Online Monitoring of Excitation Control Systems

Kiyong Kim, Henry Jansen, and Michael Basler
Basler Electric Company
Highland, United States of America

***Abstract*— This paper proposes a device to monitor and analyze excitation control systems, by comparing the response of an actual system to that of a defined model (digital twin). It can be used to validate excitation control system models and for detecting an anomaly of the system. Based on this, preventive maintenance measures can be taken into consideration before an outage is forced. Online estimation to identify machine parameters is preferred because it does not require service interruption such as the partial load rejections required in the traditional approach. Estimation accuracy in practical environment conditions is important to a successful detection of the generator incipient failures. A Swarm Intelligence (SI) technique is proposed to identify the generator parameters. The performance of the proposed method is evaluated with an actual large generating system.**

***Index Terms*—Digital twin, parameter estimation, particle swarm optimization, power system simulation, synchronous generator.**

I. Introduction

It is important that changes in excitation control system's parameters, such as generator reactances and time constants, are accurately included in the computer model, known as a digital twin, so that any potential threats to system stability are recognized and improvements are made. The North American Electric Reliability Corporation (NERC) MOD-026-2 standard requires the performance of offline tests to verify operation of the generating system to its defined mathematical model on a routine basis. This verification requires the identification of system model parameters. Continuous monitoring is also part of the NERC requirements of periodic validation of the simulation models which are based on typical operating conditions of the units, rather than the quite unusual conditions associated with the staged tests (e.g., low power input). In order to meet this requirement, a practical online parameter estimation technique is preferable.

Estimation of synchronous generator parameters is a problem that has attracted the attention of many researchers since the late sixties. Various techniques for parameter estimation were proposed in the literature [2]-[6]. One of the methods was the estimation of parameters from Standstill Frequency Response (SSFR) test data [2], [3]. In this approach, curve fitting techniques are used to derive the transfer functions of the d-axis and q-axis using available test data. Then, parameters of the model are calculated from nonlinear equations. Other methods in [4], [5], include least squares, infinite-norm, and 1-norm estimators. In [6], a Park's transformation model and synthetic data were utilized to estimate synchronous machine parameters employing least squares minimization techniques. An observer was utilized to estimate the unmeasurable states using known information to include the damper circuits.

A practical approach was proposed to validate model parameters based on staged tests or recorded online system disturbance data [7]. It uses non-linear recursive least square method to minimize the difference between the simulated model response and the recorded data. This approach has been tested with various generating systems to check its use for model validation.

This present paper proposes a device with an online parameter estimation tool for continuously monitoring excitation control system performance. A set of dynamic response data associated with naturally occurring disturbances is recorded. This recorded data is used to identify the excitation control system model parameters that provide the best match between simulation results and recorded data using a Particle Swarm Optimization (PSO) technique [8].

This proposed device enables online model validation capability. Also, it can be used to continuously monitor the generator model parameters and compare with the given generator parameters to detect an anomaly of the generating system, which is illustrated in Fig. 1.

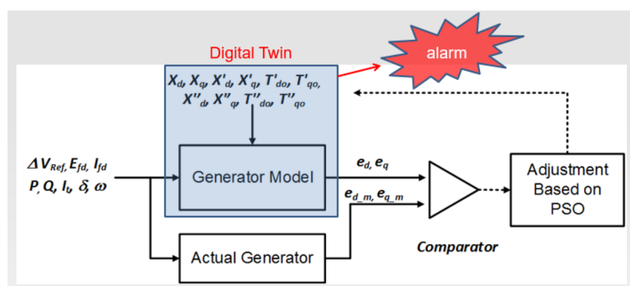

Figure 1. Detection of an anomaly in the generating system.

II. Model Validation

A typical power plant model is described in Fig. 2. This is implemented in the proposed device using the standard IEEE models. In this paper, exciter and generator models are considered for continuously monitoring its performance. It automatically estimates the best model parameters to fit the model's responses to the actual system responses.

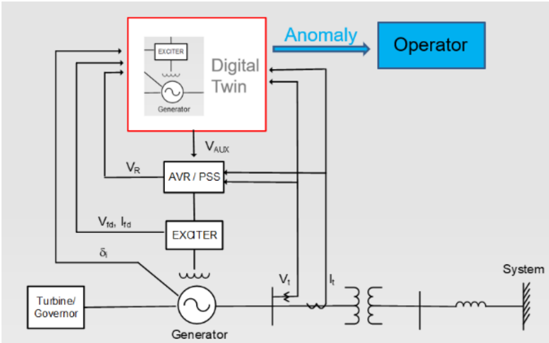

Figure 2. Model validation of a power plant.

The online estimation computation sequence consists of five steps as shown below:

1. If the generating system is running at steady state condition, the exciter and generator system parameters are estimated and compared with the expected parameter values.
2. When a system disturbance is identified, data logging is triggered to record three phase generator voltages and currents, field voltage, field current, and speed for five seconds.
3. The sampled field voltage, generator current, and speed are applied to the system model with the provided nominal parameter values to obtain the simulated response.
4. The simulated model response at each sample step is compared with the recorded system disturbance response.
5. New model parameters are adjusted based on the difference between the simulated responses and the actual responses using the PSO technique until best match is obtained.

For the PSO iterations, ten fixed sets of generator parameters from various generating systems are implemented for initial particle positions. The nominal parameter values are set by the user. The variation of parameter values is limited to a percent of the nominal values, which is a user setting and its default range is set to a maximum of 100% and a minimum of 50% of the nominal values.

The IEEE standard d-q axis synchronous generator model in [9] and the exciter models in IEEE Std 421.5™-2016 [10] are utilized for the simulation models. The differential equations of each model are solved by the Euler method.

A. *Exciter Parameters (T_e, K_c, and K_d)*

The exciter model parameters are continuously estimated to fit the exciter model's responses to the actual exciter responses. For a static exciter, it continuously monitors the rectifier loading factor (K_c) proportional to commutating reactance based on the automatic voltage regulator (AVR) output applied to the static exciter and the generator field current.

If an ac rotating exciter with non-controlled rectifier model is utilized, a system disturbance is captured to estimate the exciter field time constant (T_e), the rectifier loading factor (K_c), and the demagnetizing factor (K_d).

For brushless exciters, the residual voltage may cause a considerable error in parameter estimation, which is due to the magnetic hysteresis effects of the magnetization characteristics of the brushless exciter [11]. Thus, a bias input added to the regulator output is estimated to compensate the effect of residual voltage (V_{res}) for the brushless exciter.

B. *Steady State Parameters of the Generator (X_d and X_q)*

If the generator is operating at the steady state, it monitors the average steady state values of the field voltage and current, three phase terminal voltages and currents. With these monitored values, the generator synchronous reactances (X_d and X_q) are continuously estimated based on the following equations (1), (2):

$$\hat{X}_q = \frac{e_d + R_a i_d}{i_d} \tag{1}$$

$$\hat{X}_d = \frac{I_{fd}\hat{K}_{sd} - e_q - R_a i_q}{i_d} \tag{2}$$

where $\hat{K}_{sd}$ is the generator saturation coefficient at steady-state condition. The synchronous machine parameters vary with different loading conditions because of changes in the magnetic saturation. Thus, it is important to consider the saturation effects to estimate the correct parameter values.

C. *Dynamic State Parameters (X_d, X_q, X'_d, X'_q, X''_d, X''_q, T'_{do}, T'_{qo} T''_{do}, and T''_{qo})*

When a system disturbance is detected based on the considerable change in the field voltage, its dynamic responses are recorded for five seconds. The sampled generator field voltages and generator current at each step are applied to get the model's responses with the given nominal parameter values. The d-axis and q-axis generator voltages and currents depends on the internal rotor angle (δ_i), which is obtained by a keyphasor. If it is not available, it may be calculated based on the measured values of E_t, P, and Q with the manufacturer supplied values of R_a, X_q by (3).

$$\delta_i = tan^{-1}\left(\frac{X_q I_t cos\phi - R_a I_t sin\phi}{E_t + R_a I_t cos\phi + X_q I_t sin\phi}\right) \tag{3}$$

As described in [11], the model's d-q axis stator voltages can be expressed as follows in (4) and (5).

$$e_d = -R_a i_d + \overline{\omega} L''_q i_q - \overline{\omega} L''_{aqs}\left(\frac{\Psi_{1q}}{L_{1q}} + \frac{\Psi_{2q}}{L_{2q}}\right) \tag{4}$$

$$e_q = -R_a i_q + \overline{\omega} L''_d i_d + \overline{\omega} L''_{ads}\left(\frac{\Psi_{fd}}{L_{fd}} + \frac{\Psi_{1d}}{L_{1d}}\right) \tag{5}$$

In the above equations, the q-axis stator voltage is calculated based on the d-axis current (i_d), the d-axis parameters (L_{fd}, L_{1d}, …), and $R_a i_q$. Since $R_a i_q$ is much less than the other terms, the PSO iteration can be performed with the following fitness function depicted in (6), where e_q^k and I_{fd}^k are the model's field voltage and generator terminal currents and where $e_{q\_m}^k$ and $I_{fd\_m}^k$ are the actual system measured responses at the k-th sample step, respectively.

$$J_q = \sum_{k=1}^{N}\left\{\left(e_{q\_m}^k - e_q^k\right)^2 + \left(I_{fd\_m}^k - I_{fd}^k\right)^2\right\} \quad (6)$$

Similarly, for the q-axis parameters, the PSO iteration is done using the following fitness function depicted in (7), where e_d^k and $e_{d\_m}^k$ is the model's sampled d-axis stator voltage and the actual system's measured voltage at the k-th sample step, respectively.

$$J_d = \sum_{k=1}^{N}\left(e_{d\_m}^k - e_d^k\right)^2 \quad (7)$$

Once the PSO iterations for each axis are complete, the PSO iteration with combined fitness function $J = J_d + J_q$ is performed for a fine adjustment of the d-axis and q-axis parameters, simultaneously.

III. EVALUATION OF THE PROPOSED METHOD

A device is designed to measure the generator voltages and currents, the field voltage and current every 1 ms. It can be configured to trigger data log by two modes, voltage step mode activated by the user button or a system event, which causes a considerable variation in the field voltage. For the voltage step mode, a random sequence of voltage steps is used to minimize the generator power variation. The maximum voltage variation for the random voltage step is user programmable. This event will trigger the data log and start the PSO iterations automatically to estimate the generator parameters. This mode is useful to identify the generator parameters when the manufacturer data is not available or to validate the model of the generator.

When the trigger mode is selected, it will identify a system event based on the triggering conditions. Whenever a system event is identified, it will capture the system response and automatically estimate the generator parameters to compare with the provided parameter values. If no event is detected in the trigger mode, the steady state parameters (X_d and X_q) are continually estimated. This feature is useful for continuously monitoring the generator performance or detecting an anomaly of the generating system. Four different case studies are illustrated in the paper to show its benefits.

- Case 1: Model validation of a 150 kW generating system
- Case 2: Monitoring a 970 MVA generator's performance
- Case 3: Estimation of a generating with a brushless exciter using a real time digital simulator for various system disturbances
- Case 4: Identification of an anomaly using a real time digital simulator for an intermittent generator stator fault

A. Model Validation

A small generating set was used for model validation. The generator is a salient pole machine, rated at 150 kW, 480 volts, 1800 rpm and utilizes a static excitation system. The original equipment manufacturer (OEM) supplied data is not available for this genset. Thus, voltage step mode is used to identify the generator parameters.

First, a rough estimate of the open circuit time constant was performed based on the step response at no load. Then a saturation curve test was performed in order to verify generator saturation characteristics. The steady state parameters (X_d and X_q) are also estimated based on 50% of the rated power. Other parameters are assumed with typical generator parameters from a similar generating system. These values are used as nominal values with the variation limited to maximum 100% and minimum 50% of the nominal value. This process illustrates a way to identify the generator parameters and validate the generator model if these are not available. Fig. 3 shows a typical curve fitting after the PSO iteration.

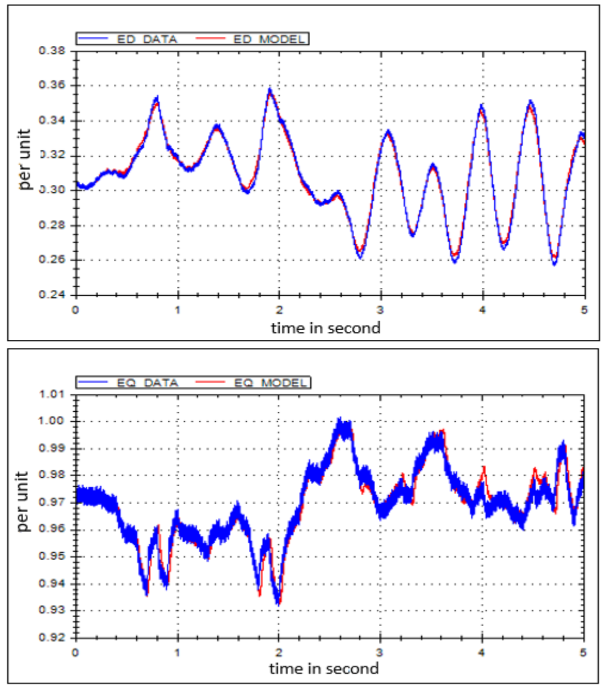

Figure 3. Comparison of the d-q axis voltages.

In order to evaluate the estimation consistency of the generator parameters, voltage step tests have been repeated at various loading conditions and the results are shown in Table I.

TABLE I. Estimation of Generator Parameters at Various Loading Conditions

Generator Parameter	Power Level in pu			
	P=0.2	P=0.3	P=0.4	P=0.5
X_d	2.014	2.120	2.109	2.120
X_q	1.219	1.221	1.221	1.220
X'_d	0.218	0.223	0.225	0.255
X''_d	0.198	0.198	0.198	0.198
X''_q	0.223	0.224	0.221	0.221
T'_{do}	1.936	1.951	1.820	1.819
T''_{do}	0.005	0.005	0.005	0.005
T''_{qo}	0.059	0.066	0.080	0.080

B. Monitoring a 970 MVA Generator's Performance

The proposed method was also evaluated on a large steam turbine generating system. The generator is rated at 970 MVA, 22 kV, and 3600 rpm. The original rotary excitation system was replaced with a static excitation system. Thus, a saturation curve test was repeated to get a better measurement of the generator characteristics saturation factor. Nominal values of the generator parameters are set by the manufacture data. When the generator was connected to the grid, a sequence of small generator voltage step tests were performed. As shown in Fig. 4, a very good fit has been achieved.

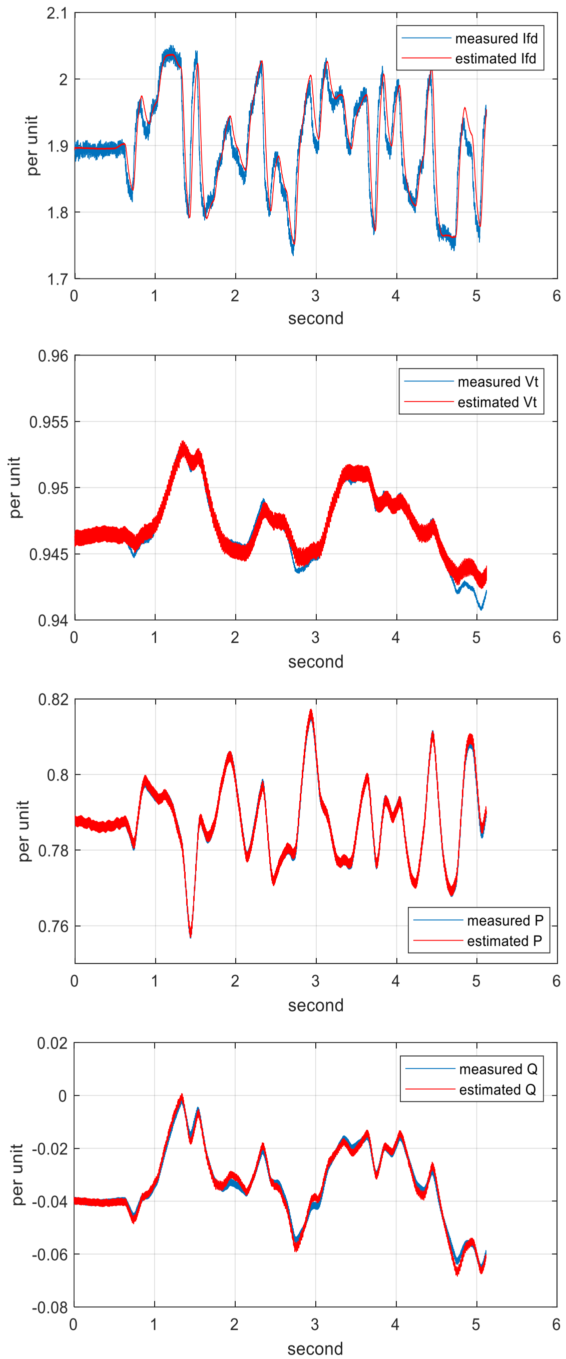

Figure 4. Response due to random sequence of voltage steps.

C. *Estimation of Excitation Control System Parameters with a Rotary Exciter*

A real time digital simulator was utilized to simulate a generating system with a rotary exciter. The salient pole generator and brushless exciter models are selected and set with data shown in Table II. A residual voltage is added to the brushless exciter model proposed by the IEEE Std 421.5™-2016 [10] to approximate the magnetic hysteresis effects [6].

In order to evaluate the estimation accuracy of the exciter and generator parameters, a device is configured to monitor the generating system parameters based on a system disturbance. System disturbances due to three-phase faults in the area electric power system were activated to trigger the data log and parameter estimation. For this case, no change in the generator parameters is expected. Thus, a good fit is accomplished as shown in Fig. 5.

Other typical system events like local load change, transmission line loss, and bus voltage change have been used to estimate the generating system parameters, and the resultant parameter estimation values for each case are shown in Table II.

D. *Identification of an Anomaly Using a Real Time Digital Simulator for an Internmittent Generator Stator Fault*

Another benefit of this unit is to identify an anomaly of the generator system. Since it is undesirable to create a generating system fault for testing, its performance is evaluated using a real time digital simulator. An intermittent (1 second) internal winding ground fault at 20% from the neutral of the generator model is initiated and this event triggers the data log for estimation of the generator parameters. Fig. 6 shows the resultant for this event. The two traces depicted in Fig. 6 are not in good agreement with each other and the parameters that result in the best curve fit are beyond their programmed range. Thus, this anomaly is annunciated to the operator. The estimation results performed for all system disturbances are recorded in the estimation history for the future analysis or investigation of an annunciated alarm.

TABLE II. ESTIMATION OF EXCITER AND GENERATORING SYSTEM PARAMETERS AT VARIOUS SYSTEM DISTURBANCES

Exciter Data		**Type of System Disturbance**			
Parameter	Data	Fault	Load Change	Trans. Line Loss	Bus Voltage
T_e	0.5	0.500	0.490	0.508	0.496
K_d	0.8	0.797	0.779	0.784	0.787
K_c	0.5	0.498	0.490	0.493	0. 496
V_{res}	0.1	0.0996	0.100	0.103	0.102
Generator Data		**Type of System Disturbance**			
Parameter	Data	Fault	Load Change	Trans. Line Loss	Bus Voltage
X_d	1.071	1.072	1.078	1.076	1.056
X_q	0.704	0.708	0.704	0.704	0.704
X'_d	0.361	0.346	0.359	0.358	0.355
X''_d	0.296	0.296	0.296	0.296	0.296
X''_q	0.296	0.279	0.296	0.296	0.296
T'_{do}	6.350	6.246	6.297	6.387	6.259
T''_{do}	0.060	0.060	0.060	0.060	0.060
T''_{qo}	0.077	0.076	0.077	0.077	0.077

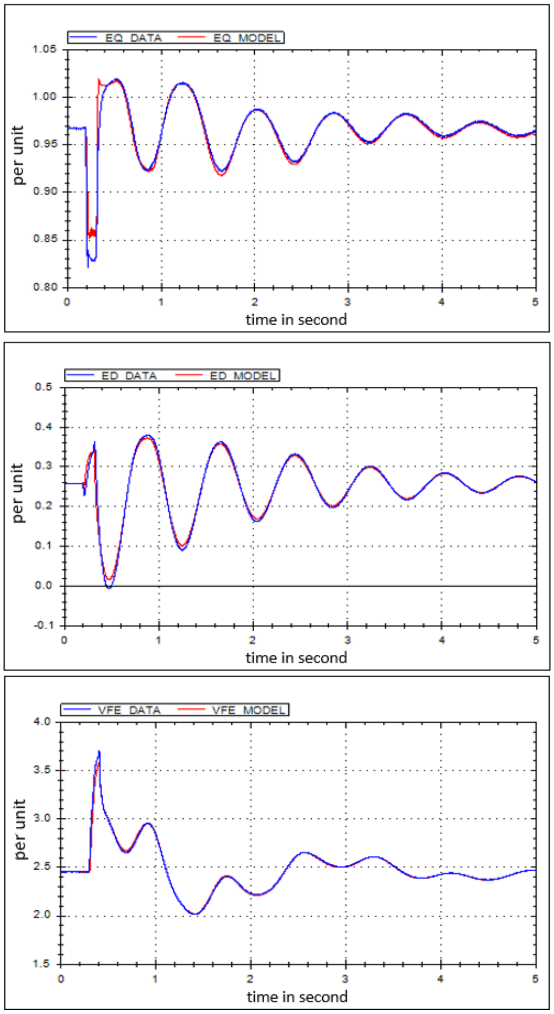

Figure 5. Depiction of a triggering event and parameter estimation due to a three-phase fault in the simulated system.

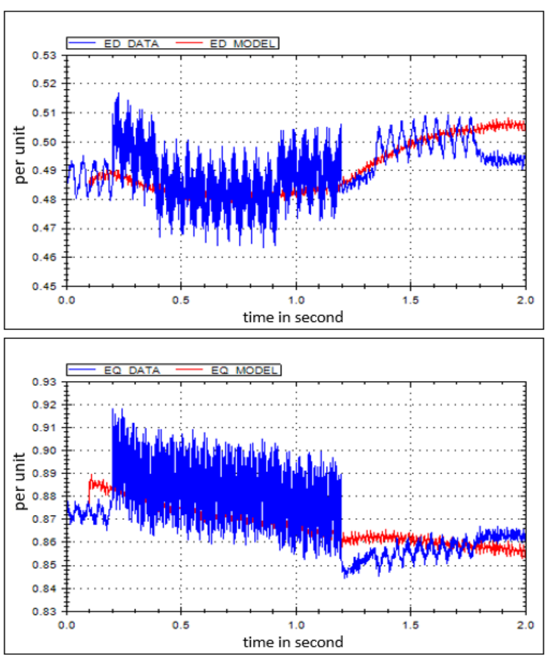

Figure 6. Depiction of a simulated intermittent stator fault of 20% from the neutral triggering the data log and parameter estimation.

IV. CONCLUSION

A new device is proposed for continuous monitoring of the responses of the AVR, exciter, and generator to a system disturbance. It compares the recorded on-line system response with the model's response to estimate the generator parameters. This can be used to validate excitation control system models of power plant as well as to detect an anomaly of the generating system. Based on feasibility test with a real time digital simulator, preventive maintenance measures may be taken into consideration before a forced outage is required.

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