrix parameters $\mathbf{A}_i$, $\mathbf{B}_i$, and $\mathbf{C}_i$ as follows:

$$\boldsymbol{\theta}^T=\begin{bmatrix}\mathbf{B}_1 & \cdots & \mathbf{B}_{n_2} & \mathbf{A}_1 & \cdots & \mathbf{A}_{n_1} & \mathbf{C}_1 & \cdots & \mathbf{C}_{n_1}\end{bmatrix} \tag{11}$$

and being $\boldsymbol{\phi}(k-1)$ a vector of dimension $(mn_1+pn_2+rn_3)\times 1$ that holds the past inputs and outputs as follows:

$$\boldsymbol{\phi}(k-1)=\begin{bmatrix}\mathbf{u}(k-1)\\ \vdots\\ \mathbf{u}(k-n_2)\\ -\mathbf{y}(k-1)\\ \vdots\\ -\mathbf{y}(k-n_1)\\ \hat{\mathbf{w}}(k-1)\\ \vdots\\ \hat{\mathbf{w}}(k-n_3)\end{bmatrix} \tag{12}$$

In [1] a class of identification algorithms is presented, where $\hat{\boldsymbol{\theta}}(k)$ is computed from $\hat{\boldsymbol{\theta}}(k-1)$, as follows:

$$\hat{\boldsymbol{\theta}}(k)=\hat{\boldsymbol{\theta}}(k-1)+\mathbf{M}(k-1)\boldsymbol{\phi}(k-1)\boldsymbol{e}(k) \tag{13}$$

being $\hat{\boldsymbol{\theta}}(k)$ the estimated parameter matrix at sample k, $\mathbf{M}(k-1)$ the gain matrix, $\boldsymbol{\phi}(k-1)$ the vector with past inputs and outputs, and $\boldsymbol{e}(k)$ the estimation error, as follows:

$$\boldsymbol{e}(k)=\mathbf{y}(k)^T-\hat{\mathbf{y}}(k)^T \tag{14}$$

being $\hat{\mathbf{y}}(k)$ given by:

$$\hat{\mathbf{y}}(k)=\hat{\boldsymbol{\theta}}(k-1)^T\boldsymbol{\phi}(k-1) \tag{15}$$

As described in [1] the multivariable least squares algorithm can be defined as:

$$\begin{aligned}\mathbf{e}(k) &= \mathbf{y}(k)^T-\boldsymbol{\phi}(k-1)^T\hat{\boldsymbol{\theta}}(k-1)\\ \mathbf{M}(k) &= \mathbf{P}(k-1)\\ \hat{\boldsymbol{\theta}}(k) &= \hat{\boldsymbol{\theta}}(k-1)+\mathbf{M}(k)\boldsymbol{\phi}(k-1)\mathbf{e}(k)\end{aligned} \tag{16}$$

and

$$\mathbf{P}(k-1)=\mathbf{P}(k-2) \tag{17}$$

$$-\frac{\mathbf{P}(k-2)\boldsymbol{\phi}(k-1)\boldsymbol{\phi}(k-1)^T\mathbf{P}(k-2)}{1+\boldsymbol{\phi}(k-1)^T\mathbf{P}(k-2)\boldsymbol{\phi}(k-1)} \tag{18}$$

with initial estimate $\hat{\boldsymbol{\theta}}$ given and $\mathbf{P}(0)$ a positive diagonal matrix.

B. State Feedback Adaptive Control

In order to perform an adaptive control of the microgrid, an extended state space formulation is obtained form the identified ARMAX model of (9) as follows:

$$x_e[k+1]=Fx_e[k]+Gu[k] \tag{19}$$

(20)

being the matrices F and G defined as

$$F=\begin{bmatrix}-A_1 & -A_2 & B_0 & B_1\\ I & 0 & 0 & 0\\ 0 & 0 & 0 & 0\\ 0 & 0 & I & 0\end{bmatrix}, G=\begin{bmatrix}0\\0\\I\\0\end{bmatrix} \tag{21}$$

and, where the state space vector x is defined as

$$x_e[k]=\begin{bmatrix}y[k-1]\\ y[k-2]\\ u[k-1]\\ u[k-2]\end{bmatrix} \tag{22}$$

By using the state space model of (19), a state feedback control can be presented in terms of the state vector as follows:

$$u[k]=-Kx_e[k] \tag{23}$$

being K is the feedback control matrix, that can be computed by using a Linear Quadratic Regulator (LQR) [32], where the performance index is defined by

$$J=\sum_{k=1}^{N}x_e^T[k]Qx_e[k]+u^T[k]Ru[k] \tag{24}$$

being Q and R matrices constraints positive and semi-positive defined. Since (24) is minimized subject to (19) which is an adaptive model with time varying features, the resulting feedback control matrix K is also time varying. Therefore, the proposed control is an adaptive optimal control.

In Fig. 5 is presented an structure of the adaptive control including the identification of the ARMAX model stage, the Digital to Analog Converters (DAC) and the Analog to Digital Converters (ADC).

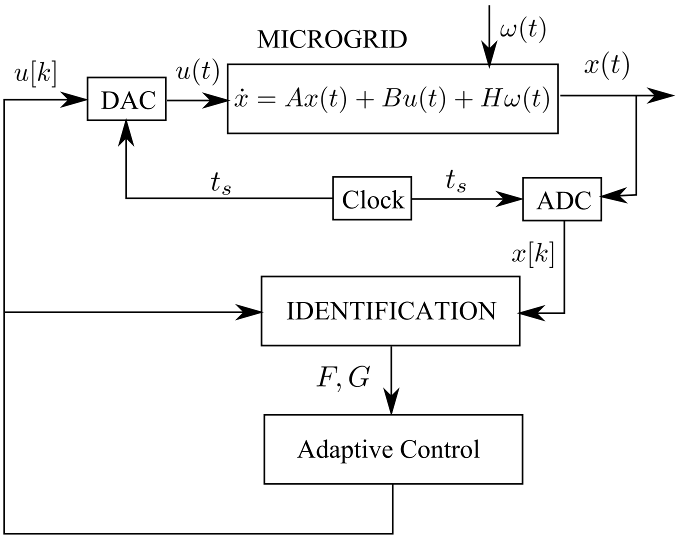

Fig. 5. Adaptive optimal control scheme based on a linear quadratic regulator

It can be seen that, even when an adaptive LQR strategy is used in this work, in general, any optimal scheme [33] or pole placement technique [34] can be used to compute the control signal based on the identified model.

IV. Results

In order to evaluate the performance of the proposed method, the adaptive control is evaluated for the two aforementioned cases of microgrids. The estimation is performed by using a second order ARMAX model, and the extended state space equation in discrete time of (19) is obtained. The adaptive control approach is evaluated under noise and noise free conditions (with or without disturbances), and considering initial conditions not equal to zero. In addition, the initial parameters are set to a random value. Also for the second case, an steady state analysis of the system is performed for the state vector. It is worth noting that the case 1 and case 2 are formulated in terms of the evolution of the state around operational points, therefore, the control signals and the states evolution tends to zero in steady state.

A. Case 1: 4 states microgrid

For the first case, the matrix is $F \in \mathbb{R}^{16\times16}$, matrix $G \in \mathbb{R}^{16\times4}$, matrices $A_i \in \mathbb{R}^{4\times4}$ and $B_i \in \mathbb{R}^{4\times4}$. Constraints matrices $Q \in \mathbb{R}^{16\times16}$ and $R \in \mathbb{R}^{4\times4}$ are selected as identity matrices. The initial value of the model parameters is selected as random value, and the initial state conditions are selected as 8 in p.u. for all the states, and the sample time is $t_s = 0.1$ miliseconds. It can be seen that, for the first case, the voltage deviation under noise free conditions are presented in Fig. 6 and Fig. 7. It can be seen that the system is regulated since all the voltage deviations at each node tends to zero. It is noticeable that the system is estimated and regulated simultaneously.

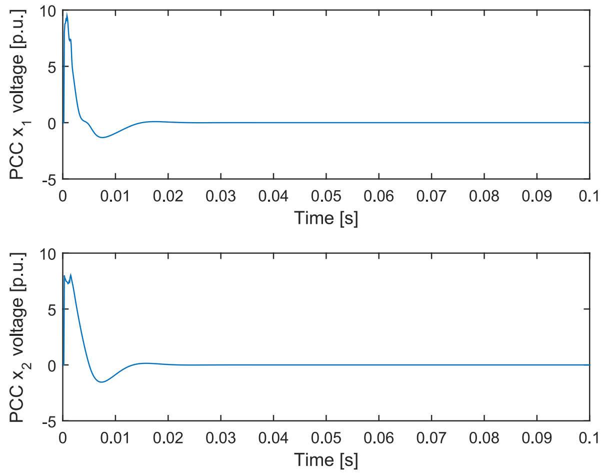

Fig. 6. PCC voltages deviations of x_1 and x_2 under a noise free scenario for case 1: 4 states microgrid

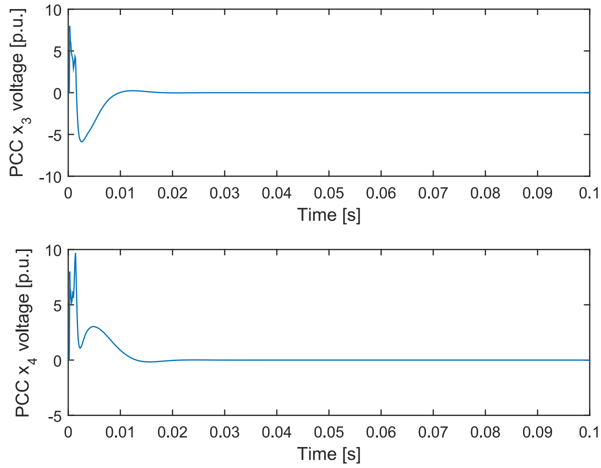

Fig. 7. PCC voltages deviations of x_3 and x_4 under a noise free scenario for case 1: 4 states microgrid

The control inputs computed by the adaptive approach, corresponding to the outputs shown in Fig. 6 and Fig. 7, of the first case, are presented in Fig. 8 and Fig. 9. It can be seen that once the system is regulated, the control signals are zero.

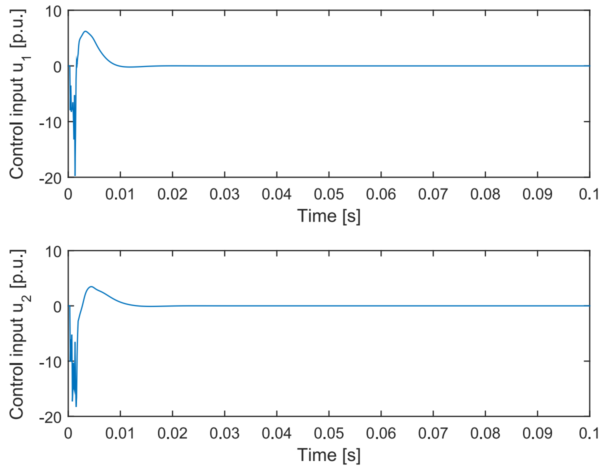

Fig. 8. Control inputs u_1 and u_2 under a noise free scenario for case 1: 4 states microgrid

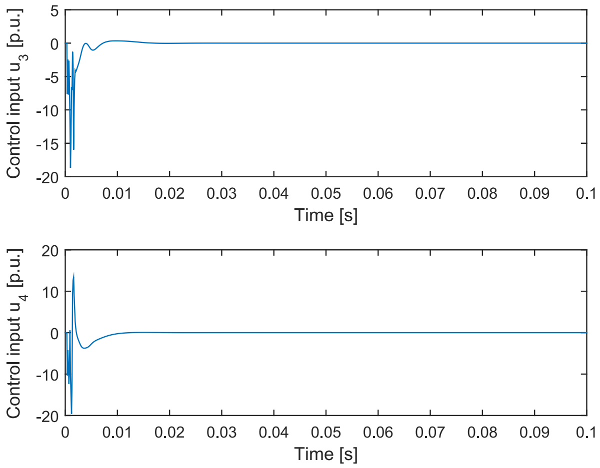

Fig. 9. Control inputs u_3 and u_4 under a noise free scenario for case 1: 4 states microgrid

The results for the PCC voltage deviation under noise conditions are presented in Fig. 10 and Fig. 11. It is noticeable that the noise is zero mean Gaussian with 10% signal-to-noise ratio. It can be seen that the voltage deviation tends around zero even in the presence of noise. It is noticeable that the settling times under noise and noise free conditions are comparable.

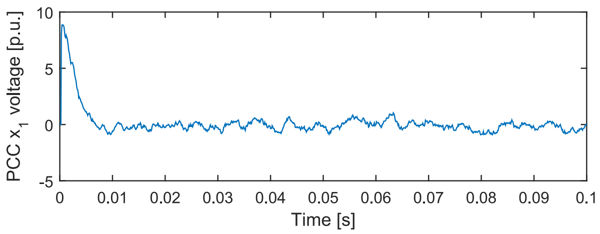

Fig. 10. PCC voltages deviations x_1 and x_2 under noise conditions for case 1: 4 states microgrid

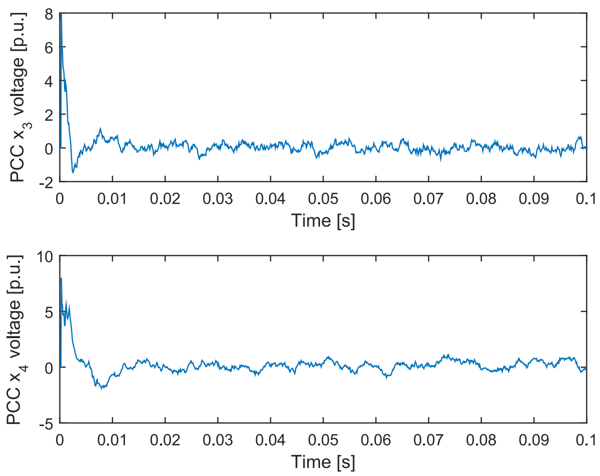

Fig. 11. PCC voltages deviations x_3 and x_4 under noise conditions for case 1: 4 states microgrid

The control inputs associated to the results presented in Fig. 10 and Fig. 11, are presented in Fig. 12 and Fig. 13. It can be seen, that also the control inputs in the noisy scenario tends around zero. It is also worth noting that the amplitude of the control signal under noise and noise free conditions are the same.

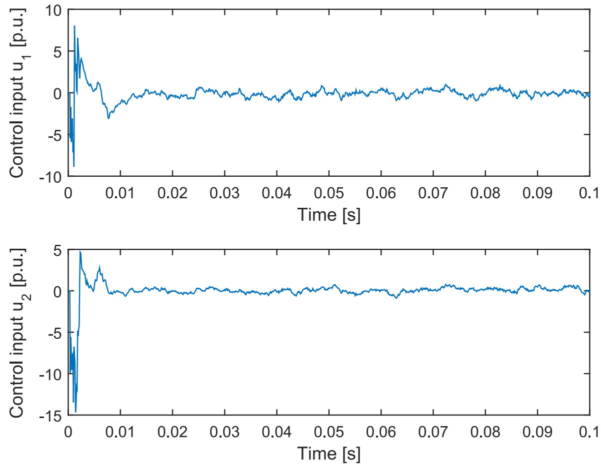

Fig. 12. Control inputs u_1 and u_2 under noise conditions for case 1: 4 states microgrid

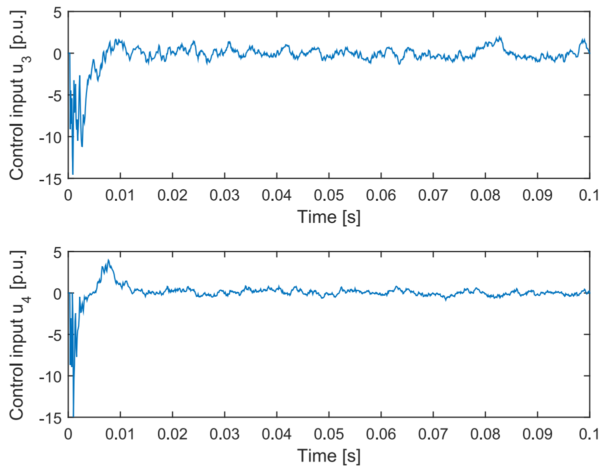

Fig. 13. Control inputs u_3 and u_4 under noise conditions for case 1: 4 states microgrid

B. Case 2: 11 states microgrid

For the second case, the matrix is $F \in \mathbb{R}^{26\times 26}$, matrix $G \in \mathbb{R}^{26\times 2}$, matrices $A_i \in \mathbb{R}^{11\times 11}$ and $B_i \in \mathbb{R}^{11\times 2}$. Constraints matrices $Q \in \mathbb{R}^{26\times 26}$ and $R \in \mathbb{R}^{2\times 2}$ are selected as identity matrices. The initial value of the model parameters is selected as random value, and the initial state conditions are selected for all the states as 0.5 in p.u., and the sample time is $t_s = 250$ miliseconds.

It can be seen that, for the second case, the power fluctuation results under disturbance free conditions are presented in Fig. 14. It is worth noting that the first 20 seconds (80 samples) are required to estimate and regulate adequately the system, achieving the settling time around 25 seconds (90 samples). The control inputs computed by the adaptive approach, corresponding to the power fluctuations of Fig. 14, are presented in Fig. 15. It can be seen that once the system is regulated, the control signals are zero.

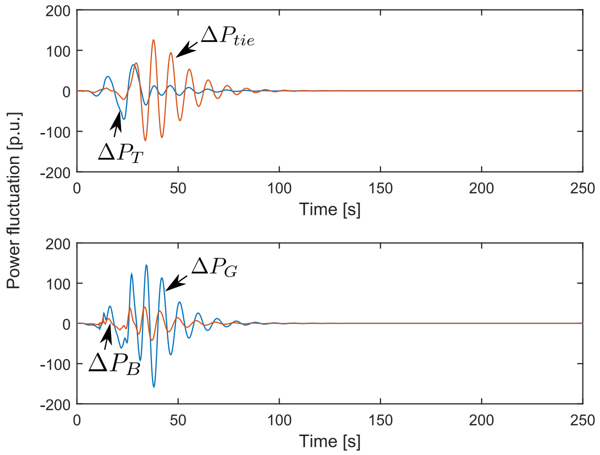

Fig. 14. Power fluctuation of the case 2: 11 states microgrid under noise free conditions

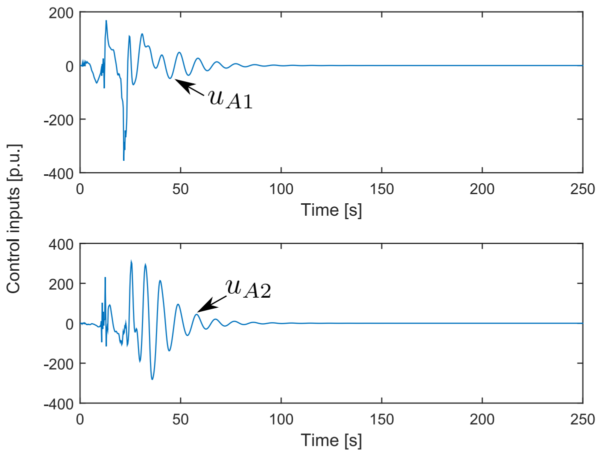

Fig. 15. Control inputs of the case 2: 11 states microgrid under noise free conditions

The results for power fluctuation under noise conditions are presented in Fig. 16.

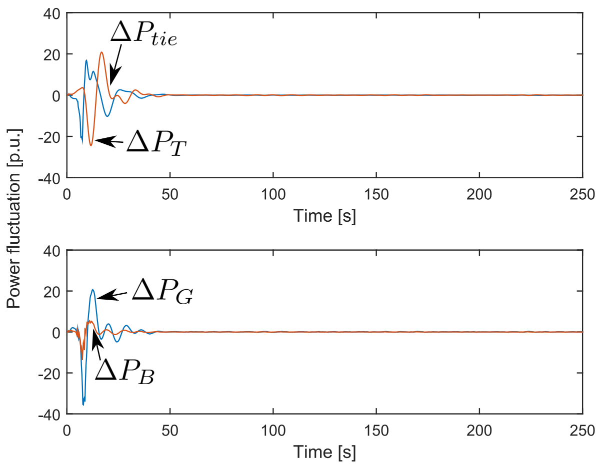

Fig. 16. Power fluctuation of the case 2: 11 states microgrid under noise conditions

It is noticeable that the noise is zero mean Gaussian with 10% signal-to-noise ratio. It is noticeable that under noise conditions the system takes around 50 seconds to achieve the settling time, however, it is remarkable that the system is being estimated and regulated at the same time. A segment of steady state of the power fluctuation is presented in Fig. 17. As shown in Fig. 17 the power fluctuations are regulated around zero.

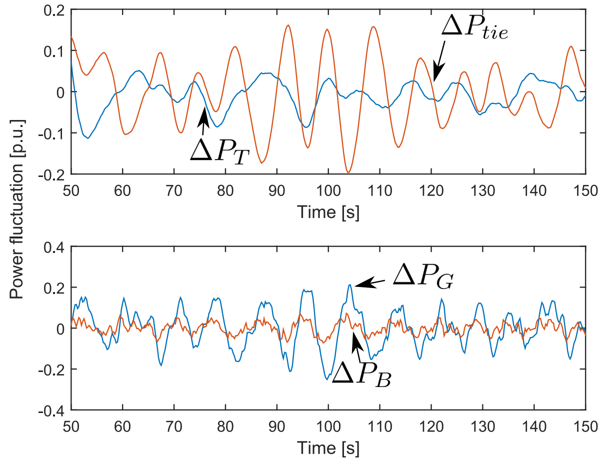

Fig. 17. Segment of steady state of Power fluctuation of the case 2: 11 states microgrid under noise conditions

The control inputs under noise conditions are presented in Fig. 18. It can be seen that once the system is regulated the control signals are computed around zero.

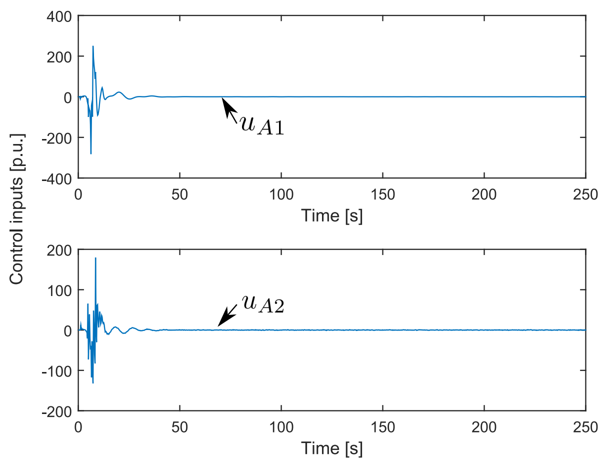

Fig. 18. Control inputs of the case 2: 11 states microgrid under noise conditions

Besides, the control inputs under noise conditions for a segment of steady state conditions are presented in Fig. 19. It can be seen that once the system is regulated the control signals are computed around zero.

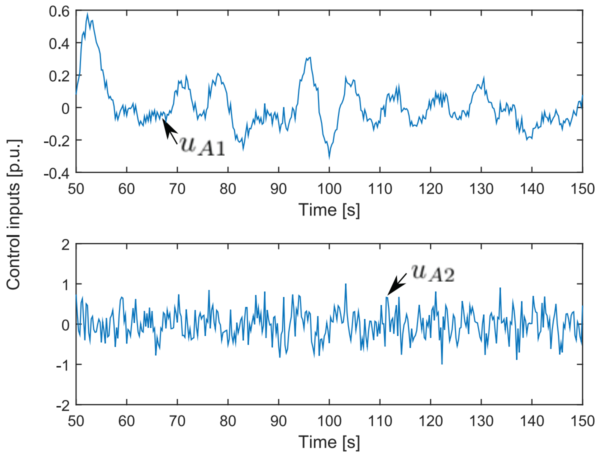

Fig. 19. Control inputs segment of steady state conditions for the case 2: 11 states microgrid under noise conditions

In addition, the frequency fluctuation of the case 2 under noise conditions are also presented in Fig. 20. It can be seen that the frequency is also effectively regulated. A segment of steady state behaviour of the frequency fluctuation of the case 2 under noise conditions is presented in Fig. 21.

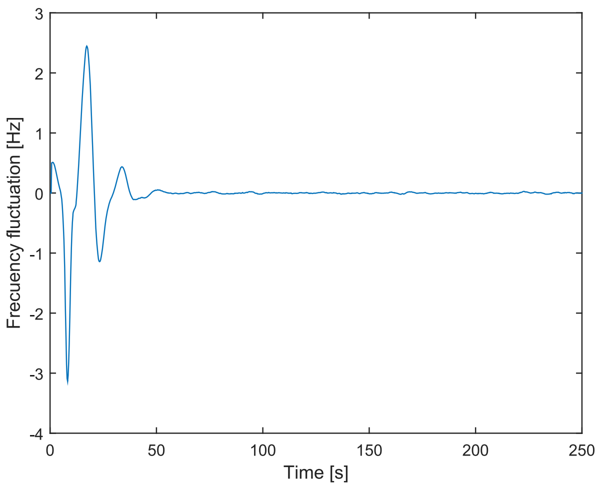

Fig. 20. Frequency fluctuation under noise conditions of the case 2: 11 states microgrid

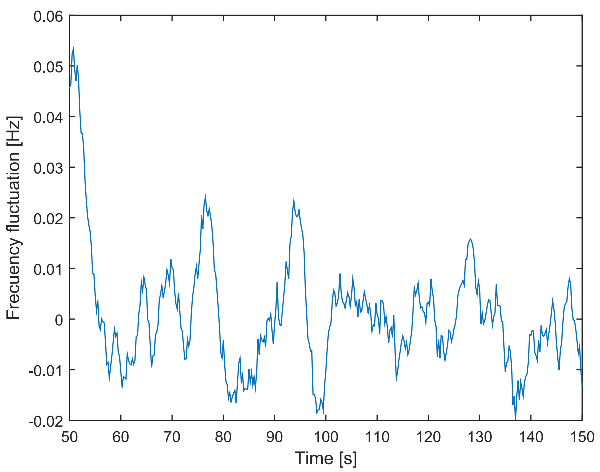

Fig. 21. Segment of steady state conditions for frequency fluctuation under noise conditions

V. Conclusions

In this paper, a novel adaptive control approach of microgrids is presented, where a robust estimation is performed based on a linear ARMAX model. In addition, an adaptive Linear Quadratic Regulator is used for optimal control based on an extended state space approach to compute the control signal. It is noticeable that the proposed multivariable adaptive control in state space effectively estimate and control the two cases of microgrid under noise and noise free conditions. The results for power fluctuation under noise conditions demonstrate the robustness of the controller and also give a correct approximation to real operating conditions.

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