Automatic Voltage Regulator Model Validation Based on Mean-Variance Mapping Optimization and Field Tests

Validación del Modelo de un Regulador Automático de Voltaje basado en Optimización de Mapeo Media-Varianza y Pruebas de Campo

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Abstract

Power system planning and operation are meaningfully based on a number of analyses which entail steady-state and dynamic simulations. In this regard, modelling the power system with enough detail is a basic requirement mainly for those applications that are based on an accurate prediction of the system dynamic response, such as the design of protective strategies and control schemes. Most models correspond only to a mathematical representation, whose parameters need to be firstly adjusted or identified based on a rational process of model validation which frequently employs experimental data. This paper proposes a parameter estimation method for accomplishing the model validation of power systems through an iterative software-in-the-loop (SIL) simulation, implemented via mean-variance mapping optimization (MVMO) in DIgSILENT PowerFactory, which allows comparing the simulation results with records obtained from field tests. The proposed method is then used to perform the model validation of the automatic voltage regulator (AVR) of Coca Coco Sinclair, Ecuador's largest hydroelectric power plant. The obtained results are finally compared with two other similar approaches: i) the "Model Parameter Identification" object of PowerFactory, and ii) the "Parameter Estimation" toolbox of Matlab-Simulink. Comparisons show the benefits of the proposal to overcome limitations of the other two methods regarding accuracy, constraints and SIL simulation capabilities.

Resumen

La operación y planificación de los sistemas de potencia son en gran medida basadas en una serie de análisis que involucran el uso de simulaciones dinámicas y en estado estacionario. En este contexto, el modelado a detalle de un sistema de potencia es un requerimiento básico para las aplicaciones que se basan en una predicción precisa de la respuesta dinámica del sistema, como el diseño de estrategias de protección y esquemas de control. La mayoría de los modelos únicamente corresponden a una representación matemática, cuyos parámetros deben ser, en primera instancia, ajustados o identificados con base en un proceso racional de validación de modelos que emplea frecuentemente datos experimentales. Este trabajo propone un método de estimación paramétrica para lograr la validación de modelos en sistemas de potencia a través de una simulación software-in-the-loop (SIL) implementada mediante la optimización de mapeo media-varianza (MVMO) en DIgSILENT PowerFactory, la cual permite comparar los resultados de las simulaciones con registros obtenidos de pruebas de campo. El método propuesto es luego utilizado para realizar la validación del regulador automático de voltaje (AVR) de Coca Codo Sinclair, la planta de generación hidroeléctrica más grande de Ecuador. Los resultados obtenidos son finalmente comparados con dos enfoques similares: i) el objeto "Model Parameter Identification" de PowerFactory y ii) la herramienta "Parameter Estimation" de Matlab-Simulink. Las comparaciones muestran las bondades de la propuesta para sobrellevar limitaciones de las otras dos metodologías, como precisión, restricciones y capacidad de simulación en SIL.

Index terms− Parameter estimation, Model validation, AVR, MVMO, PowerFactory, Simulink.

Palabras clave− Estimación de parámetros, Validación de modelos, AVR, MVMO, PowerFactory, Simulink.

1. INTRODUCTION

Power System planning and operation are based on a number of analyses concerning steady-state and dynamic system behavior simulations. In these kinds of studies the actual power system behavior is predicted using computer based simulations. For this purpose, the several physical components of the system must be adequately modeled in order to accurately represent the performance of the power system [1].

The aim is to mathematically represent the power system through a set of differential algebraic equations (DAE), whose solution represents the time domain dynamic system trajectory.

Modelling the power system with enough detail is a basic requirement mainly for those applications that are based on an accurate prediction of the system dynamic response, such as the design of protective strategies and control schemes. For instance, the tuning of power system stabilizers (PSS) requires an accurate-enough modeling of, at least, a simplified single machine infinite bus (SMIB) representation [2]. In this simplified model the generator and its automatic voltage regulator (AVR) must be modeled in order to satisfy minimum accuracy constraints. Moreover, the simulation software has to be capable of handling detailed models and guarantying reliable results [3].

In this respect, after defining a specific power system model to be analyzed, a basic query that arises is: "does it correspond to a valid model?", and the answer is: not necessarily, since the implemented model typically corresponds to a mathematical representation, whose parameters need to be firstly adjusted or identified based on a rational process of model validation [4].

In this connection, a multifaceted process of system model validation is presented in [4]. This process combines both steady-state and dynamic behavior obtained from simulations to structure a response database that is further compared with real power system measured responses. Afterwards, if this comparison is not good enough, refinements to the model must be made. This refinement can be done for each component individually or for an entire electric power area (i.e. system wide model validation [4]). In both cases, the general procedure needs to compare the time-domain responses of determined electric variables measured in field (reference signals) with those corresponding to the simulations.

If determined that refinements to the model need to be performed, it is possible to apply three typical alternatives: i) applying engineering judgment and knowledge-based criteria (which is obviously not a formal mathematical choice) [4], ii) pursuing system identification, or iii) opting for parameter estimation (or identification) [5]. The selection of the most feasible alternative will depend on the available information. For instance, the goal of *system identification* is to determine a mathematical model of a dynamic system based on experimental data. This kind of procedure is mainly opted when there is no confident information related to the physical model configuration and thus the aim is to determine the mathematical model. On the other hand, *parameter estimation* (or *identification*) is a good alternative when there is enough confidence on the available model structure so the model refinement can only focus on determining the best parameters that allow obtaining the best system or component response.

For the modeling of power plants, the models, both of the generators and their controllers, should be validated through field tests at commissioning (mainly for new plants) [4]. However, this procedure is not always performed. In these cases, an appropriate process for model validation should be carried out via application of adequately controlled field tests. Afterwards, system identification or parameter estimation is to be performed in order to accomplish the model refinement stage.

Based on the previously stated facts, this paper proposes a parameter estimation method for accomplishing the model validation of power systems. This method exploits the potential of the mean-variance mapping optimization (MVMO) [6] for solving complex optimization problems with an iterative software-in-the-loop (SIL) simulation which allows comparing the simulation results with records obtained from field tests. To this aim, the proposed method takes advantage of the flexibility of DIgSILENT PowerFactory for incorporating new routines via its scripting objects, i.e. DIgSILENT Programming Language (DPL) and DIgSILENT Simulation Language (DSL).

The proposed method is then used to perform the model validation of the automatic voltage regulator (AVR) of Coca Codo Sinclair – CCS, Ecuador's largest hydroelectric power plant, as part of a comprehensive methodology for power system stabilizer (PSS) tuning [2]. In order to highlight the benefits of the proposed method, obtained results are finally compared with two other similar methodologies: i) the Model Parameter Identification object of PowerFactory, and ii) the Parameter Estimation toolbox of Matlab-Simulink. Comparisons show the feasibility of the proposal to overcome limitations of the other two methods regarding accuracy, constraints and SIL simulation capabilities.

This paper is organized as follows: section 2 presents general concepts related to power system model validation. In section 3, the proposed parameter identification methodology is described. Section 4

contains the application of the proposal for estimating the parameters of the AVR of CCS and the results obtained from the comparison with two other similar tools. Finally, conclusions are summarized in Section 5.

2. POWER SYSTEM MODEL VALIDATION

Power system real-time decision making is directly dependent on the predictions of the actual system behavior, which are obtained from computer based simulations. In this connection, an adequate system model will ensure accurate-enough simulations, and therefore, proper decision making regarding control actions [1].

For this purpose, the various system physical components should be modeled with enough detail and precision, depending on the phenomenon to be analyzed and its corresponding time-frame of evolution.

Fig. 1 illustrates the importance of system modeling. The dashed circle labeled "Power system model" represents the performance of the power system acquired from mathematical computer-based dynamic simulations. The continuous circle labeled "Actual power system" represents the system actual behavior. The intersected shaded area denotes the part of the model which closely represents the actual system. Ideally, both circles should entirely overlap, indicating that the system model unerringly represents the actual system [1].
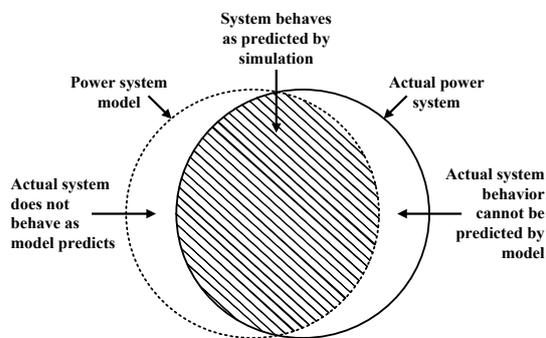

Figure 1: System Model Performance Regarding Actual System Behavior [1]

In practice, the shaded area has to be as large as possible. In this regard, it is extremely necessary to validate the system model in order to ensure that the results will represent the system behavior with sufficient accuracy. This fact is particularly important mainly when the results are used to orient the tuning and response of control actions, such as, for instance, the tuning of power system stabilizers (PSS), since the success of this procedure will be extremely dependent on a good enough system representation.

The only reliable way to validate the accuracy of system models is to carry out field tests, or monitor real perturbations (via smart measurement devices, such as IEDs, perturbation recorders, or PMUs), and compare the results with those obtained from model-based simulations [1]. In this connection, a methodology for validating power system dynamic models (focused on AVR model validation), based on Mean-Variance Mapping Optimization and field-tests records, is presented in the following subsections.

3. MODEL VALIDATION METHODOLOGY

Since the success of the PSS tuning process presented in [2] is directly dependent on accurate-enough simulations (obtained from computer-based time-domain or modal analysis), the design of a previous stage concerning system model validation is mandatory.

Considering that all physical components have to be adequately modeled for simulations to accurately represent the real-time dynamic power system behavior [1], detailed-enough system modeling is a basic requirement for the PSS tuning methodology proposed in [2]. Thus, the model of the reduced system (mainly generator and AVR models) has to be reliable, which is only possible via the application of a robust-enough model validation methodology.

Due to the complex nature of power system dynamics, the optimization problem of the parameter identification of dynamic models possesses a discontinuous multimodal and non-convex landscape that could not be successfully handled by several of the existing heuristic optimization algorithms, since their searching performance is sensitive to appropriate parameter settings, which entails a high risk of premature convergence and local stagnation [7], [8].

To overcome these drawbacks, this paper sketches a general time-domain parameter identification technique based on the MVMO heuristic optimizer, which is particularly suited for solving this task. This method uses field-test signal records as reference signals, which allow achieving high confidence levels on the underlying simplified models, and ensures an accurate estimation of parameters belonging to dynamic components.

The proposed parameter identification method begins with the definition of the dynamic models that suitably represent a specific component of the system (i.e. AVRs, HVDCs, Wind Farms, GOVs, Dynamic Equivalents, etc.). Next, an initial guess of the parameters to be identified is set. Time domain simulations are then performed for a specific set of pre-defined perturbations (i.e. actual PMU recorded contingencies or specific field-test records) that have occurred in the system. Subsequently, a set of electric signals, which are compared with the measured reference signals corresponding to the above-mentioned events, is selected. Afterwards,

the objective function for parameter identification is structured and the underlying optimization problem is solved through MVMO.

The parameter identification procedure is schematically summarized in Fig. 2. Likewise, the basic scheme for parameter identification, embedded in the iterative loop of Fig. 2, is expanded in Fig. 3, illustrating its application for validating the Automatic Voltage Regulator (AVR) model of a Power Plant.
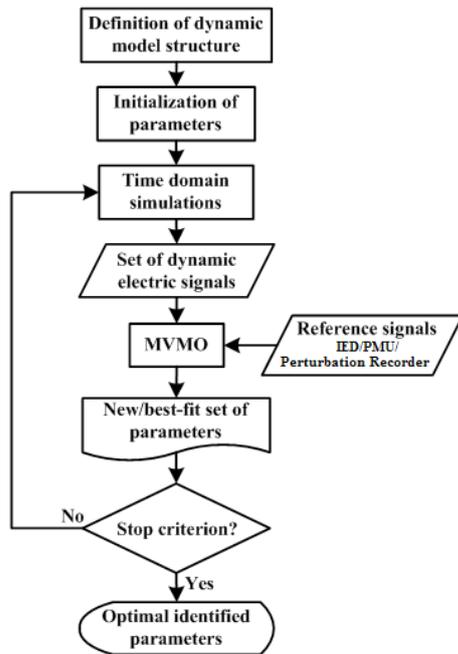

Figure 2: Framework of the Proposed Identification Approach
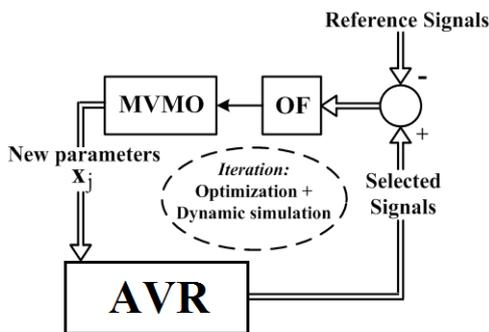

Figure 3: Parameter Identification of Power System Components

Considering the difference between recorded reference signals and the selected signals from dynamic simulations, the parameter identification, conceived as an optimization problem, can be formulated as follows:

Minimize OF (objective function):

$$\text{OF} = \sum_{np=1}^{p} \alpha_{np} \int_0^\tau g(t)\,dt \qquad (1)$$

$$g(t) = w_1\left[y_1(t) - y_{1_{ref}}(t)\right]^2 + \;\; + w_n\left[y_n(t) - y_{n_{ref}}(t)\right]^2 \quad (2)$$

Subject to:

$$\mathbf{X}_{j-min} \leq \mathbf{X}_j \leq \mathbf{X}_{j-max} \qquad (3)$$

where $y_n(t)$ and $y_{nref}(t)$ denote n-*th* recorded electric reference signals, w_n stands for n-*th* weight signal factor, τ is the simulation period, p is the number of disturbances or field-tests (np), α_{np} is the np-*th* disturbance weight factor, and $\mathbf{x}_j$ constitutes the model parameters. Moreover, any other additional constraints can be included in the model if necessary [6].

3.1. AVR model validation

The proposed approach (that in fact can be used to validate any dynamic model of any power system dynamic component) is used to estimate the parameters of an AVR model, with the later aim of making the PSS tuning process feasible.

For this purpose, the potential of DIgSILENT PowerFactory has been exploited in order to implement the complete procedure sketched in Fig. 2. This implementation is based on the software functionality that allows PowerFactory to offer versatility to model new components, as well as to develop new calculation routines by using its programming languages: DSL and DPL.

This implementation will be described in the following subsections.

3.1.1 DSL implementation

DIgSILENT Simulation Language (DSL) allows programming control models of any power system element, including protection devices and it also permits developing other components or routines oriented to run along with the time domain simulations.

The DSL model structure comprises three parts [9]:

- *Interface:* To set the model name, title, classification and set of variables.
- *Code definition:* To define the properties of parameters and initial conditions.
- *Equation code:* To include all equations necessary to define the simulation model, i.e. differential equations (state equations) that describe the relationships between input

and output signals. These relationships can vary from simple linear functions (transfer functions between an input and an output) to highly complex nonlinear functions (non-continuous functions of multiple inputs and multiple outputs).

DSL language uses the modeling of block diagrams (or transfer functions in terms of Laplace or frequency domain) in order to develop a DSL model, since this is the most common way to find information regarding control devices.

In this specific case, the DSL functionality has been used in order to perform two tasks:

- To implement the AVR model.

- To compute, at each integration step, the function $g(t)$, which is a fundamental component of the objective function OF . To this aim, the *Composite Frame* presented in Fig. 4 has been designed in order to determine $g(t)$ as follows:

$$ g(t) = \text{w}\left[Ef_{simu}(t) - Ef_{real}(t)\right]^2 \qquad (4) $$

where w = 100 (weight factor), Ef_{simu} is the simulated induced voltage (AVR output) and Ef_{real} is the recorded induced voltage (from field tests). In this particular case, only one field test has been carried out using a rectangular pulse response test (it could also be a step response test) performed at the AVR reference input signal (*usetp*).

Ef_{real} constitutes the recorded reference signal that comes from the field test. These time discrete values are then stored in a *"Measurement File"*, while the corresponding simulated values (Ef_{simu}) come from the output of the corresponding AVR, previously implemented in DSL. Both recorded and simulated signals are used to compute g(t) inside the *Obj_cal* block.
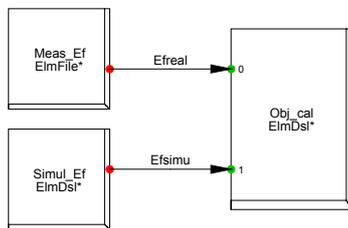

Figure 4: Composite Frame for g(t) Computation

3.1.2 DPL implementation

DIgSILENT Programming Language (DPL) offers an interface to develop automatic tasks in DIgSILENT Power Factory. This functionality allows

the creation of new user-defined calculation functions [9].

The main features of DPL are: particular programming language, similar to C++, arithmetic and standard functions availability, logic functions, loops: do {...} while (...), conditionals: if (...) then {...} else {...}, access from the script to any system variable or parameter, use of each command inside the script, ability to automatically define results and create graphs, among others.

The object of the DPL command constitutes the central element. This object allows the connection of different parameters, variables or objects to various functions or internal elements in order to present results or change parameters. The DPL script is designed to run a set of operations to communicate itself with the database in order to read and/or change settings, parameters or results directly in the database objects.

Based on the specified features of DPL functionality, its potential has been used to perform the optimization task depicted in Fig. 2. Therefore, the MVMO implemented in PowerFactory by [6] has been adequately adapted to solve the optimization problem defined by -. To this aim, the objective function must be implemented into the *"Subroutine for function evaluation"* as explained in [6]. This implementation uses as input the time domain discrete values of $g(t)$ that are periodically stored in a *Result File* (*ElmRes*) at every integration step. This file is then loaded via the DPL script and its stored data is used to compute the OF. For this purpose, the integration method based on the trapezoidal rule presented by has been also implemented into the *"Subroutine for function evaluation"* DPL.

$$ \int_a^b f(x)dx \approx (b-a)\left[\frac{f(a)+f(b)}{2}\right] \qquad (5) $$

4. AVR MODEL VALIDATION RESULTS

The process described in Section 3 is applied to Coca Codo Sinclair (CCS), Ecuador's largest generation hydroelectric power plant (1500 MW), with the procurement of great results.

First, a vastly employed and amply described field test consisting on a rectangular pulse response to mimic a disturbance has been applied to the AVR of CCS' unit U1. This test consists in applying a rectangular pulse of 5% during 1 s at the reference input signal (*usetp*) of the AVR presented in Fig. 5 under a no-load operation. This pulse produced a response in the AVR output (*uerrs*) which was adequately recorded using, in this case, a perturbation recorder available at the power plant.
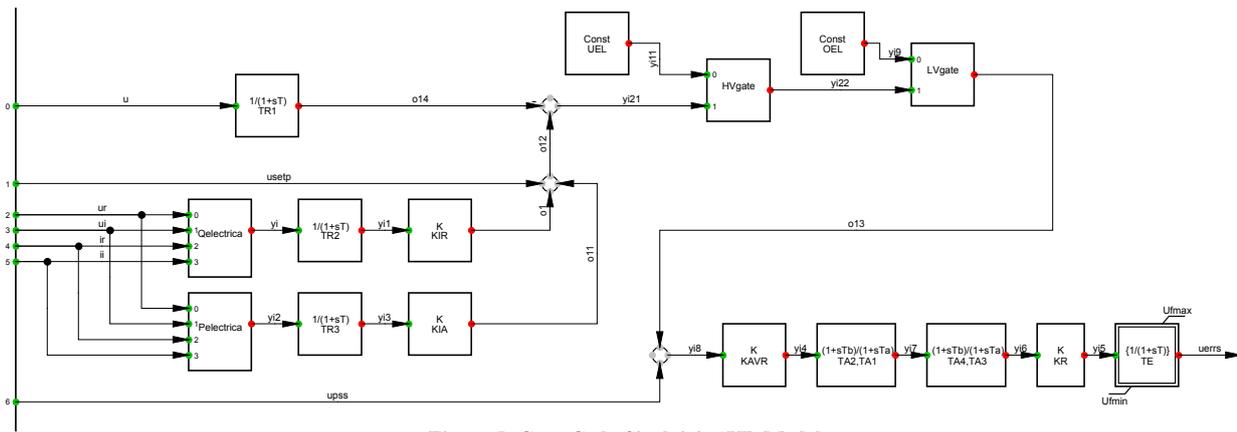
Figure 5: Coca Codo Sinclair's AVR Model

Fig. 6 presents the AVR output signal (red continuous line) recorded during the field test when the pulse was applied to the reference input signal (blue dotted line).
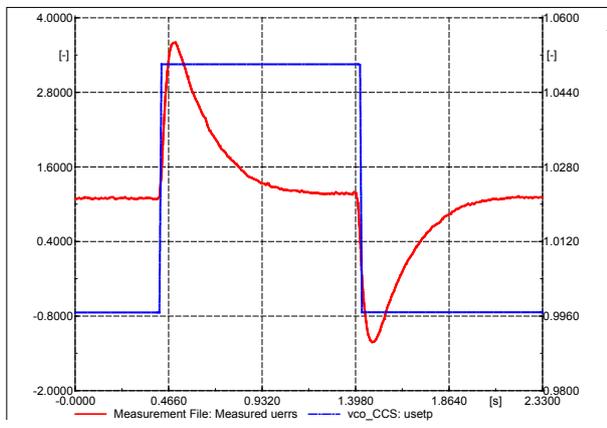

Figure 6: Pulse and Response Test Results

The AVR output recorded signal is then used as the reference signal (Ef_{real}) in order to perform the proposed parameter identification approach. To this end, a proper no-load operation model has been previously implemented in DIgSILENT PowerFactory. This simplified model is depicted in Fig. 7 (note that the model requires a load to be initialized; however, this load is parameterized with a negligible value).
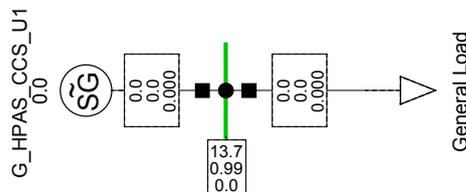

Figure 7: No-load Operation CCS Unit 1 Model

Once the simplified model has been implemented, the complete procedure, sketched in Fig. 2 and 3, is performed via the DPLs implemented in PowerFactory (i.e. the MVMO [6] and the objective function subroutine). For this, time domain simulations are iteratively performed in order to evaluate the OF at each iteration. This evaluation is then used for running the MVMO.

In this particular case, six parameters are selected to be identified via the proposed approach: TA1, TA2, TA3, TA4, KAVR and TE. It is also important to highlight that, based on the technical specifications of the AVR of CCS [10], two additional constraints were to be included in the optimization model:

$$0 \le TA2 \le TA1 \tag{6}$$

$$TA4 \ge TA2 \tag{7}$$

Fig. 8 shows the convergence of the objective function after the optimization process has finished (which comprises a total elapsed time of 136.6 s for 1000 function evaluations considering an integration step size of 1 ms). It can be noticed that the minimum value is reached at around 550 function evaluations.

Finally, the obtained optimum parameters are uploaded to the model in order to carry out a comparative simulation. Fig. 9 presents a comparison between the field-test-recorded AVR output signal (Ef_{real}) and the simulated AVR output signal (Ef_{simu}) obtained with the optimum parameters. It is to be noted how the simulated AVR output signal (blue dotted line) closely resembles the actual dynamic response obtained from field test (red continuous line).
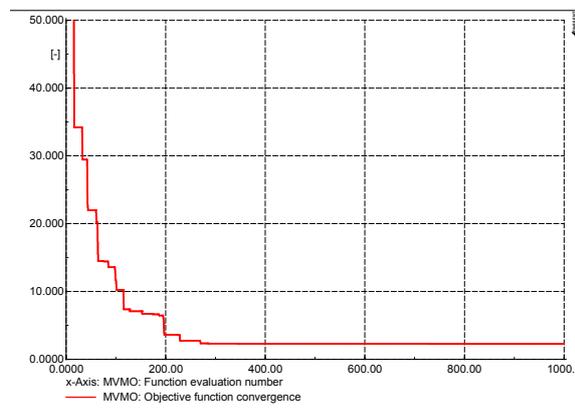

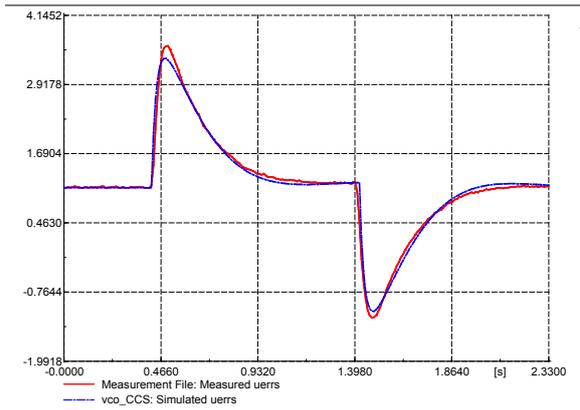**Figure 8: Objective Function Convergence**

Figure 9: Measured vs. Simulated AVR Output Signals

In order to highlight the performance of the proposed approach, it has been compared with two other parameter estimation methodologies. That is: i) the Model Parameter Identification object of PowerFactory, and ii) the Parameter Estimation toolbox of Matlab-Simulink.

Regarding the application of the model parameter identification object of PowerFactory, it is important to note the following features:

- The application can, in fact, run along with any time domain simulation, making the SIL simulation viable.

- The only possible constraint is that each parameter value can be greater than zero. This feature constitutes a great limitation, since it is not possible to include realistic physical constraints.

As far as the functionality of the parameter estimation tool of Matlab-Simulink is concerned, the following features must be considered:

- The application cannot run along with any time domain simulation, making the SIL simulation impossible.

- Following the last comment, the application needs not only measurements of the output signal of the controller but it also requires records of the controller input. This aspect can be a limitation in those cases where measurement points in the field are not available (that in fact was the case of CCS where the controller input could not be measured).

As stated, the parameter identification process of the AVR of CCS was also run with the two already presented additional tools, considering proper adjustments in order to minimize the effects of the

above mentioned limitations. In the case of Matlab-Simulink, the unavailability of measurements of the AVR input was tackled assuming simulations with typical parameters (obtained from [10]) as pseudo-measurements.

Fig. 10 and 11 depict the results obtained with the model parameter identification object of PowerFactory and the parameter estimation tool of Matlab-Simulink, respectively, after replacing the optimum parameters resulted from each method. From all results, it is possible to observe that both the proposed method and the PowerFactory object allow obtaining a good performance in matching the measured output signal, with comparable dynamic behavior. Even more, it is possible to observe that around the peak value, the PowerFactory object seems to outperform the proposed method. On the other hand, the Matlab-Simulink tool shows larger errors. This is obviously caused by the limitation of Matlab-Simulink of not allowing SIL simulations.

In order to make a quantitative and more technical comparison, the mean square error coefficient (MSE) [3] of all results, with respect to the measured AVR output signal, is computed and presented in Table 1.
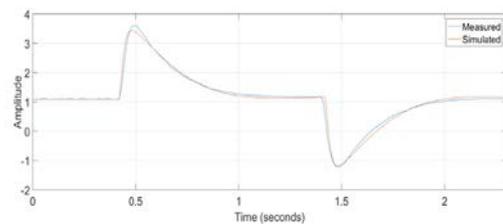

Figure 10: Measured vs. Simulated AVR Output Signals with the "Model Parameter Identification" Object of PowerFactory
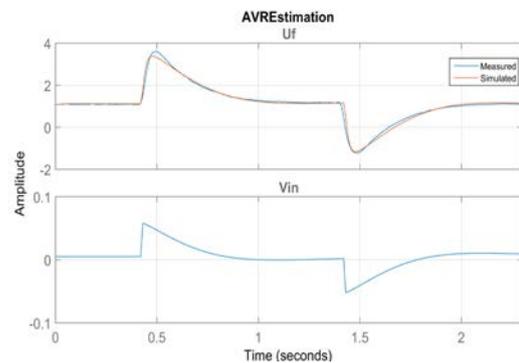

Figure 11: Measured vs. Simulated AVR Output Signals with the "Parameter Estimation" Tool of Matlab-Simulink

MSE is the squared norm of the difference between real data and the approximation divided by the number of elements, as shown by , and allows obtaining an average quantification of the accuracy of each estimation. The closer this coefficient is to zero, the better the accuracy of the parameter estimation is.

$$\text{MSE} = \frac{\left\| Ef_{simu}^{j} - Ef_{real}^{j} \right\|^2}{N_{samples}} \qquad (8)$$

Results show that the proposed methodology outperforms the other two methods for parameter estimation in terms of MSE, which will translate into better identification accuracy. In addition, although the results of the parameter identification object of PowerFactory seem to be almost as accurate as those obtained with the proposed MVMO-based method (and even more accurate around the peak as shown in Fig. 10); these parameters are not completely correct. In fact, since it is not possible to consider sophisticated constraints (such as or), the results have shown that this particular requirement was not met (i.e. TA2 > TA1 in the PowerFactory method), and thus neither were the technical specifications.

Table 1: Parameter Identification Performance for each Method

METHOD	MSE
MVMO-based	0.058
PowerFactory	0.061
Matlab-Simulink	0.202

As a summary of the obtained results, the proposed MVMO-based parameter estimation method has demonstrated to offer superior features in comparison with the other methods, both in giving a better average accuracy, this noticed in a lower MSE, and in accomplishing more robust results since it allows considering realistic physical constraints.

5. CONCLUSIONS

This paper proposes a parameter estimation method for accomplishing the complex task of dynamic model validation of power systems. The proposal is based on the mean-variance mapping optimization (MVMO) algorithm and uses records from field tests as the target or reference signals. The proposed method takes advantage of the software-in-the-loop (SIL) simulation feasibility for comparing the simulation results with records obtained from field tests. Also, a practical implementation of the proposed method has been described by using the DIgSILENT Programming Language (DPL) and DIgSILENT Simulation Language (DSL) scripting options.

The proposed method has been applied to estimate the parameters of the automatic voltage regulator (AVR) model of Coca Coco Sinclair CCS, showing a superb performance in both accuracy and robustness. A fair comparison with other two similar methodologies, that is: i) the Model Parameter Identification object of PowerFactory, and ii) the

Parameter Estimation toolbox of Matlab-Simulink, has been also presented. The results have shown the feasibility of the proposal to overcome limitations of the other methods related to accuracy, constraints and SIL simulation capabilities.

REFERENCES

[1] CIGRE Task Force, "Analysis and Control of Power System Oscillations", Study Committee 38, final report, December 1996.

[2] P. Verdugo, J. Cepeda, A. De La Torre and K. Paucar, "Testbed for PSS Tuning Using Synchrophasor Measurements and a Real-Time Digital Simulator", 2017 IEEE PES Conference on Innovative Smart Grid Technologies Latin America (ISGT-LA), Quito, Ecuador, September, 2017.

[3] J. Cepeda, "Real Time Vulnerability Assessment of Electric Power Systems using Synchronized Phasor Measurement Technology", Ph.D. Thesis, Instituto de Energía Eléctrica, Universidad Nacional de San Juan, San Juan, Argentina, December, 2013.

[4] E. Allen, D. Kosterev and P. Pourbeik, "Validation of power system models", 2010 IEEE Power and Energy Society General Meeting.

[5] R. G. K. M. Aarts, "System identification and parameter estimation", Lecture Notes, University of Twente, 2012.

[6] J. Cepeda, J. Rueda, I. Erlich, et al, "Mean-Variance Mapping Optimization Algorithm for Power System Applications in DIgSILENT PowerFactory", PowerFactory Applications for Power System Analysis Book, Chapter 12, Springer International Publishing, 2015.

[7] J. Cepeda, J. Rueda, and I. Erlich, "Identification of Dynamic Equivalents based on Heuristic Optimization for Smart Grid Applications", IEEE World Congress on Computational Intelligence, Brisbane, Australia, Junio de 2012.

[8] K. Lee, and M. El-Sharkawi, Modern heuristic optimization techniques, John Wiley & Sons, New York, 2008.

[9] DIgSILENT GmbH, DIgSILENT Power Factory Version 15 User's Manual, Gomaringen, Germany, March 2015.

[10] Guangzhou Electrical Aparatus Research Institue, "EXC9000 Static Excitation System Users' Manual".

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