24th International Conference on Renewable Energies and Power Quality (ICREPQ'26)
Santander (Spain), 10th to 12th June 2026
E&Q Journal - ISSN:2659-8779. Volume 4. July 2026

Automatic Tuning of Operator-Supplied Dynamic Models in PSS®E Based on Real-Plant Measurements

M. Lozano Deiros[1], D. Marquina Cordero[1] and D. M. Rivas Ascaso [1]

[1] CIRCE – Technology Center
Parque Empresarial Dinamiza – Avenida Ranillas, Edificio 3D, 1 50018 Zaragoza (Spain). +34 976 976 859,
circe@fcirce.es

Abstract.

Transmission system operators require dynamic models calibrated to match real plant behavior, yet tuning is often manual, slow, and difficult to reproduce. This paper presents a fully automated calibration framework for renewable generation models based on Differential Evolution algorithms (DE), particularly Differential Evolution **[1]**, implemented through the PSS®E Python API **[2]**. The calibration is formulated as a bounded nonlinear time-domain optimization problem in which candidate parameter sets are iteratively evaluated via dynamic simulations and compared against field measurements. The methodology is demonstrated on REE's PPMREE5 module by tuning a set of 15 parameters selected for their impact on the frequency-response behavior. Using active-power frequency response tests under over- and under-frequency events, the proposed approach improves the agreement between simulated and measured responses and accurately reproduces both transient and steady-state behavior. The results show that the framework provides a systematic, reproducible and scalable alternative to manual tuning for renewable plant model validation.

Key words. Dynamic Model Calibration, Power System Dynamics, PSSE, Genetic Algorithms, Grid Code Compliance

1. Introduction and Background

The increasing penetration of renewable energy sources, particularly wind and photovoltaic (PV) power plants, is fundamentally altering the dynamic characteristics of modern power systems. As synchronous machines are progressively displaced, system inertia decreases and frequency stability becomes increasingly dependent on converter-based resources. Under these conditions, accurate dynamic models of renewable power plants are essential to perform reliable stability studies and ensure compliance with grid-code requirements.

Transmission system operators (TSOs) typically define the model structure and simulation platform, while plant owners or engineering consultants are responsible for tuning model parameters so that simulated responses match commissioning or field-test measurements. [3] However, this calibration process is commonly performed through manual and iterative trial-and-error procedures. Such workflows are time-consuming, operator-dependent, and often difficult to reproduce or audit, especially when multiple renewable plants must be validated within tight regulatory timelines.

Evolutionary optimization techniques have previously been applied to parameter identification problems in power systems, including dynamic model tuning and controller optimization. However, their systematic integration into practical TSO validation workflows for renewable plants remains limited. In particular, automated calibration directly embedded within a PSS®E-based compliance process has not been widely documented for large-scale renewable portfolios.

This paper proposes a fully automated calibration framework based on Differential Evolution (DE) directly embedded in the PSS®E environment, aimed at reducing manual effort and improving reproducibility in TSO validation processes.

The main contribution of this work lies in bridging measurement-based calibration with real compliance workflows, using actual plant data and operator-supplied models. Compared to traditional manual tuning, the proposed approach provides clear advantages in terms of scalability, repeatability, and reduced engineering effort.

However, the method also presents several limitations. In particular, inherent challenges such as parameter identifiability and potential collinearity between parameters may affect the uniqueness and robustness of the estimated solutions, as these aspects are not explicitly addressed in the current formulation. Future work will focus on incorporating strategies to better handle these limitations and improve the reliability of the parameter estimation process.

2. State of the Art

Parameter identification and model validation are long-standing and critical tasks in power system dynamic studies. In the context of renewable generation, Asmine et al. established a foundational measurement-based view of model validation, defining it as the process of comparing simulated and recorded responses under staged tests or real disturbances, and highlighting playback-based validation as one of the most meaningful approaches for wind power plants. That work also stressed two issues that remain highly relevant today: first, that simplified RMS models cannot perfectly reproduce all measured dynamics, and second, that model acceptance still depends on defining what constitutes an "adequate" fit between simulation and measurement. [4]

More recently, the availability of phasor measurement unit (PMU) data has enabled online and non-intrusive calibration methods, moving beyond offline staged tests and manual engineering adjustment. In this direction, Khazeiynasab and Qi proposed a PMU-based generator parameter calibration framework using adaptive Approximate Bayesian Computation with Sequential Monte Carlo (A-ABC-SMC), in which event playback is combined with an empirical Gramian-based parameter screening step to identify the most identifiable parameters before calibration. Their results show that likelihood-free Bayesian methods can estimate posterior distributions of model parameters efficiently, even under large prior uncertainties and across multiple events. [5]

In parallel, black-box optimization has emerged as an attractive alternative when the objective function is expensive, nonlinear, and not easily differentiable. In particular, Khazeiynasab and Qi also proposed a PMU-based black-box calibration method using a stochastic radial basis function (RBF) surrogate model, where the discrepancy between measured and simulated active and reactive power is minimized under parameter bounds derived from prior information. This approach is especially relevant because it avoids explicit likelihood evaluation, treats dynamic simulation as a black box, and directly targets computational efficiency through surrogate-assisted optimization. [6]

Despite these advances, several limitations remain. First, much of the recent PMU-based literature is focused on synchronous generators rather than renewable power plant aggregate models. Second, advanced Bayesian or surrogate-based methods like the one described in [5], while powerful, may introduce substantial methodological complexity that can hinder their direct adoption in practical TSO validation workflows. Third, many studies are validated on benchmark systems or generator-level models, whereas fewer works address automated calibration of operator-supplied renewable plant models directly within certified industrial simulation environments. Therefore, there remains a clear need for practical and reproducible calibration workflows that combine measured plant data, automated parameter tuning, and direct integration with tools such as PSS®E, while remaining simple enough for engineering deployment in compliance-oriented validation processes.

3. Methodology

The calibration problem is formulated as a bounded nonlinear optimization in the time domain. A population of candidate parameter vectors is initialized within physically meaningful limits derived from manufacturer data, grid-code constraints and engineering judgment.

For each candidate parameter set:

1. The parameters are automatically injected into the PSS®E model [2].
2. A dynamic simulation is executed under the same disturbance conditions used in plan testing.
3. The simulated response is compared with measured data using a time-domain cost function.

The overall calibration workflow is summarized in the following figure.

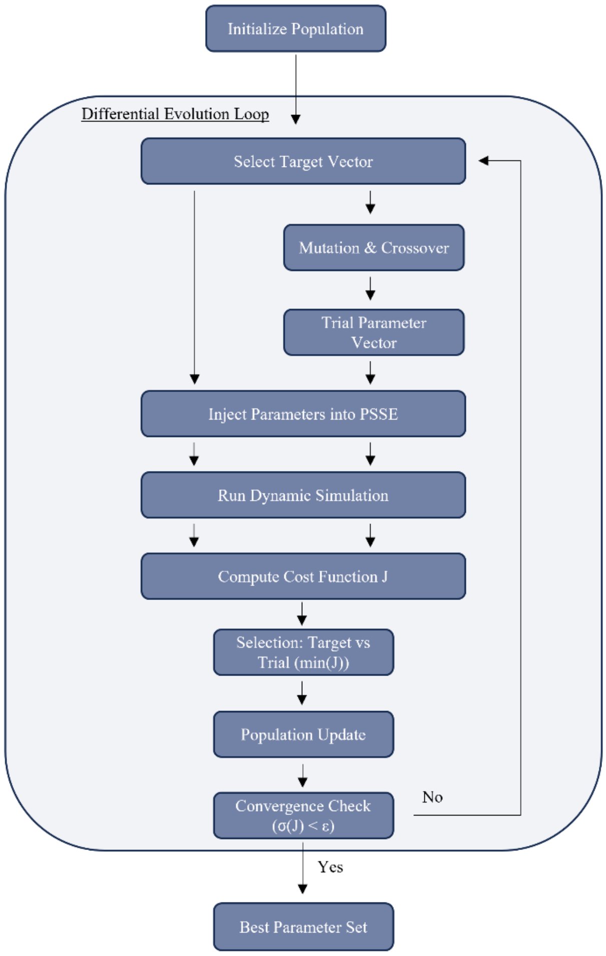

Fig. 1. Flowchart of the proposed Differential Evolution-based algorithm for dynamic model calibration.

The cost function J is defined as the sum of absolute errors between the simulated and measured signals over the evaluation window. No additional weighting is applied.

$$J = \sum_{i=1}^{N} |y_{sim}(i) - y_{meas}(i)|$$

N is the number of samples of the signals over the interval simulated.

The optimization was performed using a population of 90 individuals over 10 generations, resulting in approximately

900 dynamic simulations per calibration process. Convergence was determined based on the dispersion of the objective function values within the population. Specifically, the optimization stopped when the standard deviation of the population cost J fell below 1 % of its own mean value. [7]

Differential Evolution (DE) is a population-based stochastic optimization algorithm particularly suited for nonlinear and non-convex problems. At each iteration, new candidate solutions are generated by combining existing individuals through mutation and recombination operators [1] [7]. In this work, a DE/rand/1/bin strategy is adopted, where mutant vectors are generated from randomly selected individuals and combined with target vectors based on a crossover probability. The selection process retains the candidate with the lowest cost function value.
This approach is especially appropriate for dynamic model calibration, as it does not require gradient information and can efficiently explore high-dimensional parameter spaces with complex interactions.

Given that each candidate solution requires an independent dynamic simulation, the evaluation process is inherently parallelizable. In this work, parallel execution of simulations has been implemented to significantly reduce computation time.
This parallelization enables the efficient evaluation of large populations and improves the scalability of the proposed framework, making it suitable for practical TSO workflows involving multiple plants and scenarios.

4. Application and Results

The proposed framework was applied to the calibration of the PPMREE5 power park module provided by REE [8], which represents aggregated renewable generation behavior. Although the complete model contains 62 parameters, engineering sensitivity analysis identified 15 key parameters governing active power frequency-response characteristics. This dimensionality reduction improves computational efficiency while preserving dominant dynamic behavior.

Real plant measurements obtained during over-frequency and under-frequency active power response tests were used as validation scenarios. Prior to calibration, the initial parameter set showed noticeable deviations with respect to the measured plant response under frequency disturbances. After the optimization process, the calibrated model exhibits improved agreement with the measured trajectories in both transient and steady-state regions.

The calibrated model accurately reproduces ramp rates, power recovery characteristics and final steady-state power levels under both disturbance types. The full calibration process required approximately 1 hour of computational time, substantially reducing the engineering effort compared to manual iterative tuning.

Figure 1 illustrates the comparison between measured plant active power response and simulated response before and after calibration. The figure highlights the improvement achieved by the optimization process in both transient and steady-state regions.

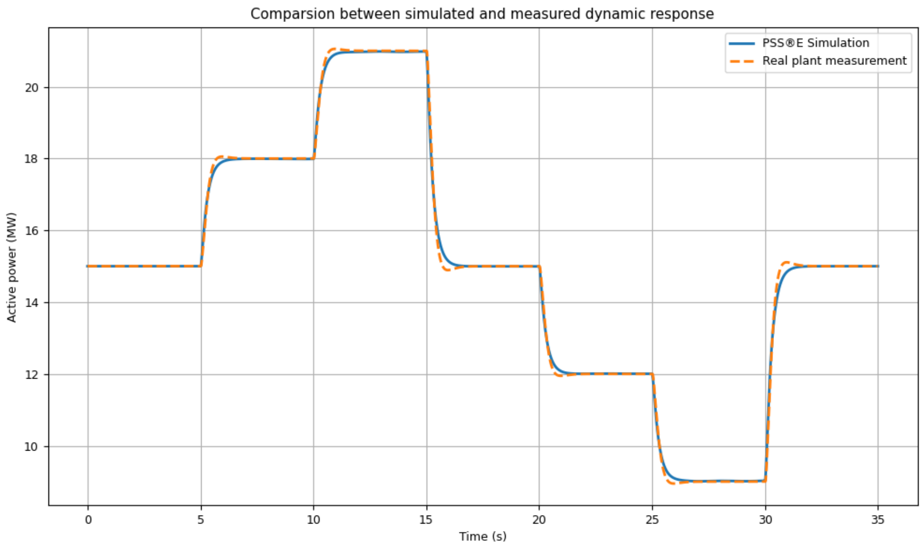

Fig. 2. Active power response under over- and under-frequency conditions: comparison between the automatically calibrated PSS®E simulation and a test generated from the certified plant model.

The results confirm that evolutionary optimization techniques can provide a robust and reproducible framework for renewable plant dynamic model validation. The proposed workflow supports improved reliability of stability studies in low-inertia systems and facilitates efficient grid-code compliance processes in power systems with high renewable penetration.

It is worth noting that the improvement is not limited to steady-state accuracy, but also includes transient dynamics such as ramp rates and response delays, which are critical for frequency stability studies.

The robustness of the calibrated parameters suggests that the optimization process captures the dominant dynamics governing plant response under frequency disturbances.

5. Conclusion

This paper has presented an automated calibration framework for renewable plant dynamic models based on Differential Evolution and integrated into the PSS®E simulation environment.

The results demonstrate that the proposed methodology can significantly improve the agreement between simulated and measured plant responses while reducing the need for manual tuning. The approach provides a reproducible and scalable solution aligned with TSO validation requirements.

The incorporation of parallel simulation execution further enhances computational efficiency, enabling practical application to large-scale validation workflows.

Future work will focus on extending the methodology to multi-event calibration scenarios, improving cost function formulations, and exploring parameter identifiability and sensitivity analysis techniques to further enhance robustness.

6. Further Information

Questions concerning the content of the extended abstract may be addressed to any of the authors:

M. Lozano Deiros
e-mail: mlozano@fcirce.es

D. Marquina Cordero
e-mail: dmarquina@fcirce.es

D. M. Rivas Ascaso
e-mail: dmrivas@fcirce.es

7. References

[1] R. Storn y K. Price, «Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces,» *Journal of Global Optimization,* vol. 11, pp. 341-359, 1997.

[2] Siemens PTI, PSSE Program Application Guide, Siemens Industry Software Inc, 2023.

[3] Ministerio para la Transición Ecológica, «Procedimiento de Operación 9: Información intercambiada por el operador del sistema,» BOE, 2019.

[4] M. Asmine et al, «Model Validation for Wind Turbine Generator Models,» *IEEE Transactions On Power Systems,* vol. 26, nº 3, pp. 1769-1781, 2011.

[5] S. Rashid Khazeiynasab y J. Qi, «Generator Parameter Calibration by Adaptive Approximate Bayesian Computation with Sequential Monte Carlo Sampler,» *IEEE Transactions on Smart Grid,* vol. 12, nº 5, pp. 4327-4338, 2021.

[6] S. Rashid Khazeiynasab y J. Qi, «PMU Measurement Based Generator Parameter Calibration by Black-Box Optimization with A Stochastic Radial Basis Function Surrogate Model,» de *52nd North American Power Symposium (NAPS)*, 2020.

[7] Scipy Developers, «scipy.optimize.differential_evolution,» 2024. [En línea]. Available: https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.differential_evolution.html.

[8] Red Eléctrica de España, «PPMREE5 Model User Guide Version 5,» 2024.