

Identification of Dynamic Equivalents based on Heuristic Optimization for Smart Grid Applications

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Abstract—Vulnerability assessment is one of the main tasks in a Self-Healing Grid structure, since it has the function of detecting the necessity of performing global control actions in real time. Due to the short-time requirements of real time applications, the eligible vulnerability assessment methods have to consider the improvement of calculation time. Although there are several methods capable of performing quick assessment, these techniques are not fast enough to analyze real large power systems in real time. Based on the fact that vulnerability begins to develop in specific regions of the system exhibiting coherent dynamics, large interconnected power systems can be reduced through dynamic equivalence in order to reduce the calculation time. A dynamic equivalent should provide simplicity and accuracy sufficient for system dynamic simulation studies. Since the parameters of the dynamic equivalent cannot be easily derived from the mathematical models of generators and their control systems, numerical identification methods are needed. Such an identification task can be tackled as an optimization problem. This paper introduces a novel heuristic optimization algorithm, namely, the Mean-Variance Mapping Optimization (MVMO), which provides excellent performance in terms of convergence behavior and accuracy of the identified parameters. The identification procedure and the level of accuracy that can be reached are demonstrated using the Ecuadorian-Colombian interconnected system in order to obtain a dynamic equivalent representing the Colombian grid.

Keywords—dynamic equivalent; heuristic optimization; Mean-Variance Mapping Optimization; smart grid; vulnerability

I. INTRODUCTION

The transition to deregulated markets, in addition to certain market-oriented policies (e.g. greater competition between agents, market pressures, etc.), has pushed the operation of electric power systems dangerously close to their technical limits, related to reduced generation reserve margins, increased demands for large power transactions (due to increasing interconnections) and physical limitations in the transmission network. Under these conditions, critical perturbations may cause cascading events that could eventually drive the system to blackouts [1]. Nowadays, the emerging intelligent technology has allowed designing the structure of the so-called “Smart Grid”, which is supposed to efficiently respond to the actual system conditions and provide autonomous control actions to enhance the system security in real time [2]. This

new scheme requires special control strategies which should be adjusted depending on the real time event progress. In this context, it is necessary to introduce a “Self-Healing Grid” functionality, which can provide critical information in real time, fast vulnerability assessment (VA), and perform timely and adaptive wide control actions [1]. VA is one of the main tasks to be necessarily considered in such a structure, since it has the function of detecting the need for performing global control actions. Besides, VA is carried out by checking the system performance under the severest contingencies with the purpose of detecting the conditions that could initiate cascading events and system collapses [3]. A vulnerable system is a system that operates with a “reduced level of security that renders it vulnerable to the cumulative effects of a series of moderate disturbances” [3]. Vulnerability begins to develop in a specific region of the system (i.e. the Vulnerable Area), which is characterized by four different symptoms of system stress namely, voltage instability, poorly-damped power oscillations, frequency deviations outside limits and overloads [4].

Many methods have been proposed for vulnerability assessment [3]. Nevertheless, since self-healing-grid applications have to be performed in real time, the eligible vulnerability assessment methods have to consider the improvement of calculation time. For instance, modern high – performance computing (HPC) techniques (e.g. parallel or distributed processing) allow the improvement of calculation time [1], however these techniques are not fast enough to analyze large power systems in real time.

Based on the fact that vulnerability begins to develop in the so-called vulnerable areas, large interconnected power systems can be partitioned into areas in order to improve the vulnerability assessment computation time. The system area of interest (i.e. study area) could be modeled with enough detail whereas the interconnected areas (i.e. external area) have to be adequately represented by simplified dynamic models.

Dynamic equivalence is the process of reducing the complexity of external area model while retaining its dynamic effect on the study area, so that the dynamic response attributes of the latter are preserved [5]. This task is accomplished within three main stages: i) Coherency identification and grouping of generators, ii) Aggregation of coherent generators and their control devices, and iii) Network reduction [6]. As a result, the

external areas are replaced by simplified aggregated models, that is, dynamic equivalents (DEs). Moreover, in the competitive power market, utilities are usually not willing to share details of their systems due to confidentiality. In this situation, DEs offer the option to account for dynamic effects associated to unknown portions of the interconnected system. The use of DEs is also of great value for controller design studies, which requires smaller system models.

Supposing that external areas are well defined (i.e. once the aforesaid first stage was performed), identifiability analysis (i.e. the aggregation stage) of the DE is the most critical step, since it is fundamentally a problem in uniqueness of solution for specific attributes of the underlying mathematical model [7]. The basic question of identifiability of the DE parameters is whether the assumed model is not uniquely identifiable, which could be aggravated considering the lack of information of some system components and the nonlinearity of power systems, which are highly influenced by the continuously changing and sometimes unpredictable operation regime. Therefore, the implementation of traditional approaches for real-time generator aggregation and reduction would be unfeasible. Hence, some methods for generator aggregation using measurement data have been recently proposed in the literature aiming at determining DEs in real-time [8].

Once the structure of a DE is pre-specified, its parameters can be identified on the basis of real-time measured data, so it can be used for real-time stability studies. Several optimization algorithms have been used in existing literature to solve such an identification problem [9]. Nevertheless, they may be easily trapped into local optimum, since their searching performance depends on appropriate parameter settings, and hence premature convergence and local stagnation may cause serious difficulties, especially when handling problems with non-convex or discontinuous functions [10].

This paper presents a novel approach to identify DEs in interconnected power systems exhibiting well defined area coherency. The DE is represented by a generic model of synchronous machine (SYN) connected to the boundary bus, which also includes generic control systems (i.e. automatic voltage regulator -AVR- and governor -GOV). The aim is to use dynamic measurements obtained from smart measurement devices (such as phasor measurement units -PMUs) for determining the parameters of the external area DE which allow the best fitting so that the dynamic response attributes of the study area are kept. For this purpose, an optimization problem is solved by using a novel heuristic optimization algorithm, namely, the Mean-Variance Mapping Optimization (MVMO), which provides excellent performance in terms of the accuracy of the generic model parameters and convergence behavior.

The outline of the paper is as follows: Section II gives an overview of the proposed approach, discussing the main implementation issues. In Section III, a test case is developed and evaluated. Finally, conclusions and outlook for future research are given in Section IV.

II. PROPOSED APPROACH

The overall structure of the proposed approach is illustrated in the flowchart of Fig. 1. The scheme begins with the definition of the dynamic models that suitably represent the components of the assumed DE to be connected to the study area. Next, an initial guess of the parameters to be identified is set. Time domain simulations are then performed for a specific set of predefined perturbations (e.g. realistic contingencies) that occur in the study area. Subsequently, a set of electric signals, which are compared with measured reference signals corresponding to the above-mentioned events (measured in the full-size interconnected system), is selected. Afterwards, the objective function for parameter identification is formulated and the underlying optimization problem is solved through MVMO. Since the DE has to adequately reflect the dynamic response of the original system in all considered perturbations, the identification result is the aggregation over several considered perturbations. The heuristic optimization routine is repeated until a stop criterion is fulfilled (e.g. completion of a pre-specified number of function evaluations, or no-improvement of the best fitness).

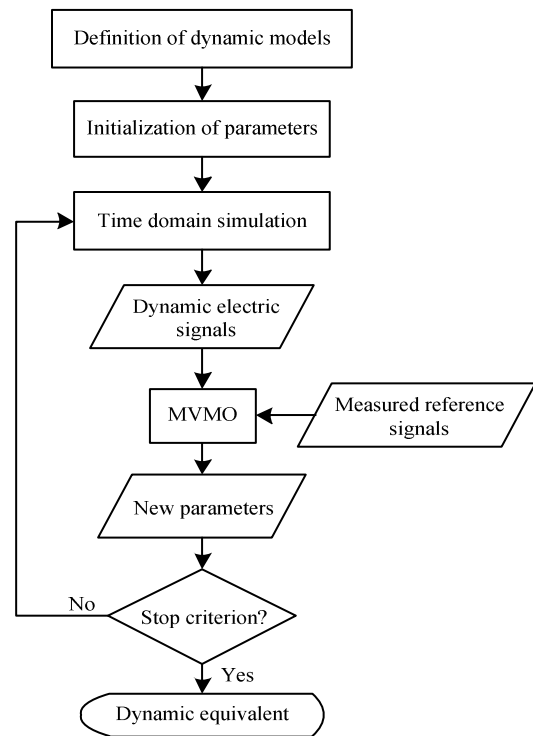


Figure 1. Framework of the proposed approach

A. Definition of the Dynamic Models

1) *Synchronous machine*: Several mathematical models of a synchronous machine based on some modifications of the original well-known Park's model exist in the literature. The detail level of the models depends mainly on the purpose of the study. Hence, in this paper, the subtransient generator model (also referred to as the sixth-order generator model) is used to represent the SYN since it is the most detailed and representative of most of generators in stability studies. The

assumed model is described in detail in [11] and all reference parameter ranges used in this paper for the identification can be found in chapter 4 in [12].

2) *Automatic Voltage Regulator*: the generic AVR is modelled in this paper using the IEEE AC4A type model, whose block diagram is shown in Fig. 2. It exhibits a high initial response excitation associated to the gain K_A that enables adaptability to different dynamic conditions [13].

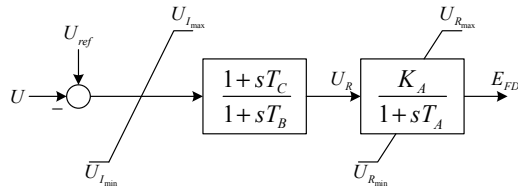


Figure 2. Generic AVR model

3) *Governor System*: a generic model for a thermal GOV is shown in Fig. 3. Basically, if there is a speed deviation, the power order will be adjusted to give a torque output of the turbine which achieves steady state [14].

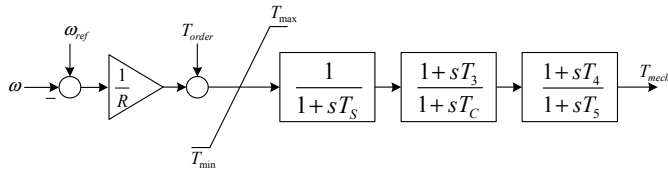


Figure 3. Generic GOV model

B. Parameter Identification

DE parameter estimation presented in this paper uses a time domain identification technique based on dynamic measurements or detailed simulation results (i.e. measured or simulated reference signals) which can be obtained from time domain simulations with the full-size system, or from recorded data through smart-measurement devices (PMUs or perturbation recorders). The parameter identification, as an optimization task, is depicted in Fig. 4.

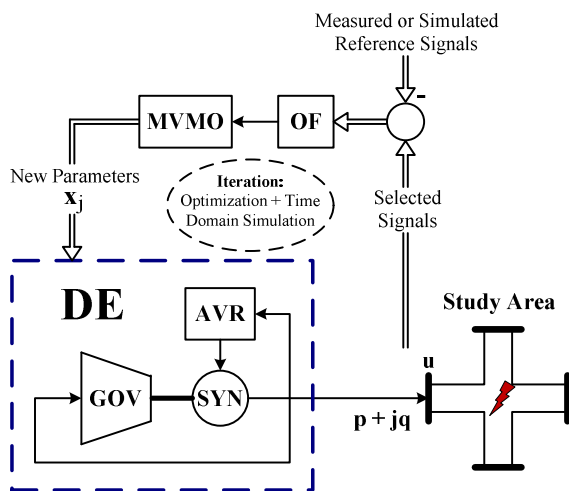


Figure 4. Identification of DE parameters

Using the difference between the reference signals and the selected signals, the following optimization problem is structured:

Minimize

$$OF = \sum_{np=1}^p \alpha_{np} \int_0^{\tau} \left[w_1 (y_1 - y_{1ref})^2 + \dots + w_n (y_n - y_{nref})^2 \right] dt \quad (1)$$

subject to

$$\mathbf{x}_{j-min} \leq \mathbf{x}_j \leq \mathbf{x}_{j-max} \quad (2)$$

where y_n is the n -th electric signal, y_{nref} is the n -th electric reference signal, w_n is the n -th weight signal factor, τ is the simulation period, p is the number of perturbations (np), α_{np} is the np -th weight perturbation factor, and $\mathbf{x}$ constitutes the solution to the problem, that is, the set of DE parameters.

Since different types of perturbations as well as dissimilarity of the range of values in the signals are considered, different weighting may sometimes be appropriate.

C. Mean-Variance Mapping Optimization

The parameter identification defined in the previous Section can be solved by several alternative methods. In this paper a new heuristic optimization algorithm called Mean-Variance Mapping Optimization (MVMO) is introduced, which is particularly suited for solving this task. The theoretical background of MVMO has been published in [15]. Applications to power systems are shown in [10] and [16]. Based on the application experiences, MVMO has been slightly modified recently as will be described next.

The internal searching space of all variables in MVMO is restricted to the range $[0, 1]$. Hence, the real min/max boundaries of variables have to be normalized to a value between 0 and 1. During the iteration it is not possible that any component of the solution vector will violate the corresponding boundaries. To achieve this goal, a special mapping function is developed. The input parameters of this function are the mean and variance of the best solutions that MVMO has discovered so far. The mapping function transforms a variable x_i^* varied randomly with unity distribution to another variable x_i which is concentrated around the mean value. The distribution of the new variable x_i does not correspond with any of the well-known distribution functions even though there are some similarities to the Gauss function. The transformation $x_i^* \rightarrow x_i$ is as follows:

$$x_i = h_x + (1 - h_1 + h_0) \cdot x_i^* - h_0 \quad (3)$$

where the h -function is defined as:

$$h(\bar{x}, s_1, s_2, x) = \bar{x} \cdot (1 - e^{-x \cdot s_1}) + (1 - \bar{x}_i) \cdot e^{-(1-x) \cdot s_2} \quad (4)$$

h_x , h_1 and h_0 are the outputs of the h -function (4) based on different inputs given by:

$$h_x = h(x = x_i^*), \quad h_0 = h(x = 0), \quad h_1 = h(x = 1) \quad (5)$$

Note that the output of (3) is always within the bounds $[0, 1]$ for every generated x_i^* .

The shape of the h-function is determined by the mean $\bar{x}$ and the slope variables s_1 and s_2 . The effect of these parameters on the form of the function is illustrated in Fig. 5. The distinctive property of MVMO is the ability to search around the local best-so-far solution with little chance of being trapped into one of the local optimums. This is shown for two variables in Fig. 6. As it can be seen, the search is focused around the mean values which are for both variables 0.5 in this example. However, there are some samples also outside the mean areas, i.e. the algorithm performs global search but the emphasis is around the means.

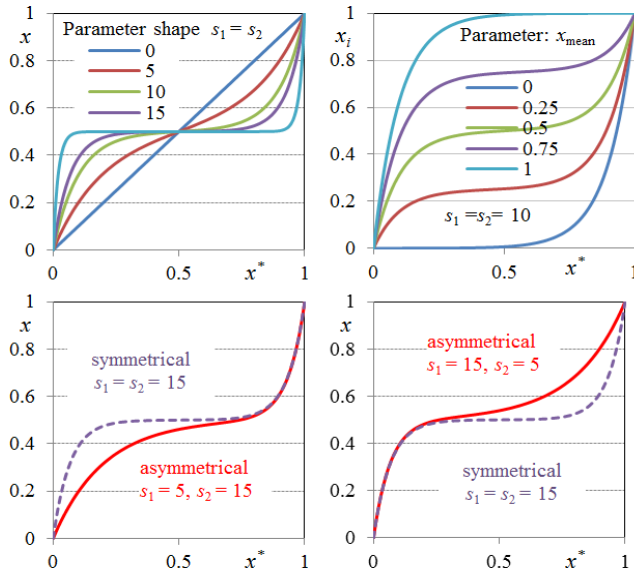


Figure 5. Effect of parameters on the mapping function

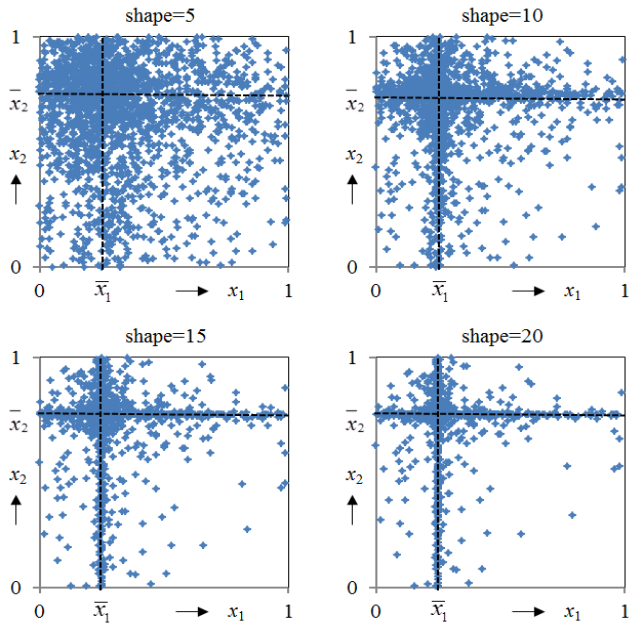


Figure 6. Searching space depending on the shape factor. Number of variables=2, $\bar{x}_1=0.25$, $\bar{x}_2=0.75$; shape = $s_1 = s_2$ for both variables

Mean and slope variables are calculated from the archive where the n best populations are stored, as follows:

$$\bar{x}_i = \frac{1}{n} \sum_{j=1}^n x_i(j) \quad (6)$$

$$s_i = -\ln(v_i) \cdot f_s \quad (7)$$

with the variance

$$v_i = \frac{1}{n} \sum_{j=1}^n (x_i(j) - \bar{x}_i)^2 \quad (8)$$

The variance is calculated only for different variables in the archive. The factor f_s can be used to change the slope of the function e.g. when the accuracy needs to be improved (increase $f_s > 1$) or more global search is required (decrease $f_s < 1$).

In contrast to the previous publication [15] the slopes s_{i1} and s_{i2} of variable x_i are not calculated directly from (7) but using the following algorithm:

$$\begin{aligned} & s_{i1} = s_{i2} = s_i \\ & \text{if } s_i > 0 \\ & \quad \text{if } s_i > d_i \\ & \quad \quad d_i = d_i \cdot \Delta d ; s_{i1} = s_i ; s_{i2} = d_i \\ & \quad \text{else} \\ & \quad \quad d_i = d_i / \Delta d ; s_{i1} = d_i ; s_{i2} = s_i \\ & \quad \text{end} \\ & \text{end} \end{aligned} \quad (9)$$

The initial values of d_i are set for all variables at the beginning of the optimization. Experience so far shows that values around 1-5 are suitable to guarantee good initial performance. With the suggested modifications the robustness of the algorithm and the zero variance handling are improved. Zero variance can occur when all variables of x_i in the archive are identical. In this case the previous non-zero value is used further. Sometimes the variance can oscillate over a wide range. By using the factor d_i instead of s_i , which is a function of variance, a smoothing effect is achieved. Furthermore, the asymmetrical properties of the mapping functions are utilized. The mean and variance are not calculated before the archive is filled up completely. In this stage searching is performed with $s_{i1}=s_{i2}=0$ which corresponds with a straight line between zero and one as the mapping function. Usually an archive size of 2-5 is sufficient. A larger archive size will result in a rather conservative searching with orientation on the saved best populations.

The flowchart of the MVMO algorithm is shown in Fig. 7. As parent of the new population, the best population saved in the archive (first position) is used. Then a few variables are selected and reflected on the mapping function. Alternative selection methods are described in [15].

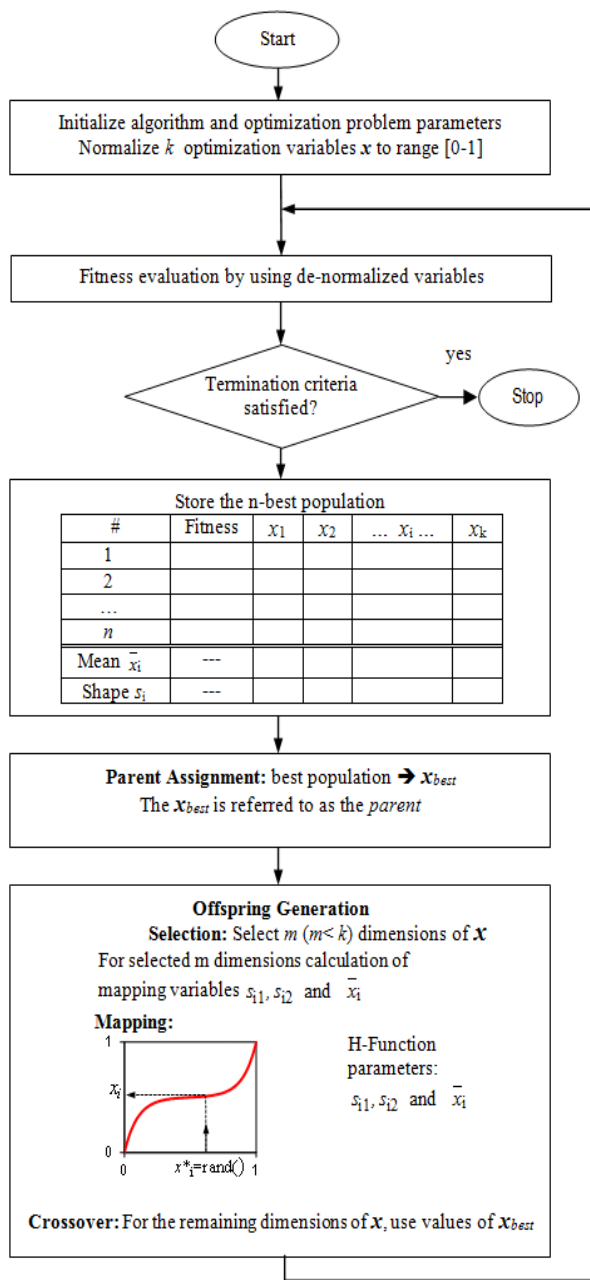


Figure 7. Flowchart of the MVMO algorithm

MVMO shows excellent convergence behavior in comparison with other heuristic methods. Especially at the beginning of the iteration it outperforms all other methods. For instance, Fig. 8 presents the convergence behavior of the unified solution to the problem of determining optimal PSS location and tuning with minimum damping treasure fulfillment, for the IEEE New England 39 bus test system. The standard particle swarm optimization algorithm (PSO) has been used for comparison. Note that, MVMO outperforms outstandingly the standard PSO in terms of both convergence speed and the minimum reached, since the MVMO is able to locate the optimal area in the search space. Moreover, it can continue exploring that area for any better solution without being trapped in one of local optimums.

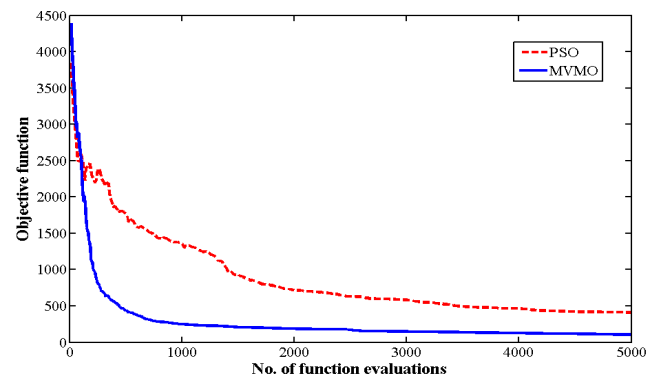


Figure 8. Performance of MVMO in comparison to standard PSO. Task: optimal PSS location and tuning in the IEEE New England 39 bus test system; 45 optimization variables

III. TEST RESULTS

Numerical experiments were performed on a Hewlett Packard Pavilion dv3 personal computer with an Intel® Core™ 2 central processing unit (CPU), 2.2 GHz processing speed, and 4GB RAM. The simulation environment used to accomplish the implementation aspects and to test the proposed approach was DigSILENT Power Factory®. DigSILENT Simulation Language (DSL) and DigSILENT Programming Language (DPL) were used to program the models of DE controllers and the MVMO algorithm, respectively. The approach is tested on the Ecuadorian-Colombian interconnected power system, whose reduced single line diagram at 230 kV transmission level is depicted in Fig. 9. The Colombian system (external area) comprises 1,729 buses and 109 generators, with a total installed capacity of 11,081 MW for supplying a peak load of 8,780 MW, whereas the Ecuadorian area (study area) has 320 buses and 64 generators, with 3,227 MW of installed capacity and a total peak load of 2,663 MW. Using the full-size system reference signals (i.e. tie line active power flows between buses Pomasqui 230 and Jamondino 220, and boundary bus voltage at bus Jamondino 220) obtained from two different perturbations' time domain simulation results, the proposed approach is applied in order to obtain de Colombian DE. The simulated perturbations are:

- *Fault 1:* a three phase short circuit in one circuit of the transmission line between buses SRosa 230 and Totoras 230, applied in the middle of the line at 0.1 s with a duration of 100 ms.
- *Fault 2:* a three phase short circuit in one circuit of the transmission line between buses Milagro 230 – Pascuales 230, applied in the proximity of bus Milagro 230 at 0.1 s, followed by the opening of the circuit at 0.2 s.

The optimization problem has 22 variables (i.e. reactances and time constants of SYN, gain and time constants of AVR, as well as droop and time constants of GOV). The SYN variables were adjusted considering typical limits and ratios between them, as described in chapter 4 (pp. 152 - 153) of [12]. Besides, typical ranges for AVR and GOV variables can be obtained from operating experience and sensitivity studies. The CPU time of MVMO was approximately 6.81 h.

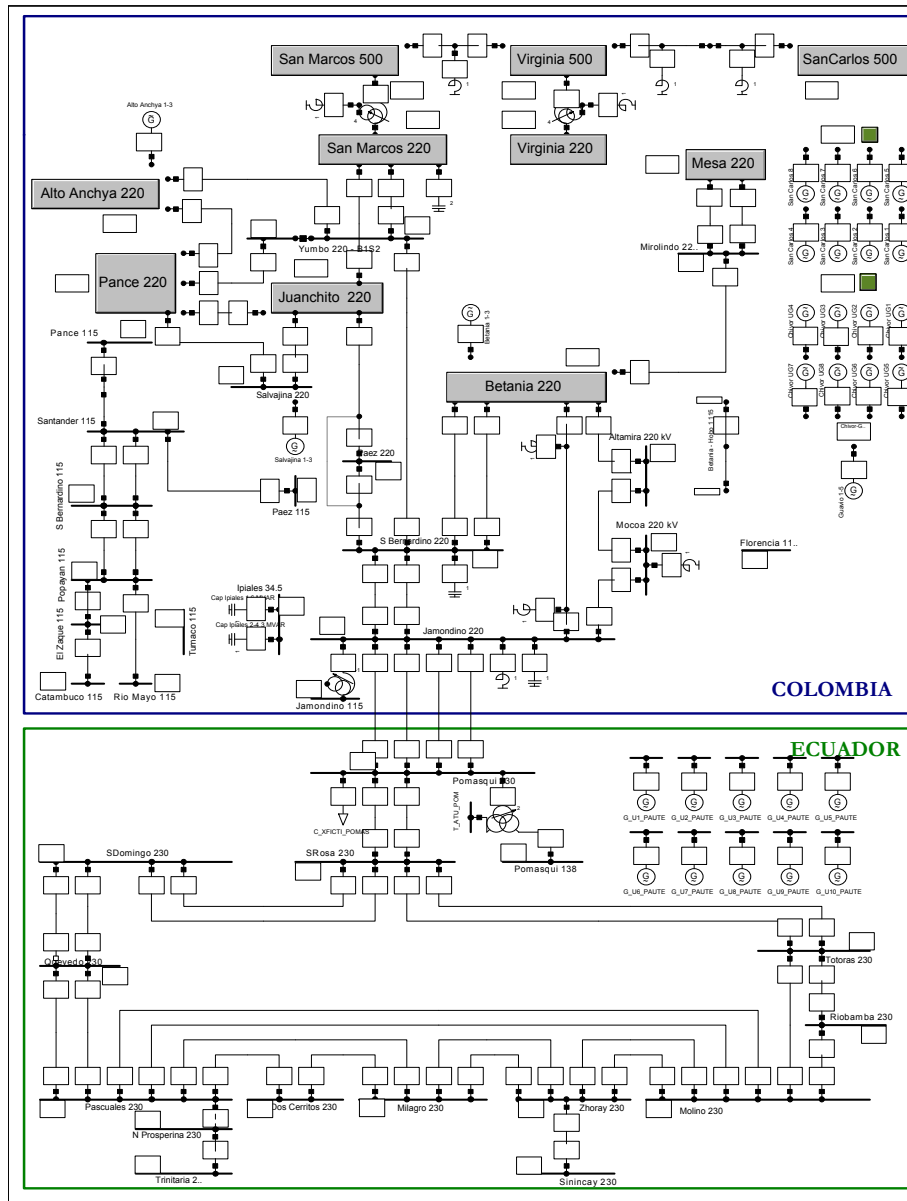


Figure 9. Ecuadorian-Colombian interconnected power system

The convergence behavior of the main optimization variables and the objective function is shown in Fig. 10, whereas some of the identified parameters are summarized in Table I. Note that the parameters (i.e. high inertia time constant and low governor droop value) do not correspond with common parameters of individual generators, rather characterize the generic parameters of the external area's aggregated generators and their controls.

For comparison with the original simulation results, both faults have been calculated with the obtained DE model and parameters from the optimization. Results are shown in Fig. 11, 12 and 13. In the figures, detailed system responses are shown using red dotted lines, and the simulation results that consider the DE of the Colombian grid are depicted with blue solid lines.

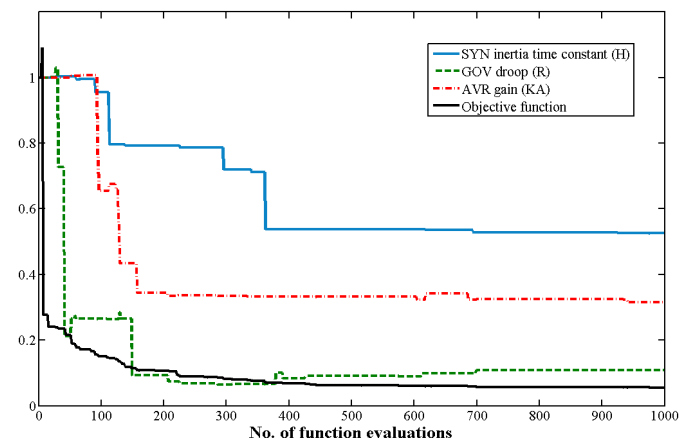


Figure 10. Convergence of simultaneous parameter optimization; variables and objective function are normalized to the initial values

TABLE I. RESULTS OF PARAMETER IDENTIFICATION

Parameter	Identified value
H (s)	116.62
R (%)	1.51
K_A (p.u.)	96.98

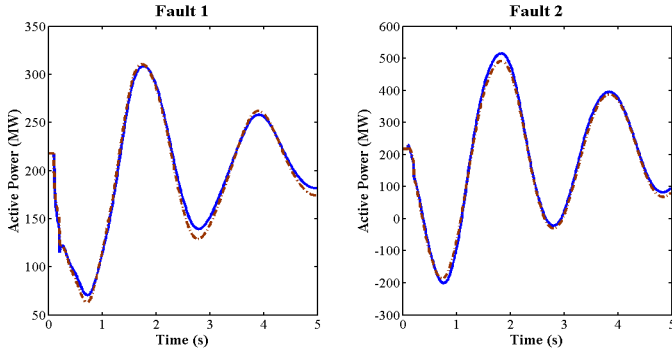


Figure 11. Tie line active power

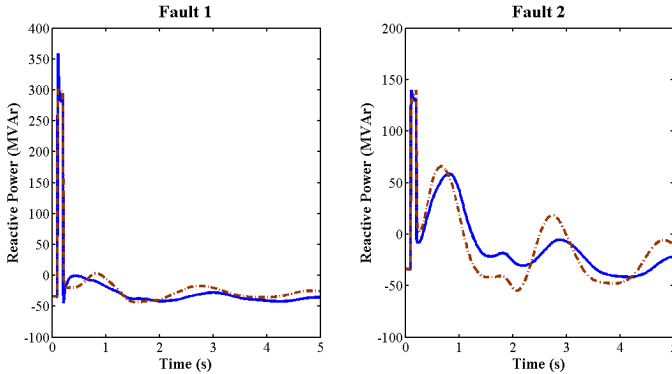


Figure 12. Tie line reactive power

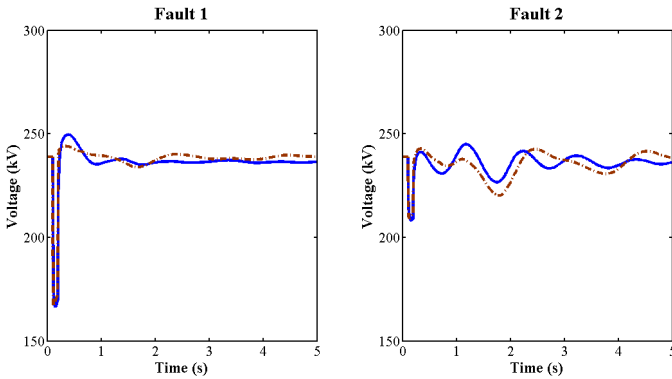


Figure 13. Boundary bus voltage

Note that the responses obtained at the boundary bus and tie line using the DE can properly reflect the dynamic process of the original system at the interconnection boundary, especially in terms of the transmitted active power flow, which is of high relevance for rotor angle stability analysis in the study area. Although such a high correspondence could not be achieved for the tie line reactive power flow and bus voltage, the dynamic response of the DE can still properly reflect the dynamic influence of the external area.

Additionally, it is worth mentioning that performing a five-second time domain simulation with the full-size system requires approximately 3.3 min, whereas it takes only 11 s when the Colombian DE is considered. This result highlights the tremendous improvement in computation speed, which is a basic requirement for real-time applications.

IV. CONCLUSIONS AND FUTURE WORK

With the emerging task of structuring Self-Healing Grid functionalities, real-time VA has become an essential challenge, considering the improvement of calculation time as a fundamental concern. Based on the fact that vulnerability begins to develop specific system sections, large interconnected power systems can be partitioned into areas in order to improve the vulnerability assessment computation time. One solution seems to be using DE of the interconnected systems. Since, the traditional aggregation methods are not feasible to deal with some real-time constraints, such as the lack of information of some system components, the nonlinearity of power systems, and the continuously changing and sometimes unpredictable operation regime, measurement data based methods constitute a good option.

In this paper, a simplified methodology to identify DEs has been proposed, where the identification task is tackled as an optimization problem. The method is based on a novel heuristic optimization algorithm, namely, the Mean-Variance Mapping Optimization (MVMO), which provides excellent performance in terms of convergence behavior and accuracy of the identified parameters. The identification procedure and the level of accuracy that can be reached are demonstrated using the Ecuadorian-Colombian interconnected system in order to obtain a DE representing the Colombian grid. The Colombian DE parameters are simultaneously calculated for two perturbation scenarios based on time domain simulations. The reasonable accuracy of the DE model is verified by comparing the results with those obtained using the detailed model.

The proposed approach has attempted to reduce the complexity in identifying generic parameters of DEs representing external areas while keeping the dynamic influence in the study areas, since calculations with lesser computational effort is a key requirement to perform real-time smart grid tasks. Furthermore, the application of the MVMO to identify interconnected area DEs has yet again demonstrated the advantages of heuristic optimization algorithms to solve practical problems fast and without extensive analytical formulations.

Future research work is being directed towards implementation of a real-time adaptive parameter identification scheme to manage short-term operating state changes and to incorporate expert knowledge by combining the proposed approach with other computational intelligence tools. Also, further tests are to be performed to evaluate the reliability of the identification when handling noisy measurements.

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