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Identification of hydrogenerator parameters using linear model and optimization approach

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This paper presents a methodology for the identification of key dynamic parameters of a synchronous generator and excitation system based on measured transient and frequency responses. Identification is formulated as an optimization problem, where the objective function is constructed as a weighted sum of normalized root mean squared errors between the simulation model output and the measured data. The linearized model of the hydrogenerator and hydro turbine, derived from a nonlinear fifth-order model of generator, hydraulic turbine, and PI governor, is obtained for identification purposes. This identification approach is based on optimization and can be used in practice where typical identification methods are not feasible. Real test data from a voltage regulation experiment in a hydroelectric power plant were used to identify five selected parameters: transient reactances, d-axis open circuit time constant, exciter gain, and generator inertia.

Keywords: synchronous generator parameter identification, hydrogenerator, optimization

1 Introduction

Identification of synchronous generator parameters is a crucial aspect for power system analysis, stability assessment, and control. Accurate parameter identification improves system modelling, fault diagnostics, and enables robust controller design. Various optimization and system identification techniques have been developed to estimate generator parameters based on measured data. These approaches include meta-heuristic algorithms, frequency response tests, recursive estimation methods, and advanced evolutionary strategies.

IEEE Std 115-A [1] serves as a framework of standard methods used for the identification of generator parameters. The problem of these standard methods is that they are based on the hard to achieve experiments in existing power plants, such as sudden three-phase fault. Researchers try to address these problems with constantly developing new identification methods for the synchronous generator parameters. Recent studies have focused on system identification using frequency response tests and equivalent circuit modelling and have also explored different methodologies for identifying the parameters of synchronous generators.

These methodologies include recursive least squares and Kalman filters that provide a model-based approach for parameter identification, particularly in adaptive control applications. However, these methods can suffer from approximation errors when applied to complex system models, requiring modifications such as the introduction of forgetting factors to improve accuracy [2]. Furthermore, the H_∞ identification method has been explored for its robustness against noise and uncertainties, which makes it suitable for real-time system modelling and predictive control design [3]. Some authors used a mix of original approach to generator parameter identification and parameter optimization fitting, ensuring high accuracy through iterative parameter fitting procedures [4]. Furthermore, evolutionary programming has emerged as a promising alternative to traditional methods, demonstrating resilience to high-noise environments and improved convergence characteristics compared to Kalman filter-based approaches [5].

Particle Swarm Optimization (PSO) has been widely applied because of its capability to efficiently estimate generator parameters by minimizing an objective function based on measured transient and frequency response data. PSO is also used due to its ability to find the global minimum of the objective function. Research has shown that PSO is effective in identifying operational parameters, although the convergence time may be affected by the number of parameters estimated [6]. The PSO algorithm has also been used to identify the synchronous generator parameters from the actual transient network data [7]. Another widely used approach is Genetic Algorithms (GA), which has demonstrated robust performance in identifying generator parameters under various conditions, including real-time scenarios and isolated load cases [8, 9]. The short circuit simulation test has been used by the authors in [10] to obtain the transient response of current i_d and the similarity between this response and the output of the simulation model has been compared by a genetic algorithm to obtain the generator parameters. Other authors used an excitation disturbance test and a genetic algorithm to identify generator parameters [11].

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Our proposed generator parameters identification approach is based on optimization, that compares data obtained from voltage control test in the local power plants and simulation model output. This approach benefits from the fact that local power plants are required to perform such tests after modifications or replacements of the excitation system. To reduce computational complexity, a special linearized model is created for this approach, which accurately captures the frequency and transient characteristics of the identified generator. The linear model description is provided by the second section of this article. The proposed identification approach is described in the third section and the last fourth section is used to prove the methodology on the simulation example. The example presents identification from measurements taken at a local hydro power plant after the replacement of the excitation controller.

2 Power plant model

Although the nonlinear model of the generator can be used for the parameter identification approach documented later in this article, the linearized power plant model has some crucial advantages over the complex non-linear model. The main advantages of using the linear model are as follows:

- The computational complexity is lower for the linear model simulation.
- The frequency response is obtained directly from the linear model.
- The modelling approach is simpler and does not require advanced tools for simulation.
- Stability analysis is performed by computing the eigenvalues of the state-space model matrix **A**.

The Heffron-Phillips model is often chosen as the linear generator model for short-term simulation analysis. However, this model is highly simplified for parameter identification. For the identification process, we utilized a linearized model of a hydrogenerator and a linearized model of a hydro turbine with PI governor. Linear models are derived from non-linear models of the fifth-order generator model and the turbine model, which can be found in [12] using linearization techniques. Based on the Heffron-Phillips model concept, where the generator, exciter, and voltage regulator are described within a single model, we obtain the following linear model representation:

$$
\begin{aligned}
\Delta\dot{\delta} &= \omega_0 \Delta\omega \\
\Delta\dot{\omega} &= \frac{1}{2H}\big(-k_{pe1}\Delta\delta - k_{pe4}\Delta e_q'' - k_{pe5}\Delta e_d'' \\
&\qquad + \Delta P_m\big) \\
\Delta\dot{e_q'} &= \frac{1}{T_{do}'}\Big((x_d - x_d')C_{id1}\Delta\delta - \Delta e_q' \\
&\qquad + (x_d - x_d')C_{id4}\Delta e_q'' \\
&\qquad + (x_d - x_d')C_{id5}\Delta e_d'' + \Delta e_b\Big) \\
\Delta\dot{e_q''} &= \frac{1}{T_{do}''}\Big((x_d' - x_d'')C_{id1}\Delta\delta + \Delta e_q' \\
&\qquad + (-1 + (x_d' - x_d'')C_{id4})\Delta e_q'' \\
&\qquad + (x_d' - x_d'')C_{id5}\Delta e_d''\Big) \\
\Delta\dot{e_d''} &= \frac{1}{T_{qo}''}\big(-(x_q' - x_q'')C_{iq1}\Delta\delta \\
&\qquad - (x_q' - x_q'')C_{iq4}\Delta e_q'' \\
&\qquad - \big(1 + (x_q' - x_q'')C_{iq5}\big)\Delta e_d''\big) \\
\Delta\dot{e_b} &= \frac{1}{T_a}\big(-K_P K_{vp} k_{v1}\Delta\delta - K_P K_{vp} k_{v4}\Delta e_q'' \\
&\qquad - K_P K_{vp} k_{v5}\Delta e_d'' - \Delta e_b \\
&\qquad + K_P u_{ri} + K_P K_{vp}\Delta u_{ref}\big) \\
\Delta\dot{u_{ri}} &= -K_{vi}\big(k_{v1}\Delta\delta - k_{v4}\Delta e_q'' - k_{v5}\Delta e_d'' \\
&\qquad + \Delta u_{ref}\big)
\end{aligned} \tag{1}
$$

The output variables equations for the generator, excitation and voltage control model are:

$$
\begin{aligned}
\Delta P_e &= k_{pe1}\Delta\delta + k_{pe4}\Delta e_q'' + k_{pe5}\Delta e_d'' \\
\Delta v &= k_{v1}\Delta\delta + k_{v4}\Delta e_q'' + k_{v5}\Delta e_d'' \\
\Delta Q &= k_{q1}\Delta\delta + k_{q4}\Delta e_q'' + k_{q5}\Delta e_d''
\end{aligned} \tag{2}
$$

Since the turbine governor affects the low-frequency dynamics of the system, it is essential to include at least a simplified model of the turbine and its regulation in this representation. The linear model obtained for the hydraulic turbine and the PI governor is in the form:

$$
\begin{aligned}
\Delta\dot{P_{m2}} &= \frac{2}{g_0 T_w}\Big(-\frac{3}{2}\frac{g_0 T_w}{T_s}\Delta p - \Delta P_{m2}\Big) \\
\Delta\dot{g} &= \frac{1}{T_s}\Delta p \\
\Delta\dot{p} &= \frac{1}{T_p}\big(K_{tp}(\Delta P_{ref} - \Delta P_e) + \Delta u_{ti} - \Delta g \\
&\qquad - \Delta p\big) \\
\Delta\dot{u_{ti}} &= K_{ti}\Delta P_{ref}
\end{aligned} \tag{3}
$$

and for the mechanical power of the hydraulic turbine:

$$\Delta P_m = \Delta P_{m1} + \Delta P_{m2} = \Delta g + \Delta P_{m2} \quad (4)$$

The description of the individual parameters of the simulation model is provided in the Appendix. Linear model validation has been carried out through simulation experiments, consisting of the transient response of the terminal voltage and the active power of the linear and nonlinear models to a change in the reference voltage. Furthermore, the frequency responses of the active and reactive power have been obtained for both the linear and non-linear models of the generator and turbine. The comparison of transient and frequency responses has been quantified based on the normalized root mean squared error *NRMSE* metric:

$$NRMSE = \frac{|\boldsymbol{y}_{\mathbf{ref}} - \boldsymbol{y}|}{|\overline{\boldsymbol{y}}_{\mathbf{ref}} - \boldsymbol{y}_{\mathbf{ref}}|} \quad (5)$$

Here, $\boldsymbol{y}_{\mathbf{ref}}$ is the reference data vector, $\boldsymbol{y}$ is the compared data vector, and $\overline{\boldsymbol{y}}_{\mathbf{ref}}$ is the mean value of the reference data. The advantage of this metric is that the absolute error between the reference data and the model output is normalized to the deviation of the reference data. In our case, the reference data are the outputs of the non-linear model, and the compared data are the outputs of the linear model. The comparison of the transient responses of the models is shown in Fig. 1, and the comparison of the frequency responses is shown in Fig. 2. The similarity between the linear model and the reference non-linear model can be obtained from the *NRMSE* according to (6) and the similarity results of linear model outputs are provided in Tab. 1.

$$Similarity = (1 - NRMSE) \times 100\% \quad (6)$$

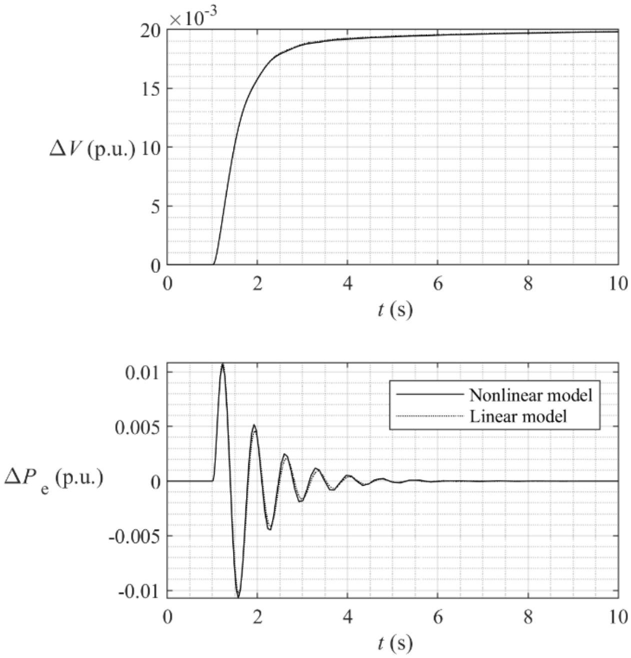

Fig. 1. Nonlinear and linear model transient response comparison

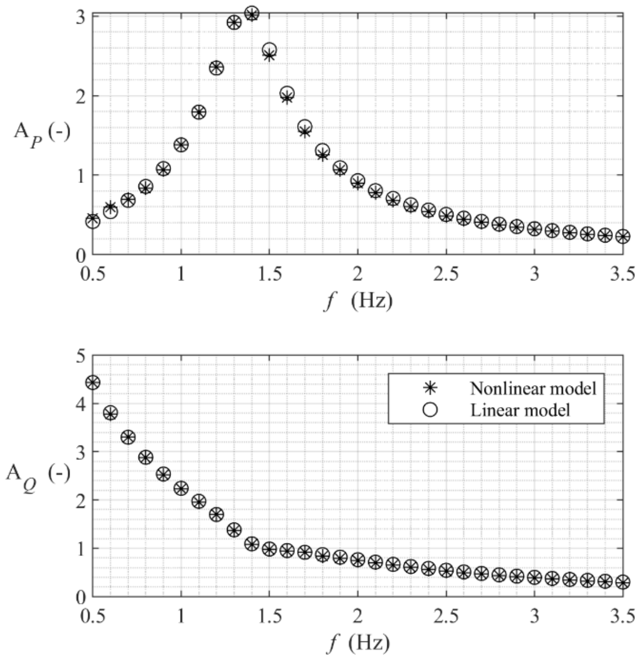

Fig. 2. Nonlinear and linear model frequency response comparison

Table 1. Similarity between nonlinear and linear models

Characteristic	Similarity (%)
Transient response of voltage	99.42
Response of active power to voltage setpoint change	90.69
Amplitude frequency response of active power	96.46

3 Identification methodology

The parameters of the simulation model of the hydrogenerator and excitation system can be classified into known parameters, known parameters that need refinement, and unknown parameters. Known parameters include controller gains, generator nominal values, and equivalent network impedance. The parameters that typically require refinement through identification include transient reactances x_d' and x_q', the open-circuit time constant in the d-axis T_{do}', and the gain of the ST4C exciter K_P. An unknown parameter is typically the total inertia of the rotating system H. Numerous methods have been developed for identifying the parameters of a synchronous generator [1]. However, not all these methods are feasible under real-world conditions. For example, power plant operators generally do not allow sudden short-circuit tests on the generator for obvious reasons. Other methods may be impractical for large generators: for example, it is not possible to disconnect the stator winding of the generator and connect a signal generator to it. However, some of these tests are performed by generator manufacturers, who provide a comprehensive list of typical parameters. To refine the typical parameters of the generator and the excitation system, the following methods can be used:

- Measurement of synchronous reactance x_d of the generator from no load tests.
- Determination of inertia H from the generator's load rejection test.
- Determination of unknown excitation system gains based on manufacturer data and obtained steady-state responses.
- Refinement of basic dynamic parameters of the generator and exciter based on the measured transient and frequency responses of the generator.

The unknown parameters and parameters that need refinement can be determined by identification. The proposed identification methodology of the generator and excitation system parameters is based on the objective function minimization using an appropriate optimization method. This function can be composed of the transient responses and the frequency response error between the measurement and the model output. The error between the measured data and the model output could be evaluated using criteria such as *NRMSE* described in the previous section. The weighted sum of the deviations between the measured data and the model is the objective function. The weights must be set according to the importance of the measured characteristic that the model should best capture.

The identification methodology can be summarized to the following procedure:

- Measure the on-load transient and frequency response tests. The transient response tests should be performed by applying a step change to the voltage setpoint and observing the generator terminal voltage and active power. The frequency response tests should be carried out by injecting a sine wave or white noise into the AVR voltage setpoint while recording the active and reactive power responses. It is advisable to conduct these tests at approximately 90% of the nominal turbine load and at the nominal voltage level.
- Select the unknown parameters and parameters that need to be refined.
- Construct the objective function and choose the error criterion.
- Minimize the error between the measured values and the model by optimization.
- Verify the model outputs to the new set of verification data.

4 Simulation example

The above methodology is illustrated in the following simulation example. The task is to identify the parameters of the hydrogenerator and excitation system x_d', x_q', T_{do}', H and K_P. The unknown parameter is H and the other parameters need refinement. The synchronous reactance is known x_d=0.91 from the no-load tests. Measurements of the required quantities have been performed in the local hydroelectric power plant to obtain the datasets needed for the identification. From the measured datasets, the frequency responses (FR) of the active and reactive generator's power, as well as the three transient responses (TR) of the generator's voltage and active power to the voltage reference step change, were obtained. The following objective function has been constructed according to the simulation model output and the measured data:

$$J = w_{FRP}e_{FRP} + w_{FRQ}e_{FRQ} + w_{SRV}e_{SRV} + w_{SRP}e_{SRP} \quad (7)$$

Here, w_{FRP}, w_{FRQ}, w_{SRV} and w_{SRP} are weights. The e_{FRP} is the *NRMSE* of the frequency response of active power, e_{FRQ} is *NRMSE* of the frequency response of reactive power, e_{TRV} is mean value of *NRMSE* of the transient responses of voltage, and e_{TRP} is the mean value of *NRMSE* of the transient responses of active power. The second task of this example is to provide recommendations for the selection of the optimization algorithm. The optimization algorithms have been set to terminate the optimization in the objective function tolerance of 10^{-4}, except for the Bayesian optimization, which does not terminate by this parameter. The selected optimization methods are mainly from Matlab Global Optimization toolbox and the Genetic algorithm developed in our department [13], marked as Genetic Algorithm – Sekaj:

- Bayessian optimization
- Pattern Search
- Genetic Algorithm – Matlab
- Genetic Algorithm – Sekaj
- Particle Swarm

Table 2 shows the parameter values identified using the above optimization methods. The similarities calculated based on the NRMSE criteria of the frequency and transient responses obtained for each optimization method are shown in Tab. 3. In this table, TR1 is the first measured transient response, TR2 is the second, and TR3 is the third one. All optimization methods used in the example converge to the same minimum, but with slightly different identified parameters and similarity values. This suggests that the optimization methods must compromise the way the model captures different measured data. The highest similarity has been found in the voltage transient response of the model and the lowest in the active power transient response. This is partially due to the influence of noise, vibrations, and generator oscillations on the measured active power signal, which the simulation model cannot fully match. The graphical comparison of the measured data and the model output for the parameters obtained from the pattern search algorithm are shown in Figs. 3 and 4. All optimization algorithms used in the example can be suggested to perform this identification task in the case of found minimum. The main difference in their impact on identification is in the computational time and iterations for convergence. These results are summarized in Tab. 4 and from them it should be recommended to use the Genetic algorithm – Sekaj or the Particle swarm algorithm. However, the computational time is low for all optimization algorithms used in the example, and it should also be recommended to use some of them to guarantee the found minimum.

Table 2. Comparison of optimization methods

Method	x_d'	x_q'	T_{do}'	H	K_P
Bayesian optimization	0.28	0.52	4.3	2.29	5.35
Pattern search	0.28	0.5	4.51	2.32	5.47
Genetic algorithm – Sekaj	0.28	0.51	4.33	2.3	5.35
Genetic algorithm – Matlab	0.28	0.51	4.35	2.3	5.38
Particle swarm	0.28	0.5	4.42	2.31	5.4

Table 3. Identified similarities for transient and frequency responses in terms of NRMSE

Similarity metric	Bayesian optimization (%)	Pattern search (%)	GA Sekaj (%)	GA Matlab (%)	Particle swarm (%)
TR1 V	90.15	90.87	90.46	90.49	90.7
TR1 P	62.26	60.09	60.88	60.79	60.46
TR2 V	88.92	89.76	89.3	89.34	89.57
TR2 P	69.13	67.87	68.21	68.15	68.04
TR3 V	88.06	88.89	88.44	88.49	88.71
TR3 P	57.34	56.69	56.73	56.7	56.72
FR P	67.79	63.78	65.2	65.08	64.48
FR Q	76.08	77.71	76.76	76.83	77.29

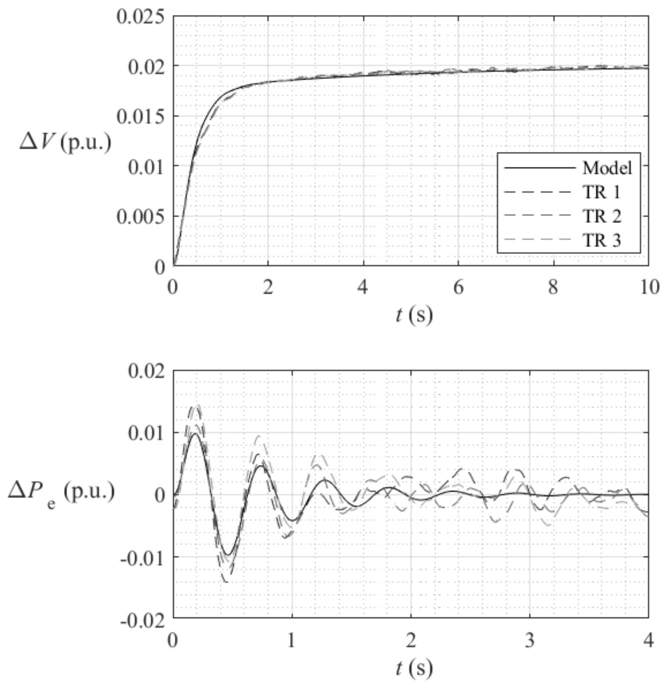

Fig. 3. Comparison of identified model transient response to measured data

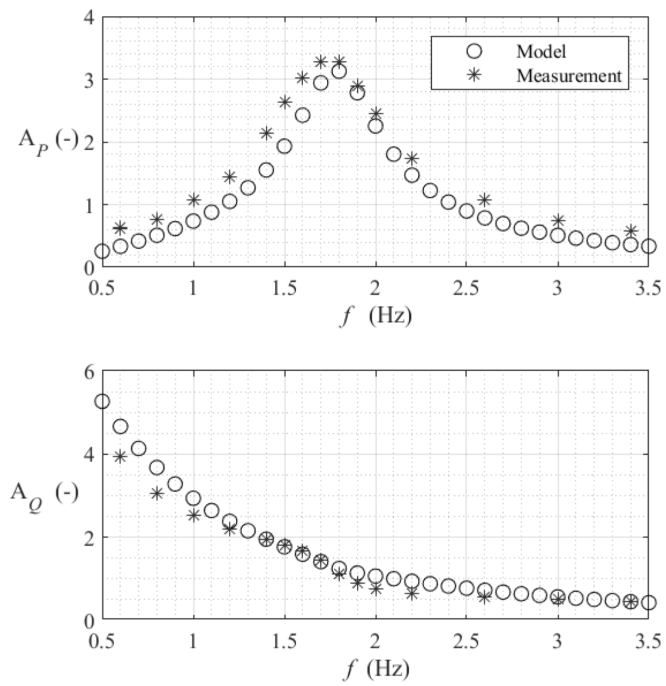

Fig. 4. Comparison of identified model frequency response to measured data

Table 4. Comparison of optimization methods

Optimization method	Iterations	Computation time (s)	Practical usability
Bayesian	693	3600	Low
Pattern Search	490	131	High
GA Matlab	59	231	Medium
GA Sekaj	88	83	High
Particle Swarm	78	99,5	High

5 Conclusion

This paper presents a methodology for identification of key dynamic parameters of a synchronous generator and excitation system based on measured transient and frequency response data. The identification process is based on minimization of weighted objective function using selected optimization algorithms. A linearized hydrogenerator model, derived from the nonlinear fifth-order model and the turbine model, were used to reduce computational complexity while preserving the essential dynamic behaviour.

The methodology has been verified using real measurement data obtained from a voltage regulation test conducted at a local hydroelectric power plant after replacing the excitation system controller. Transient responses of voltage and active power, as well as frequency responses of active and reactive power, were used to build the objective function.

Several optimization methods were compared in terms of the accuracy of the identified model, convergence speed, and practical usability. These included Bayesian optimization, pattern search, particle swarm optimization, and two variants of the genetic algorithm. All methods converged to similar values of the objective function, with minor differences in the identified parameters and the resulting model accuracy.

The proposed methodology is suitable for identifying the parameters of the generator and excitation system in real power plants using practical test data. However, this method also has certain limitations, as it relies on the optimization process. The selection of the upper and lower bounds of the generator parameters for identification depends on the designer choice. The initial generator parameters for the q-axis are often inaccurate, and it is not always possible to rely on the manufacturer's datasheet when selecting their intervals. From this perspective, the methodology is more focused on the identification of a hydrogenerator model, which contains fewer q-axis parameters.

Future work will focus on extending this methodology to online identification and incorporating uncertainty quantification into the optimization process. Another important direction will be the extension of the proposed approach to multi-machine systems and the identification of two parallel-operated synchronous generators. In such cases, the identification will need to account for mutual electromagnetic coupling between the two machines, making the problem more complex but also more representative of the operation of the real-world power system.

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Appendix

Symbol	Description
$\Delta\delta$	Deviation of rotor angle
$\Delta\omega$	Deviation of rotor angular speed
ω_0	Synchronous speed
ΔP_m	Deviation of mechanical power input
ΔP_e	Deviation of electrical active power output
ΔQ	Deviation of reactive power output
Δv	Deviation of terminal voltage magnitude
$\Delta e_q'$	Deviation of q-axis transient EMF
$\Delta e_q''$	Deviation of q-axis subtransient EMF
$\Delta e_d''$	Deviation of d-axis subtransient EMF
Δe_b	Deviation of excitation voltage
Δu_{ri}	Integrator state in AVR (voltage regulator)
Δu_{ref}	Deviation of voltage reference
ΔP_{ref}	Deviation of power reference (governor input)
Δp	Intermediate signal in turbine-governor model
Δg	Gate opening (turbine control variable)
Δu_{ti}	Integrator output in turbine governor control
ΔP_{m2}	Turbine mechanical power component
H	Inertia constant
x_d, x_d', x_d''	Direct-axis synchronous, transient, and subtransient reactances
x_q', x_q''	Quadrature-axis transient and subtransient reactances
T_{do}'	Open-circuit transient time constant (q-axis)
T_{do}''	Open-circuit subtransient time constant (q-axis)
T_{qo}''	Open-circuit subtransient time constant (d-axis)

T_a	Time constant of exciter dynamics
T_s	Servo time constant in turbine governor
T_w	Water hammer time constant
T_p	Time constant of turbine power response
K_P	Exciter gain
K_{vp}, K_{vi}	Proportional and integral gains of voltage regulator
K_{tp}, K_{ti}	Proportional and integral gains in turbine governor
C_{id1}, C_{id4}, C_{id5}	d-axis current response state gains
C_{iq1}, C_{iq4}, C_{iq5}	q-axis current response state gains
k_{pe1}, k_{pe4}, k_{pe5}	Active power response state gains
k_{q1}, k_{q4}, k_{q5}	Reactive power response state gains states
k_{v1}, k_{v4}, k_{v5}	Voltage response state gains

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