Development of Dynamic Equivalents for MicroGrids using System Identification Theory

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Abstract—**Large deployment of MicroGrids will have a considerable impact on the future operation of the electrical networks and will greatly influence the power system dynamics mainly at the Medium Voltage (MV) level whenever the upstream system has been lost. In dynamic studies the whole power system cannot be represented in a detailed manner because the huge system dimension would require a very large computational effort. Therefore dynamic equivalents for MicroGrids need to be derived. The proposed approach is based on system identification theory for developing dynamic equivalents for MicroGrids, which are able to retain the relevant dynamics with respect to the existing MV network.**

Index Terms—**Dynamic behaviour, dynamic equivalents, microgenerators, MicroGrids, parameter estimation, system identification.**

I. Introduction

DISSEMINATION of small size dispersed microgeneration, connected to Low Voltage (LV) distribution systems is expected to become an effective mean to face the continuous demand growth. The need of reducing greenhouse emissions, recent technological developments related with the improvement of microgeneration efficiency and the possibility of exploiting renewable energy resources are important factors that will contribute, in a short term, to an effective penetration of microgeneration in LV grids. Such large deployment of microgeneration is leading to the adoption of a MicroGrid concept, which was investigated within the framework of the MicroGrids EU R&D project [1].

A MicroGrid (MG) comprises a LV network, its loads, several modular generation systems connected to it through inverter interfaces and an embedded control and management system. Microgeneration technologies include renewable power sources, such as wind and photovoltaic (PV) generators, microturbines, fuel cells and also storage devices such as flywheels or batteries. When properly controlled the MG flexibility allow two different modes of operation: Normal interconnected and emergency mode [2]. Under normal conditions the MG is connected to the MV network, either importing or exporting some amount of power. Following the disconnection from the MV network, the MG can operate autonomously like a physical island.

A. General overview

It is expected that, in a near future, several MG can be connected on several adjacent Medium Voltage (MV) feeders coexisting with MV loads and distributed generation units. The MG operation flexibility will then be extended to the MV level through suitable control schemes, leading with the Multi-MicroGrid (MMG) concept, which is being developed within the framework of the EU More-MicroGrids Project, Contract No. 019864 (SES6). In order to study the dynamic behaviour of such systems it is necessary to use simulation tools with an adequate modelling of such MG.

The simulation platform developed to evaluate the MG concept as well as the feasibility of MG inverter control strategies [2, 3] has been used in this research. However, from the possibility to have many MG connected to the MV network, a large number of active sources together with their inverter interfaces should be considered and therefore a high dimensional system will arise. So, the use of detailed models that are able to accurately simulate the MG dynamic behaviour becomes not practical due to the considerable computational effort required to solve the resulting system with a large number of nonlinear ordinary differential equations.

Thus, in order to simulate the relevant dynamics of several MG with respect to the MV network, it is necessary to speed up numerical simulations and therefore identification of dynamic equivalents for MG is required.

Conventional dynamic equivalence techniques consist on the following steps [4]: (i) Coherency identification; (ii) aggregation of coherent generators; (iii) static network reduction; (iv) aggregation of control devices. However, in general, power systems physical components are nonlinear systems. More specifically, in a MG, microgenerators are connected to the LV network through inverter interfaces and, some of them, namely photovoltaic systems and fuel cells are not characterized by angles and angular speeds. Additionally, in contrast with conventional large power systems, decoupling active and reactive powers is not practical, since the MG is a very resistive network. So, classical methods are not suitable to derive MG equivalents. To overcome those problems and since such equivalent derivation is very difficult to handle

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using analytical techniques, system identification theory has been exploited to obtain dynamic equivalents for MG.

In contrast with analytical modelling, system identification deals with the problem of building mathematical models based on observed data from the system to be modelled. After choosing a suitable model structure, the data is used in order to fit the model properties to those of the system. Depending on the assumed level of prior knowledge and physical insight about the system effectively used when selecting a model structure, two possible kinds of models arise: Black box and grey box models [5]. In the context of black box modelling, artificial neural networks were already successfully applied to build dynamic equivalents for MG [6] and for other power systems integrating distributed generation with loads [5].

In this research the available physical knowledge about the MG dynamics is exploited. The model structure is built using known physical laws with the unknown parameters estimated from data. This procedure belongs to the grey box modelling approaches and is commonly known as physical modelling, since the model structure corresponds to a physical parameterization [7].

The equivalent model thus obtained was used to replace one MG in a dynamic simulation tool when several perturbations at the MV level occur, like MV network islanding and load following in islanding mode. Its performance was evaluated through simulations and the results confirm the accuracy and the helpfulness of the obtained MG dynamic equivalent.

II. MicroGrid Architecture

A MG is defined as a LV distribution system in which small modular generation systems are connected together with LV electrical loads, as depicted in Fig. 1.

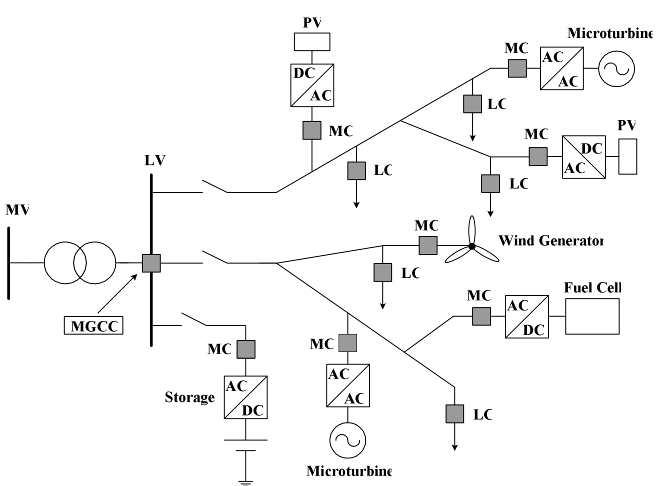

Fig. 1. MicroGrid architecture comprising microsources, loads and control devices.

The MG is centrally controlled and managed by a MicroGrid Central Controller (MGCC) installed at the MV/LV substation, which possesses several key functions and heads the hierarchical control system. It supports adequate technical and economical management policies and provides set points to both Microsource Controllers (MC) and Load Controllers (LC). Therefore a second hierarchical control level is established at the Microsources (MS) and loads level: MC control locally the active and reactive power production levels of controllable MS and LC control electrical loads through the application of an interruptability concept.

III. MG Operation and Control in a Multi-MicroGrid

From the extension of the MG operation flexibility to the MV level, suitable control schemes should allow operating the MMG under both normal interconnected and emergency mode in a similar way that a MG. Thus, MMG islanding can take place either by unplanned events like faults in the upstream power system or by planned actions like maintenance requirements. Following a MMG disconnection from the upstream system, MG will be kept in operation connected with the MV network, with the synchronous machines providing voltage and frequency control.

Concerning dynamic equivalency, in contrast with conventional power system, a MG is an inverter dominated grid and both coherency identification and aggregation of coherent generators tasks do not make sense in such a power system. Thus in order to build dynamic equivalents for MG based on physical modeling, the MS dynamic models and inverters as well as the main control strategies that assure a successful MG islanding and its operation in islanded mode are briefly analyzed in the following sections.

A. *Microsources and Storage Devices Modelling*

Several MS models, including fuel cells, microturbines, wind generators and PV arrays have been modelled [8]. However, in this work only Solid Oxide Fuel Cell (SOFC) and high speed Single Shaft Microturbines (SSMT) are used with their power electronic interfaces (DC/AC inverters for SOFC and AC/DC/AC converters for SSMT). Storage devices were also used and were modelled as constant DC voltage sources with power electronic interfaces (AC/DC/AC converters for flywheels and DC/AC inverters for batteries).

B. *Inverter Modelling and Control of MG Operation*

An inverter can be operated according two different control strategies: PQ inverter control and Voltage Source Inverter (VSI) control [9]. The PQ inverter injects into the grid the power available at its input. The reactive power injected corresponds to a pre-defined value, which can be defined either locally using a local control droop or centrally from the MGCC [2]. When analysing the long term dynamic behaviour of a MG, inverters are modelled only by their control functions, so that fast switching transients are neglected.

The VSI emulates the behaviour of a synchronous machine providing voltage and frequency references to the MG under islanded operation. However it can also be operated in normal interconnected mode, in parallel with the MV network. If the angular frequency is w_{grid}, the VSI active power output is defined by the frequency droop characteristic as depicted in Fig. 2.

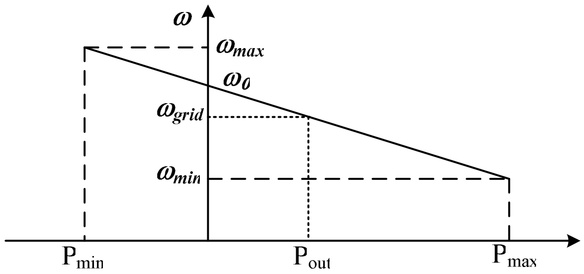

Fig. 2. Frequency droop control.

In order to control VSI units, terminal voltage and current are measured to compute active and reactive powers. Frequency and output voltage amplitudes are established through a droop control approach. This control principle allows VSI to react to system disturbances (for example load or generation changes) based only on information available at its terminals [10].

C. Secondary load frequency control

Whenever the MG is operated in islanded mode, following transients a steady state deviation from the nominal frequency will be observed. As a result of the control droop implemented in the VSI, the main storage unit will support all power deviations by injecting or absorbing some amount of active power proportionally to the MG frequency deviation.

Although acting as a voltage source, storage devices have a finite capacity for storing energy due to physical limitations. Therefore the system frequency should be restored to the nominal value, w_0, in order to the VSI active power returns to zero. For that purpose, two main secondary control strategies can be followed: local secondary control using a PI controller at each controllable MS or centralized secondary control mastered by the MGCC. In both cases, target values for active power outputs of the primary energy sources should be defined based on the frequency deviation error [11], as depicted in Fig. 3. However, in this research only the local secondary control strategy was considered.

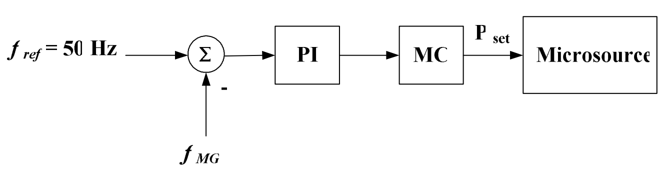

Fig. 3. Local secondary load frequency control for controllable MS.

When a MMG is disconnected from the upstream power system, the synchronous machines connected to the MV level will be responsible to balance demand and supply. However, following a disturbance in the MV level, like load following, system frequency changes leading to VSI active power variations according to its droop characteristic. Therefore local secondary load frequency control of controllable MS tries to restore the system frequency to the nominal value through the definition of a new active power set point for the primary energy source. As a result the MG will contribute together with the synchronous machines to balance active power demand and supply.

IV. Identification of Nonlinear Dynamic Systems

In contrast with analytical modelling, system identification deals with the problem of building mathematical models based on the observed data from the system. Based on a suitable model structure, the data is used for fitting the model properties to those of the system to be modelled [7].

The data is collected during an especially designed system experiment. In general, the problem of system identification consists basically in setting up a suitable model structure and in adjusting its parameters in order to minimize the performance function generally quantified by an error criterion. Both system and model are fed with the same inputs, $u(t)$, and the corresponding outputs, $y(t)$ and $\hat{y}(t \mid \theta)$, respectively, are compared for $t=1, \ldots, N$, where N is the number of collected data samples, yielding an error signal

$$\varepsilon(t \mid \theta) = y(t) - \hat{y}(t \mid \theta) \tag{1}$$

which should be used in some sense for adapting the model, as depicted in Fig. 4. The term $v(t)$ accounts for the fact that the system outputs will not be an exact function of the input data.

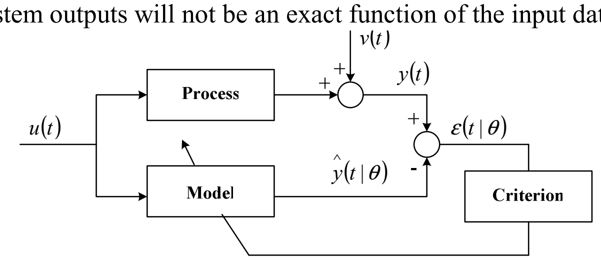

Fig. 4. Building mathematical models using system identification theory

The model has to be augmented with a suitable identification criterion that measures how well the model fits the system dynamic behaviour and with an algorithm that will adapt the model parameters so that the minimum of the identification criterion can be achieved. The model performance feedback is used directly to change the parameters through an estimation algorithm, so that the model output improves.

Parameter estimation of a nonlinear model is usually based on optimization algorithms in order to search for the best parameter vector θ, which provides predictions that are in some sense close to the system outputs. The most commonly used measure of closeness is usually taken as a square function of the error given by equation (1), i.e.

$$\hat{\theta}_N = \arg\min_{\theta} V_N \, ; V_N = \sum_{t=1}^{N} \left\| \varepsilon(t \mid \theta) \right\|^2 \tag{2}$$

In [5] the nonlinear optimization techniques are distinguished between local and global techniques. The nonlinear local optimization techniques provide numerical solutions through iterative search methods, which start from an initial point in the parameter space and search in directions obtained by neighbourhood information such as first and possibly second derivatives of the identification criterion, also called loss function. These algorithms are sensitive to an initial point and do not guarantee convergence to a global optimum.

In contrast, the so called global optimization methods are not guided in their search process by local derivatives. Evolutionary Strategies (ES) constitute one of the most prominent global search techniques [5].

Particle Swarm Optimization (PSO) algorithm has also been used in system identification domain and when compared to EA, PSO presents some attractive characteristics and in many cases proved to be more effective [12]. Evolutionary Particle Swarm Optimization (EPSO) combines the best of ES and PSO, through the introduction of the particle movement operator to generate diversity [13] and constitutes a promising optimisation tool to be used in parameter estimation.

Finally it remains to evaluate whether the model is good enough for the intended purpose – the model validation. In this stage it is checked if the preceding steps have been carried out successful or not. If the model does not satisfy the validation criterion it is necessary to go back in the procedure and revise the various steps.

V. BUILDING DYNAMIC EQUIVALENTS FOR MICROGRIDS

The proposed approach for MG dynamic equivalents development exploits system identification theory, namely a physical modeling approach, since the procedure is mainly based on the available physical knowledge, as already mentioned previously. The MG dynamic equivalent is required to be integrated in dynamic simulation tools in order to emulate the relevant dynamics of a MG with respect to the MV network following transients, namely MMG islanding and load following in islanded mode. Therefore, the knowledge about the MG dynamics was used together with the identification procedure main stages, as described in the following sections.

A. Data collection

For analysis purposes the whole MMG network is divided into to parts: The internal network, where disturbances take place and where the response of the dynamic equivalent is to be observed and the external system where detailed information on the system response is not required, and therefore it is desirable to represent it by a simpler equivalent model. Thus the external system corresponds to the MG detailed model and the internal network to the remaining MMG network.

The physical laws that describe the MG dynamics allow distinguishing between two different dynamic responses among the several MS into the MG: a) The main storage device with a VSI control inverter displays fast dynamic response while b) the controllable MS with a PQ inverter control display slow dynamic responses. In addition, concerning to the simulation time, those MS connected to the LV grid through inverters with PQ control are the main responsible for the large simulation times. Therefore, based on those assumptions, a suitable dynamic equivalent for MG comprises the detailed model of the main storage device VSI control and an aggregated model corresponding to remainder MG system, henceforth called MG slow dynamics reduced model, as depicted in Fig. 5.

The MG dynamic equivalent will interact with the internal network through the system boundary: the boundary bus and the tie line. It will be excited by both boundary bus voltage and system frequency deviations and reacts by varying the injected current into the internal system according to Fig. 5.

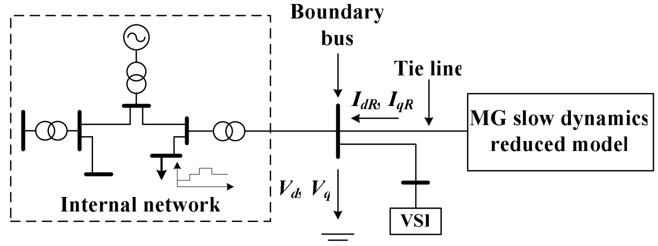

Fig. 5. MG dynamic equivalent model

B. Model structure selection

The key issue in a system identification procedure is the model structure selection. In this case the physical laws that can approximate the MG slow dynamics under the study conditions are understood, since they are similar to those that govern the active power control in a diesel group. Thus the system representation is commonly done by a continuous state space model of a given order, which is represented under *MatLab*® *Simulink*® environment through the block diagram depicted in Fig. 6.

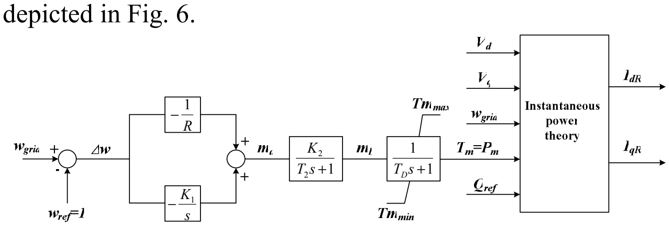

Fig. 6. Model structure of the MG dynamic equivalent

The model structure constants whose values have to be estimated during the identification procedure are gathered into the parameter vector, as

$$\theta = \begin{bmatrix} R & K_1 & K_2 & T_2 & T_D \end{bmatrix} \tag{4}$$

The variable Q_{ref} in Fig. 6 represents the reactive power set point sent by the MGCC to the main storage device VSI. The instantaneous power theory [14] was used in order to allow the model response as a current source.

C. Parameter estimation using EPSO

In order to estimate the parameter vector given by (4), EPSO is exploited together with the sum square error criterion according to equation (2). The loss function of each particle is evaluated on a suitable dynamic simulation platform. Therefore, some interaction between EPSO and the dynamic simulation platform is required. EPSO sends the parameter vector to the dynamic simulation platform and, after the time domain simulation, EPSO receives the corresponding loss function value as depicted in Fig. 7.

Taking into account the particular fact that the parameter vector is estimated on the environment in which it will be used, model validation is in some sense embedded into the parameter estimation stage.

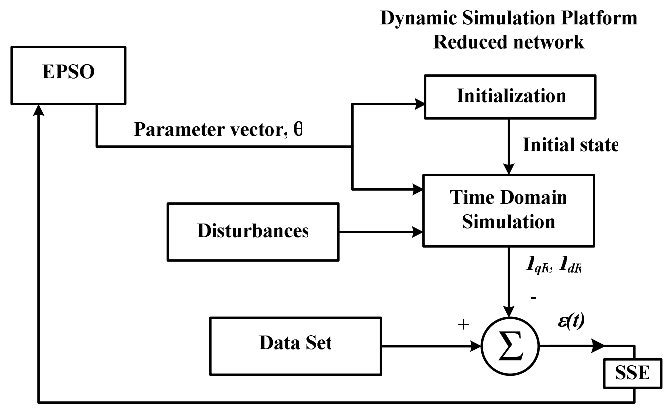

Fig. 7. Parameter estimation algorithm

VI. Dynamic Simulation Platform

A simulation platform was developed under *MatLab® Simulink®* environment as a multi-machine system in order to evaluate the performance and accuracy of the MG dynamic equivalent. This simulation platform allows simulating the MMG islanding and load following transients in islanded mode to estimate the parameters of the MG dynamic equivalent model through the algorithm presented in Fig. 7.

Dynamic models of several MS, namely SSMT, SOFC and MG main storage operating together in a LV network through their inverter interfaces as well as its control strategies, as described in section III, were implemented in this simulation platform. At the MV level a round rotor synchronous machine 6th order model together with its automatic voltage regulator (IEEE type 1 Model) and its governor-turbine model in a *d-q* reference frame [15] were implemented. Loads and transformers are modelled as constant admittances and equivalent impedances respectively. The electrical network, including both MV and LV grids, is represented by the nodal admittance matrix built in a *d-q* reference frame.

VII. Simulation Results and Discussion

The proposed approach is applied to build a dynamic equivalent for the MG presented in the test system depicted in Fig. 8, which represents a MMG. The MMG system comprises two round rotor synchronous generators (500 kVA) connected to the MV network together with MV loads and a LV feeder connected to a MV/LV distribution transformer – the MicroGrid. The MG comprises two 30 kW SSMT, a 30 kW SOFC and the main storage device (flywheel). The study system as well as the MG is distinguished in Fig. 8.

The generated data set is obtained on the detailed system representation. Following the MMG disconnection from the upstream power system, different load following scenarios in the MV network were considered. Different amounts of load connection and disconnection sequences are simulated at bus 8 (L1) and in each case the simulation is carried out over 40s (the different amounts of load are connected at t=2s and disconnected at t=20s), which is sufficient to restore the steady state conditions, using the variable step size solver ode15s with a relative tolerance 10^{-6}. The MMG operating conditions before islanding are presented in table 1.

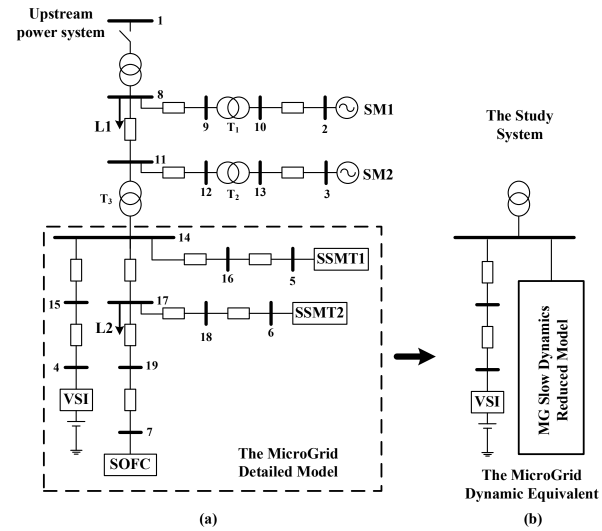

Fig. 8. Test system single-line diagram: (a) Detailed system; (b) Reduced system

TABLE I
MMG Operating Conditions Before Islanding

	Load (KVA)	DG production (kW; kVAr)
MV network	500+j100	SM1: 250; SM2: 200
MicroGrid	50+j10	SSMT1=SSMT2=15+j2 SOFC=15+j2; VSI=j5

After adapting the model parameters according to the methodology described above, the performance of the MG dynamic equivalent in describing the MG behaviour following the MMG islanding and under load following transients was evaluated. For this purpose some simulations have been carried out and the obtained results are compared with those obtained with the detailed MG model. To demonstrate the capacity of this MG dynamic equivalent over a wide range of operating conditions, its behaviour is studied under new MMG operating conditions before islanding as described in table 2.

TABLE 2
New MMG operating conditions before islanding

	Load (KVA)	DG production (kW; kVAr)
MV network	500+j100	SM1: 200; SM2: 200
MicroGrid	50+j10	SSMT1= 10+j2; VSI=j5 SSMT2=SOFC=15+j2

Under these new operating conditions the following sequence of events was simulated: 1) MV network islanding at t=5s; 2) Connection of a new amount of load at t=20s; 3) Disconnection of the amount of load connected previously at t=40 s. A comparison between the responses obtained from detailed and reduced systems is presented in Fig. 9-11.

Fig. 11 shows a comparison between the active power injected by the MG slow dynamics equivalent model and the corresponding detailed model. Following the MMG islanding a large initial frequency deviation arises as can be shown in Fig. 10. Thus the VSI injects active power according to its droop characteristics and the MG main storage inverter output is changed. The MS with secondary load frequency control participate together with the synchronous machines in frequency restoration using their proportional integral control strategy as can be observed in Fig 9 and 11, respectively.

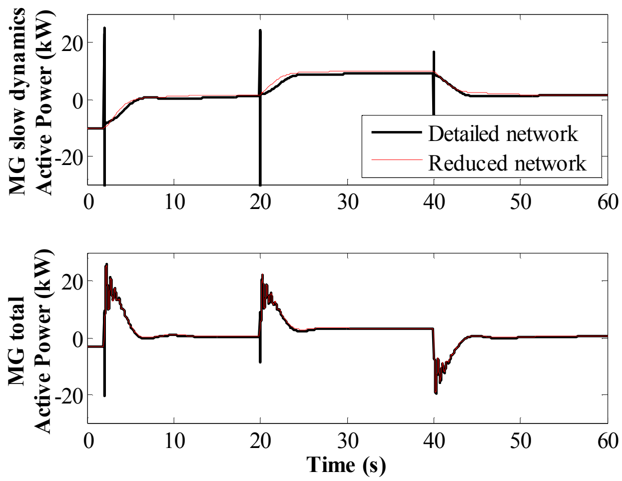

Fig. 9. Active power injected by the MG slow dynamics model and by the MG

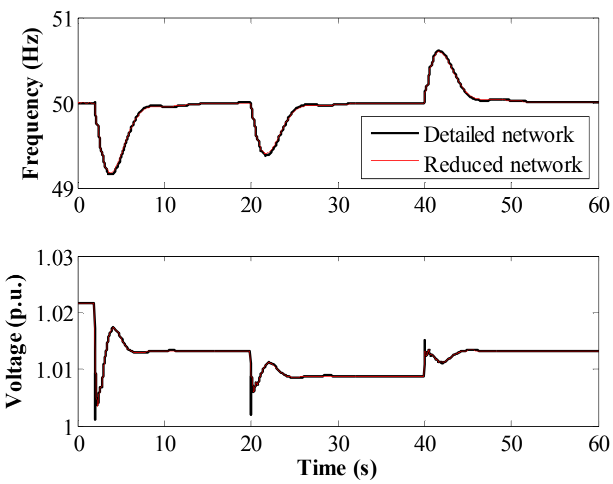

Fig. 10. System frequency and bus 14 voltage

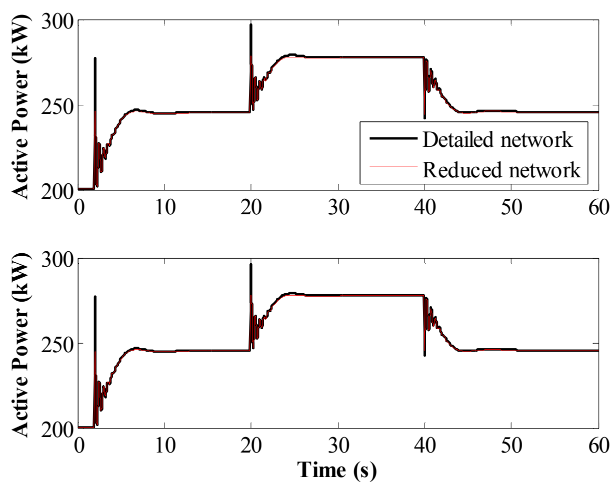

Fig. 11. Active power injected by SM1 and SM2

Though under different operating conditions, Fig. 9-11 show that the results from the MG dynamic equivalent model are still in good agreement with the MG detailed model. This fact is very important since due to the regular variations in the switching status of the distributed generation units and, in particular, due to MS active power production changes it is not required to build another MG dynamic equivalent.

VIII. Conclusions

This paper presents an application of system identification theory to build a MG dynamic equivalent suitable for representing the relevant dynamics of the MG with respect to the MV network following a MMG sudden islanding and load following transients.

The results obtained allow concluding that the physical modelling procedure, exploiting EPSO for parameter estimation constitutes a powerful tool to derive MG dynamic equivalents. The model thus obtained reproduces with high accuracy the transient behaviour results provided by the detailed model of the system. In addition, with this MG dynamic equivalent model, the computing time obtained was quite reduced.

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