Updating System Representation by Trajectory Acquisition in a Dynamic Security Framework

Sergio Bruno and Massimo La Scala

1 Introduction

After 20 years since the first re-regulating attempts, the restructuring process of electric industry can be considered completed in most countries in the world. These years brought profound modifications in the way generating plants are managed, energy resources are exploited, and the three segments, generation, transmission and distribution, are coordinated.

In addition, the way the transmission network is operated during daily normal conditions has changed. The re-regulation of the energy sector introduced new economy-driven constraints, diminishing the control that SOs have on generation and blurring the overall vision of the system and its main characteristics.

In this fast-evolving scenario, a long sequence of large, nation-wide or even larger, blackouts forced many researchers active in the field of power system dynamic and security to answer to the question if restructuring were responsible for such events [1] and, in general, if competition and security were mutually exclusive.

Some of the reports made by the Institutions that were called to investigate on the 2003 blackouts events [2, 3] showed how national and transnational grids have been managed with lacks of data and in the presence of a large number of new uncertainties. Reliable real-time data, oriented to the monitoring of system dynamics, were not available and the operators had not enough time to take decisive and appropriate remedial actions. Appropriate automated and coordinated

S. Bruno (✉) and M. La Scala
Dipartimento di Elettrotecnica ed Elettronica (DEE), Politecnico di Bari,
via Re David 200, Bari 70125, Italy
e-mail: bruno@deemail.poliba.it

M. La Scala
e-mail: lascala@poliba.it

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controls were scarce or failed the chance to take immediate remedial actions against events which trigger the fast response of the system.

Similar conclusions were also address by the IEEE PES Power System Dynamic Performance Committee [4]. What it has become clear after the blackouts of 2003 is that, despite the revolution driven by electric industry restructuring and energy market re-regulation, the general approach to power system security has not changed [4]. Regardless all technological improvements, very few new countermeasures and approaches to system security have been implemented to improve immunity from blackouts [5].

Solutions to the enhancement of power systems security include adaptive relays [5], real-time measurements and control systems [wide-area measurement systems (WAMS) and wide-area measurement and control systems (WAMC)] [5–7], FACTS (flexible AC transmission system) and HVDC (high-voltage direct current) technology [5], methodologies for automation and control [8], communication systems for real-time data exchanges [9], online dynamic security assessment (DSA) [10].

In [11], the authors have shown the potentials of exploiting Phasor measurement units (PMUs) and WAMS in monitoring and controlling power system dynamic security. In particular, the authors have shown how the emerging technology on communication systems and fast computing allows the implementation of an online environment where control center operators have the capability to monitor in real-time the power system dynamic behavior, recognize threats to its integrity, evaluate and implement suitable control actions.

A suitable approach for evaluating and implementing such control actions is given by online DSA. DSA can be defined as the evaluation of the ability of the system to withstand specified contingencies, surviving to the subsequent transients and reaching an acceptable steady state operating point [12]. The DSA analysis entails the evaluation of the ability to keep system trajectories in an acceptable state space domain and gives indication about remedial actions when necessary [13]. DSA differs from static security assessment (SSA) because the latter involves just the evaluation of a secure steady state operating point (preventive control) or a post-contingency secure steady state operating point (corrective control), usually referred as secure equilibrium point, with no regard to transient phenomena.

DSA requires the prediction (simulation) of system transient trajectories that must be contained in a domain that satisfies stability and a set of practical requirements. Relying on simulations (time–domain, energy functions, hybrid methods, etc.), the dynamic behavior of the system is predicted, power systems are planned and operated, limitations are established and the need for stability countermeasures is assessed.

Clearly, the accuracy of static and dynamic parameters (in other words the database of parameters necessary for modeling power system components) can be crucial in the assessment of system transient behavior. A major criticism about the use of simulation tools for dynamic assessment and control is based on the observation that initial databases linked to the dynamic parameters are not enough reliable, whereas there is enough confidence about steady state and topology data since they are continuously updated by state estimators.

The same objection can be brought up for all those methods that make use of system representations for assessing control actions in real-time or in extended real-time. Estimation and periodic verification of the synchronous machine parameters and control parameters are necessary for guaranteeing reliable simulations and the results in preventive and corrective dynamic control, response-based control schemes [14, 15] and WAMC.

The problem of assessing dynamic parameters is particularly relevant for synchronous machines and controls, whose characteristics and main dynamic parameters are in general not known or inaccurate, as some may drift over time or with operating condition [16]. In addition, some of the data that are adopted in dynamic simulations simply do not exist and must be estimated. Very often, to simplify and speed up the analysis, dynamic simulations are carried out adopting external equivalents that represent large portions of the network external to the area of interest. Dynamic parameters adopted for external equivalents are seldom updated and, in most of cases, are based on offline studies.

System wide measurements of power system disturbances are frequently used in event reconstruction to gain a better understanding of system behavior [17, 18]. In undertaking such studies, measurements are compared with the behavior predicted by a model. Differences are used to tune the model, i.e., adjust parameters to obtain the best match between the model and the measurements.

The main difficulty in treating power system estimation is represented by model non-linearities and discontinuities. Parameter estimation techniques are well established for linear models [19, 20], whereas parameter estimation for large nonlinear systems is a relatively open field.

There are many nonlinear components in a typical generator unit. The capability of the transfer function identification method to estimate such nonlinear generator parameters (windup/non-windup limiters and exciter saturation, etc.) is not clear. Furthermore, the derivation of the actual parameters, such as exciter gains and time constants from the transfer functions is cumbersome and needs symbolic manipulation of dynamic models. In [21], an estimation strategy based on stochastic approximation methods is proposed. This method copes with noise and nonlinear features of exciter and voltage regulator models. In [22], the authors adopt a Gauss–Newton method to compute a set of model response and trajectory sensitivities for identifying parameters that can be reliably estimated from available measurements.

In this chapter, the authors propose an approach based on a nonlinear optimization for estimating dynamic parameters. It is also assumed that WAMS is adopted to collect measurements able to update dynamic parameters every time a disturbance occurs. In the proposed procedure, time–domain simulation trajectories are compared with actual recorded data to update the parameters. The adopted nonlinear programming optimization methodology permits to minimize the quadratic function given by the difference between measured and simulated trajectories following the weighted least square (WLS) approach.

The prominent feature of the proposed method is a wide flexibility. Due to its formulation, the methodology can be implemented even in the case of missing or bad data, and can make use of any measured trajectory. The methodology can also be implemented for estimating almost any parameter that influence power system dynamic in the transient stability time framework.

2 Methodology and Architecture Structure

The proposed approach has a simple design structure. Whenever a significant perturbation is experienced, the measurement system (likely a WAMS) has to record selected trajectories of main system variables subsequent to the disturbing event. These perturbed trajectories are then sent to the control center and stored. An ordinary state estimator and a topology processor, due to signals and measurements acquired in steady state conditions, estimate system state and topology before the disturbance. Knowing the initial state and the nature of the disturbance, the control center simulates the same dynamics that has just been experienced and makes a comparison between measured and simulated data.

If this comparison reveals a significant dissimilarity, the proposed optimization algorithm can be run to minimize the difference between simulations and reality, and to find the best system representation that, at that moment, describes the system.

Please note that the time requirements for implementing this procedure are not very strict. Even though modern fast communication and computing systems guarantee technological feasibility for developing this procedure in a real-time framework, there is probably no need for it. In ordinary power system operation, the update of dynamic parameters is operated very seldom. Therefore, updating dynamic parameters on daily or hourly base would be sufficient to bring significant improvements in power system dynamic security control.

Probably, the ideal solution is to apply the procedure in the extended real-time framework. This could mean that at any programmed operation on the system (such as disconnection or closure of transmission lines, injection of significant amount of reactive power, synchronization with a group of generators), the control center operator can run the proposed procedure for updating the power system dynamic model. The main advantage is that the procedure would be carried out in correspondence with sufficiently large electromechanical oscillations, when the dominant modes are not masked by system noise. Another advantage is that, since the time schedule of a programmed operation is known, the procedure can be carried out manually and not automatically, with a great simplification in the required monitoring architecture. Of course, large oscillations due to faults can provide more in deep information, especially on wide-area phenomena (for example inter-area oscillations). In this case, an automatic detection and triggering of the estimation procedure is needed.

The procedure for estimating dynamic parameters can be schematized as in Fig. 1. The output z^{meas} represents system trajectories experienced by the power

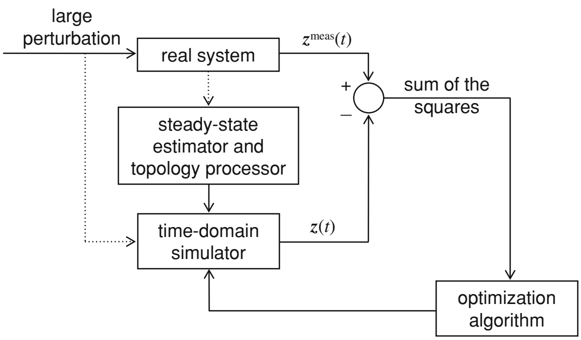

Fig. 1 Architecture of the proposed methodology

system after a large disturbance, whereas z represents the system response to the same disturbance as evaluated with a time–domain simulator. The two trajectories z and z^{meas} are the input for a recursive optimization algorithm that updates system dynamic parameters by minimizing the difference between them.

Simulated trajectories $\boldsymbol{z}$ and measured variables $\boldsymbol{z}^{meas}$ must be compared at the same time instant t to correctly detect mismatches and update the model. Consequently, it is unavoidably that synchrophasor technology has to be adopted [i.e. Phasor measurement units (PMUs)] to refer each sampled measurement at a specific time instant with sufficient accuracy. The same technology ensures that it is possible to sample the trajectory with a frequency sufficient to capture the information associated with basic electromechanical oscillation modes. Finally, WAMS technology provides a system-through vision on large area able to capture not only the local response of the system, but also the wide area one (such as inter-area oscillations).

2.1 Mathematical Formulation

The proposed approach is based on the formulation and the solution of an optimization problem that aims at obtaining the best match between measured and simulated trajectories. This optimization problem is a non-linear problem in the discrete time–domain solved by a recursive algorithm.

The mathematical formulation is based on the common power system dynamic representation. Power system electromechanical behavior on transient time-scale can be modeled through a set of nonlinear differential and algebraic equations (DAEs), represented in Eq. 1. The equations take into account the dynamic behavior of all main system components, generators, exciters, network and loads.

$$\begin{aligned} \boldsymbol{x}(t) &= f(\boldsymbol{x}(t), \boldsymbol{V}(t), \boldsymbol{p}) \\ g(\boldsymbol{x}(t), \boldsymbol{V}(t), \boldsymbol{p}) &= 0 \end{aligned} \tag{1}$$

In (1), $\boldsymbol{x}$ is the vector of state variables, whereas $\boldsymbol{V}$ is the $2n$-dimensional vector of nodal voltages, being n the total number of nodes.

$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{x}_1^{\mathrm{T}} & \boldsymbol{x}_2^{\mathrm{T}} & \cdots & \boldsymbol{x}_m^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \tag{2}$$

$$\boldsymbol{V} = \begin{bmatrix} \boldsymbol{V}_1^{\mathrm{T}} & \boldsymbol{V}_2^{\mathrm{T}} & \cdots & \boldsymbol{V}_n^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \tag{3}$$

In (2), the generic i^{th} element of the $\boldsymbol{x}$ vector ($\boldsymbol{x}_i$) represents the state vector for the i^{th} synchronous machine, m is the total number of generators. The element $\boldsymbol{V}_j$ in (3) represents the nodal voltage at the j^{th} bus.

The vector $\boldsymbol{p}$ represents the set of parameters that must be updated in the optimization algorithm. For example, the element of vector $\boldsymbol{p}$ could be represented by the basic dynamic parameters of a synchronous machine (inertia, damping, reactances, time constants, etc.). In this case $\boldsymbol{p}$ is formulated as:

$$\boldsymbol{p} = \begin{bmatrix} \boldsymbol{p}_1^{\mathrm{T}} & \boldsymbol{p}_2^{\mathrm{T}} & \cdots & \boldsymbol{p}_m^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}. \tag{4}$$

In general, the method is flexible enough to be applied to other parameters, such as load modeling constants, control device reference signals, etc.

The proposed method is based on the discretization of the DAEs set (1). The DAEs set can be discretized through any implicit rule (such as the trapezoidal rule) and written in implicit form:

$$\hat{\boldsymbol{H}}(\hat{\boldsymbol{y}},\boldsymbol{p}) = 0 \tag{5}$$

where

$$\hat{\boldsymbol{y}} = \begin{bmatrix} \boldsymbol{y}_0^{\mathrm{T}} & \boldsymbol{y}_1^{\mathrm{T}} & \cdots & \boldsymbol{y}_i^{\mathrm{T}} & \cdots & \boldsymbol{y}_{n_T}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \tag{6}$$

$$\hat{\boldsymbol{H}} = \begin{bmatrix} \boldsymbol{H}_0^{\mathrm{T}} & \boldsymbol{H}_1^{\mathrm{T}} & \cdots & \boldsymbol{H}_i^{\mathrm{T}} & \cdots & \boldsymbol{H}_{n_T}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}. \tag{7}$$

with

$$\boldsymbol{H}_i(\boldsymbol{y}_i,\boldsymbol{p}) = \boldsymbol{0} \quad i = 0, 1, 2, \ldots, n_T \tag{8}$$

$$\boldsymbol{y}_i = \begin{bmatrix} \boldsymbol{x}_i^{\mathrm{T}} & \boldsymbol{V}_i^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \tag{9}$$

and n_{T} representing the total number of the time steps relative to the integration interval [0, T].

The optimization problem is aimed at minimizing the difference between measured and simulated trajectories by varying the dynamic parameter vector $\boldsymbol{p}$. The optimal solution is obtained minimizing an objective function that represents the mismatch between the two trajectories. In this paper, the WLS criterion has been adopted, leading to the definition of the objective function $J(z)$

$$J(z) = \sum_{i=1}^{n_T} \sum_{j=1}^{n_S} \frac{\left(z_{i,j}^{\mathrm{meas}} - z_{i,j}\right)^2}{\sigma_{i,j}^2}. \tag{10}$$

In (10), $z_{i,j}^{\mathrm{meas}}$ represents the j^{th} measurement at the i^{th} time step, $z_{i,j}$ is the j^{th} simulated data at the i^{th} time step, $\sigma_{i,j}^2$ is the variance at the i^{th} time step for the j^{th}

measurement, whereas n_S is the number of measured quantities at each time step. The total number of independent measurements is given by the product $n_S n_T$.

In the proposed formulation, trajectory mismatches are weighted by their variance. Implicitly, it has been assumed that measurements are affected by Gaussian white noise. For the sake of simplification, it was also assumed that measurements are not correlated between themselves (i.e. are statistical independent) and with respect to different time instants. Nevertheless, the approach can be easily extended to more complex formulations. Although the formulation of more complex covariance matrices is feasible, it implies the necessity of acquiring a huge amount of data to assess correlation factors. Under the current assumptions, the formulation of the proposed optimization problem assumes the characteristic of a maximum likelihood estimation.

The proposed optimization problem minimizes the objective function $J(z)$ in the presence of equality and inequality constraints. The equality constraints are given by the discretization of the differential–algebraic set of equations at each time step, as already formulated in Eq. 5. Time-varying inequality constraints were introduced to define a feasibility domain on parameters. For this reason, the parameter space Ω_P can be defined as the permissible range of all parameters to be estimated. This feature improves the convergence behavior of the overall algorithm avoiding trials too far from the final solution during iteration.

Under these assumptions, the optimization problem can be summarized as follows:

$$\min_{p \in \Omega_P} J(z) \tag{11}$$

subjected to

$$\hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p}) = \boldsymbol{0} \tag{12}$$

$$\boldsymbol{z} = \mathrm{z}(\hat{\boldsymbol{y}}) \tag{13}$$

$$k(\hat{\boldsymbol{y}}, \boldsymbol{p}) \leq 0 \tag{14}$$

The variable $\hat{\boldsymbol{y}}$, whose formulation is given in Eq. 6 represents the composition of all vectors of state variables and voltages evaluated at each time step. Therefore, $\hat{\boldsymbol{y}}$ represents the discretization of the whole system trajectory during the transient.

Equation (13) takes into consideration the dependence of simulated data vector $\boldsymbol{z}$ on the simulated trajectory $\hat{\boldsymbol{y}}$. Since $\hat{\boldsymbol{y}}$ is function of the parameter vector $\boldsymbol{p}$, $\boldsymbol{z}$ is an implicit function of $\boldsymbol{p}$. This can be easily shown considering that if the same simulation is carried out with different values in $\boldsymbol{p}$, the simulated trajectories are different and hence is the data vector $\boldsymbol{z}$.

Equation (14) takes into consideration the presence of inequality constraints that can be referred to minimum and maximum technical requirements (for example the inertia of a synchronous machine cannot be negative or the power flow on a line should not exceed the threshold that triggers protection relays).

All inequality constraints and objective function can be taken into consideration in the formulation of the optimization problem by introducing a penalty function $C(\hat{\boldsymbol{y}}, \boldsymbol{p})$. This method, known as "penalty factor method", allows to treat the whole problem as a minimization in the presence of sole equality constraints.

With the introduction of the penalty function, the optimization problem can be written in implicit form as

$$\min_{p \in \Omega_P} C(\hat{\boldsymbol{y}}, \boldsymbol{p}) \tag{15}$$

subjected to

$$\hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p}) = \boldsymbol{0} \tag{16}$$

The optimization problem, as represented by Eqs. (15) and (16) is a non-linear optimization problem in the discrete domain that can be solved with the use of Lagrangian multipliers.

If λ is the Lagrangian multiplier vector, the Lagrangian function can be written as:

$$L = C(\hat{\boldsymbol{y}}, \boldsymbol{p}) + \boldsymbol{\lambda}^{\mathrm{T}} \cdot \hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p}) \tag{17}$$

From (17), the set of necessary first order conditions follows:

$$\frac{\partial L}{\partial \hat{\boldsymbol{y}}} = \frac{\partial C(\hat{\boldsymbol{y}}, \boldsymbol{p})}{\partial \hat{\boldsymbol{y}}} + \boldsymbol{\lambda}^{\mathrm{T}} \cdot \frac{\partial \hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p})}{\partial \hat{\boldsymbol{y}}} = 0 \tag{18}$$

$$\frac{\partial L}{\partial \boldsymbol{p}} = \frac{\partial C(\hat{\boldsymbol{y}}, \boldsymbol{p})}{\partial \boldsymbol{p}} + \boldsymbol{\lambda}^{\mathrm{T}} \cdot \frac{\partial \hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p})}{\partial \boldsymbol{p}} = 0 \tag{19}$$

$$\frac{\partial L}{\partial \boldsymbol{\lambda}} = \hat{\boldsymbol{H}}(\hat{\boldsymbol{y}}, \boldsymbol{p}) = 0 \tag{20}$$

The set of Eqs. (18–20) can be solved by adopting the gradient-based method through an iterative algorithm described in the next section.

2.2 The Solving Algorithm

The algorithm starts when a new significant complete set of measurements, suitably normalized and synchronized, is sent from the WAMS to the control center. In the proposed approach, the control center utilizes the dynamic parameters database, measurements, signals, and the topology of the network, to simulate the same trajectory that has just been acquired. This trajectory depends on the initial value given to the dynamic parameters, represented in Fig. 2 as $\boldsymbol{p}_0$. This value is the value stored in the database, and is referred to historical data or to previous runs of this same algorithm.

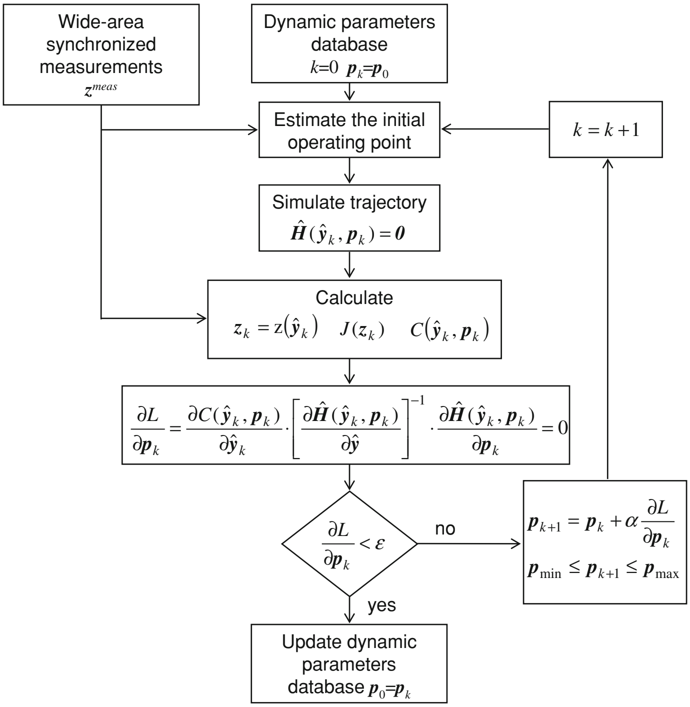

Fig. 2 Flow chart of the optimization algorithm

After this first simulation, the algorithm compares measurements with simulated trajectories and evaluates objective and penalty functions. The algorithm solves the linear set of equations (18–20) and evaluates the gradient $\partial L/\partial p_k$.

If this gradient is greater than a certain tolerance ε, the algorithm updates the $\boldsymbol{p}_k$ vector, goes back and simulates a new trajectory. The gradient $\partial L/\partial p_k$ can also be accelerated through a coefficient α which can be estimated basing on heuristics or on second-order conditions.

The algorithm is iterative and stops only when the check on tolerance is positive. At the end of the algorithm, the updated value of the $\boldsymbol{p}$ vector is stored in the database and will be used for future previsions of power system dynamics.

This approach has been widely adopted by the authors for the solution of security constrained dynamic optimization problems, exhibiting some interesting implementation properties [10, 13]. In fact, as it has been shown, the structure of the algorithm is such that ordinary time–domain simulators can be easily adapted with a plug-in module, consisting basically in the evaluation of $\partial L/\partial p_k$. This interesting feature is not common to other more sophisticated algorithms based on the second-order derivatives.

Finally, the gradient exhibits good convergence properties for this problem as it will be shown in test results.

3 Test Results

The proposed approach has been tested on a representation of the Italian national grid. The model is characterized by a degree of detail adequate for showing the feasibility of the approach in full-scale power systems. The model includes detailed information on the external systems and is characterized by about 1,333 nodes, 1,762 lines, 273 generators and 769 transformers. Non-linear loads were assumed for both active and reactive power. The parameter estimation is carried out using synchronous machines represented with a fourth order detailed model and second- and third-order excitation systems.

The set of system measurements (z^{meas}) was evaluated with a dynamic power system simulator considering an operating condition (base case) obtained from the state estimator of the Italian control center. The set of dynamic parameters adopted for the base case represents the "real" value of $\boldsymbol{p}$ that for the sake of clarity will be noted as $\boldsymbol{p}_{\text{real}}$. Tests with real measurements could be carried out only if a WAMS system were actually operated on the Italian national grid. A WAMS is necessary because it can provide a complete set of measurements, suitably synchronized and normalized.

The next step in testing the proposed approach was to build a new set of parameters. This second set represents, in the optimization algorithm, the initial value $\boldsymbol{p}_0$ (the "wrong" set of parameters stored in the dynamics database).

Knowing the initial value $\boldsymbol{p}_0$, it is possible to carry out a new simulation and calculate the first set of simulated signals z_0. With all, these inputs, it is possible to start the optimization algorithm and check if, at the final k^{th} interation, the assessed value $\boldsymbol{p}_{\text{ass}}$ is close to $\boldsymbol{p}_{\text{real}}$.

3.1 Test A

The first case was developed to show how this procedure allows in estimating model parameters (for example the model of an equivalent generator) or parameters related to power system elements that are located outside the national power system. In particular, the test was aimed at estimating the main parameters of a French generator located in Albertville, just across the Italian border.

To estimate these parameters, the objective function was built considering the mismatches between measured and simulated line flows (active and reactive) on 25 transmission lines located at the Italian border and in the mainland of the peninsula.

The algorithm was tested considering the power system behavior after a three-phase fault located in the Turin area, cleared after 0.10-s by tripping the faulted transmission line (Castelnuovo-Trino). During simulations, a feasibility domain was assumed for the parameters that had to be estimated. This domain, represented in the mathematical formulation with Eq. (14), is a very important feature of this

Table 1 Test A: Estimation of dynamic parameters for the generator in Albertville

	H (MWs)	D (p.u.)	X_d (p.u.)	Xq (p.u.)	X'_d (p.u.)	X'_q (p.u.)	T'_{d0} (s)	T'_{q0} (s)
$\boldsymbol{p}_{\text{real}}$	1,800	0	333	333	1667	1,167	500	21
$\boldsymbol{p}_0$	3,000	0	100	100	1,000	1,000	100	10
$\boldsymbol{p}_{\text{ass}}$	1,795	0	330	329	1,650	1,125	503	21

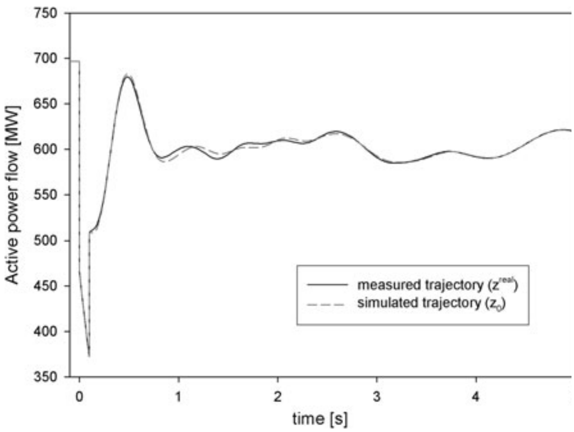

Fig. 3 Test A: measured trajectory versus simulated trajectory for the Albertville-Rondissone 400 kV transmission line (active power flow)

procedure because it allows in eliminating gross bad data and speed up the convergence of the overall algorithm.

In the followings, it is shown how the algorithm was adopted to assess all parameters of a generator located in France, right across the Italian border. Table 1 shows the value adopted for the base case ($\boldsymbol{p}_{\text{real}}$) and for the first simulation ($\boldsymbol{p}_0$), together with the assessed value $\boldsymbol{p}_{\text{ass}}$.

Note that this test can be considered a case with multiple bad data, since most of the parameters which had to be assessed were affected by very large systematic error which exceeded the usual statistics linked to the hypothesis of small drifts and random Gaussian fluctuations.

In Figs. 3 and 4, active and reactive power flow trajectories are referred to the 400 kV Albertville–Rondissone interconnecting line. In these figures, the simulated trajectories (dashed lines) refer to the first iteration of the algorithm whereas, for the sake of clarity, the optimized trajectories are not shown because they overlap the measured ones. In Fig. 4, the scale adopted is not able to show the reactive power flow trajectory during the fault. The sudden growth of reactive power exchange is due to the necessity to sustain the voltage on the nearby faulted bus.

In Table 2, the convergence behavior of the algorithm is shown. The algorithm had a satisfactory performance in terms of convergence behavior (number of iterations) and computational time. The algorithm converged in around 2 min (computational time for each iteration, considering a 5-s time window and a 0.02-s integration step, is about 20-s) when run on a Workstation XP-1000 characterized

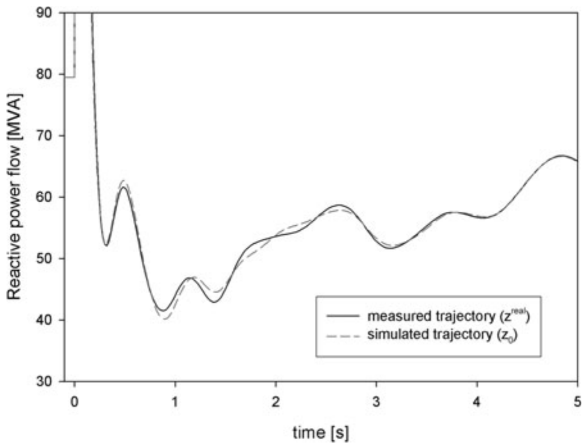

Fig. 4 Test A: measured trajectory versus simulated trajectory for the Albertville-Rondissone 400 kV transmission line (reactive power flow)

Table 2 Test A: convergence behavior

Iteration k	Objective function (p.u.)
1	208.337
2	12.441
3	0.028
4	0.049
5	0.009
6	0.001

by a CPU type 21264 ALPHA 667 MHz, 4 MB L2 cache, 512 MB RAM and 18.2 GB 10000 RPM Ultra Wide disk.

3.2 Test B

The second test has been aimed at estimating constants for voltage- and frequency-dependent load models. It has been assumed that the voltage and frequency dependence of loads, with respect to reactive and active power, can be described with the equations

$$P = P_0 \left(\frac{V}{V_0} \right)^{p_v} \left(\frac{f}{f_0} \right)^{p_\omega} \tag{21}$$

$$Q = Q_0 \left(\frac{V}{V_0} \right)^{q_v} \left(\frac{f}{f_0} \right)^{q_\omega} \tag{22}$$

where p_v, p_ω, q_v and q_ω usually depend on the nature of loads.

The simulation was carried out considering the transient subsequent to the tripping of one of the two 400-kV circuits of the transmission line Latina-Garigliano in Central Italy. The steady state condition refers to a system configuration during a Wednesday (peak-load day) at the first daily peak. The transmission line, at the moment of the tripping, was carrying about 410 MW.

The simulation was carried out considering the hypothesis that loads were wrongly modeled with a constant impedance model ($p_{v0} = 2$ and $q_{v0} = 2$), instead of the real values $p_{v\text{real}} = 1$ and $q_{v\text{real}} = 3$. Frequency dependence constants (p_ω and q_ω) were not considered because transients under study are too short for allowing a good assessment of frequency dependent variables.

Differently from Test A, where trajectories were assumed not affected by noise to evaluate the intrinsic accuracy of the algorithm, in this case it has been assumed, more realistically, that measurements are affected by random white noise. Considering that the accuracy reached on variables measured by a PMU can be estimated in about 0.1% [23], measurements z^{meas}, that should be coming from a WAMS, have been considered conservatively affected by white noise having variance 0.03%, with respect to the measured value. This hypothesis is also consistent with the results shown in [11].

The objective function to be minimized was built considering post-fault measured and simulated values of electric power output at 30 selected generating units widespread all over the grid.

Figure 5 shows, for a single trajectory, the difference between the real and the simulated system response. Figure 6 shows this same difference at the end of the optimization algorithm. The trajectories represented in Figs. 5 and 6 are related to a generator in Torvaldaliga (in the Rome area) close to the tripped transmission line.

Table 3 shows the convergence behavior of the algorithm. As remarked for Test A, the algorithm showed a good performance and converged in about 140-s. It can also be observed that, even the in presence of large deviations of parameters and simulated white noise, the algorithm is able to assess a correct value for the parameter under investigation.

Also, Test B can be considered a case characterized by multiple bad data since gross errors were hypothesized on the coefficients to be evaluated on load nodes.

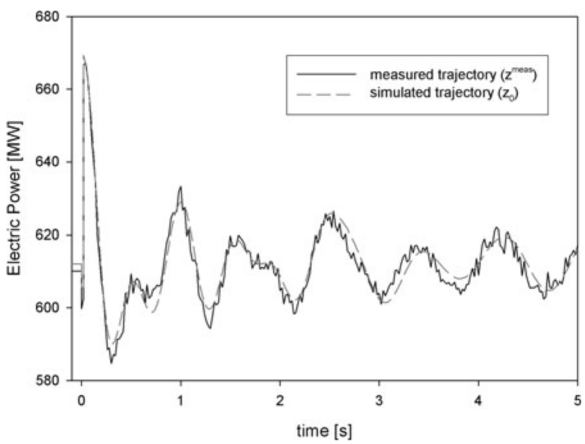

Fig. 5 Test B: measured trajectory versus simulated trajectory for the Torvaldaliga generator

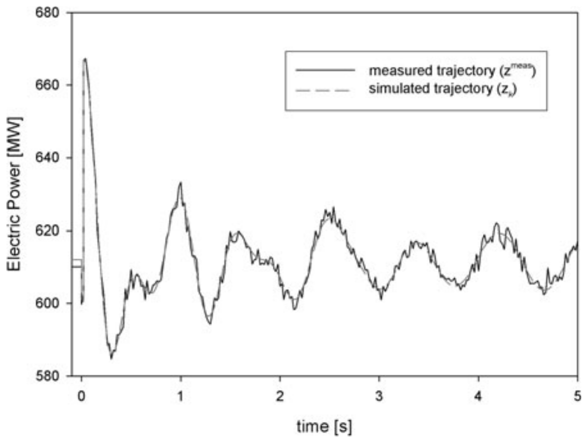

Fig. 6 Test B: measured trajectory versus optimized trajectory for the Torvaldaliga generator

Table 3 Test B: convergence behavior

Iteration k	Objective function (p.u.)	Estimated value p_{vk} (p.u.)	Estimated value q_{vk} (p.u.)
1	1,678.122	2.131	2.914
2	412.114	1.559	3.500
3	9.296	1.157	3.321
4	0.453	1.130	3.163
5	0.147	1.072	3.085
6	0.011	1.036	3.029
7	0.003	1.009	2.988

Note that this assumption is not too far from the reality since load modeling is characterized by the most uncertain parameters in dynamic simulations. Furthermore, load representation changes continuously, instant by instant, due to the nature of electric load. Assessing these parameters accurately is unavoidable for DSA calculations since they affect significantly transient simulations.

4 Conclusions

The authors proposed a methodology, based on nonlinear programming technique, for estimating dynamic parameters of power systems. Identification and updating of such parameters are crucial aspects of dynamic security assessment and control architecture. Updated data on both static and dynamic parameters guarantee more reliability in assessing preventive and control actions based on transient simulations.

The methodology is based on the formulation and the solution of an optimization problem aimed at minimizing the mismatch between online measurements and simulated trajectories. The control variable of such problem is given by the set of parameters that must be estimated.

The methodology was tested on a real representation of the Italian power system and proved to be effective and flexible enough to treat different problems such as the identification of generators external to the national power system or voltage-dependent load constants. The methodology is also flexible enough to be implemented with measurements that are commonly available at power system control centers (electric power output at generators, active and reactive power flow, bus voltage, etc.).

Even though the method does not require the implementation on an online time framework, the presence of a WAMS is unavoidable since it can provide the complete sets of synchronized and normalized measurements that are necessary to execute the proposed procedure. Therefore, the proposed architecture could be suitably implemented in a control center that makes use of a WAMS system.

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