High-Gain Observer-Based Identification Scheme for Estimation of Physical Parameters of Synchronous Generators

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***Abstract*—This paper deals with estimation of states and physical parameters of synchronous generators which is of great significance in power system analysis as well as control. To handle the difficulties associated with the existence of unknown nonlinearities in generator dynamics, the system dynamics is firstly transformed into a canonical form using a change of variables leading to an equivalent system. Then, a robust observation scheme is proposed using Phasor Measurements Units' (PMUs') data along with a combination of the well-known Genetic Algorithm (GA) and a modified version of high-gain observers. The physical parameters of synchronous generator are identified by decomposing the nonlinear function of the system dynamics into a regression model. This decomposition enables us to identify the unknown parameters accurately by using the estimated state variables and Recursive Least Square (RLS) technique. Finally, the proposed identification scheme is compared with the well-known Iterative Extended Kalman Filter (IEKF) technique throughout simulations. The obtained results approve the theoretical discussions and demonstrate the superiority and feasibility of the proposed identification methodology.**

I. Introduction

Having access to an accurate model of energy generator units that feed electrical loads plays a prominent role in analysis of dynamic performance of power systems as well as design of stabilizers. In the case of unavailability of such models, the presented models by IEEE standards, previously published manuscripts, and manufacturing companies are usually employed [1], [2]. However, one cannot turn a blind eye on the fact that these models may deviate from the real ones. Moreover, most of the parameters of power systems are time varying due to aging. These uncertainties may lead the operator of power system to take some conservative measures. Furthermore, the parameters of controllers, which have been regulated in the commissioning phase, usually require readjustments when the accurate model of system is available. These readjustments can improve the stability and dynamic performance of power systems, which result in dwindling the probability of fault occurrences, increasing equipment's longevity, and optimizing operation of power system. With Regard to these facts, it is crystal clear that the estimation of parameters of synchronous generators, which are well-known as one of the most important elements of power plants, paves the way for achieving the aforementioned goals [3].

To identify synchronous generators two general approaches exist: black-box and white-box identification schemes. In black-box identification schemes the structure of the system is assumed to be completely unknown, and the only concern is to map the input data set to the output data [4], [5]. The main drawback of these approaches is that no physical parameters is estimated. On the contrary, white-box schemes utilize the advantage of knowing the structure of synchronous generators and try to estimate physical parameters [6], [7].

Supervisory Control and Data Acquisition (SCADA) systems provide steady, low sampling density, and non-synchronous information about the network. The measurements offered by SCADA are so infrequent and non-synchronous for capturing system dynamics. Therefore, basing control methodologies and monitoring on these information rarely yield promising and high performance. To overcome the difficulties associated with SCADA systems, Wide Area Measurements and Control (WAMAC) systems have been widely used. These systems use PMUs' data which enable us to monitor synchronous power system dynamics on a more refined time scale [8].

The obtained information from PMUs have attracted a great deal of attention and a lot of researches have been launched into employing them together with the Extended Kalman Filter (EKF) technique. The EKF technique has been utilized in many researches for parameter and state estimation of power systems, e.g., dynamic state estimation of synchronous machine [9], [10], automatic parameter calibration of generators [11], parameter estimation of interior permanent magnet synchronous motor [12], and control of synchronous reluctance machines [13]. Although the EKF technique provides a nice performance, the accuracy of the estimation is hinged on the initial conditions and the sampling rate of the PMU measurements [9], [14]. So as to improve the convergence of the EKF, Iterative EKF (IEKF) technique has been utilized [9].

It has been proven that high-gain observers are among the best state estimators for unknown canonical nonlinear systems in the presence of uncertainties. These observers, as has been demonstrated in [15], are able to provide promising state estimations by only using the output of system. Since they do not require a priori knowledge regarding the uncertainties appeared in the system dynamics, high-gain observers have been widely utilized to address estimation problems in a great extent [16], [17].

As motivated earlier, an observer-based approach is proposed for estimation of synchronous generators' state variables as well as their physical parameters. The suggested method utilizes the measurements of PMU together with the GA to solve an optimization problem for estimating the internal impedance. Then, a modified version of the high-gain observer and the RLS algorithm are employed to estimate states and the remaining unknown parameters. Since the convergence of the high-gain observers and the RLS algorithm is assured [15], [18], the proposed method always converge. Furthermore, the proposed method is compared with the IEKF-based method in the simulation section, and the obtained results demonstrate that the proposed approach can estimate the states and parameters more precisely with a lower estimation time.

The rest of this paper is organized as follows. Section II presents the nonlinear dynamics of synchronous generator with immeasurable states and unknown parameters. The structure of the proposed identification scheme and the corresponding identification procedures are illustrated in Section III. Section IV contains simulations results with comparison studies to indicate the effectiveness, robustness, and fast convergence of the proposed scheme. Finally, Section V concludes the paper.

II. Dynamic Model of Synchronous Generators

The proposed estimation method considers a synchronous generator as a constant voltage source behind a transient reactance. The dynamic model can be described as follows [1]:

$$\begin{aligned}\frac{d\delta}{dt} &= (\omega-\omega_0)\omega_B,\\ \frac{d\omega}{dt} &= \frac{1}{2H}(P_m - \frac{EV}{X_d'}\sin(\delta-\theta) - D(\omega-\omega_0))\end{aligned} \tag{1}$$

where δ is the rotor angle, ω is the rotor speed, ω_0 is the synchronous speed, ω_B is the speed base, H is the inertia constant, P_m is the mechanical torque, E is the internal voltage, V is the terminal voltage magnitude, X_d' is the internal impedance, θ is the terminal voltage phase angle, and D is the damping coefficient. Since the mechanical system of the synchronous generators has slow dynamics, the model considers the mechanical power constant. Also it assumes that the impacts of damping windings are vanished and field flux is constant [9].

Identification Objective: The identification goal is to find an accurate estimation of the state variables δ and ω, and unknown physical parameters X_d', H, D [19].

In order to perform the estimation, data from a PMU can be employed. One can determine V, θ, active power P, reactive power Q, and frequency f by using PMU's measurements. The equations of P and Q are as follows:

$$\begin{aligned}P &= \frac{EV}{X_d'}\sin(\delta-\theta),\\ Q &= \frac{-V^2 + EV\cos(\delta-\theta)}{X_d'}.\end{aligned} \tag{2}$$

Model (1) is nonlinear and has unknown parameters that make the estimation process a challenging task. To perform the estimation, it is required to transform the model dynamic (1) into normal form. Towards this end, let us use the following change of variables:

$$\begin{aligned}z_1 &= \delta-\theta,\\ z_2 &= (\omega-\omega_0)\omega_B\end{aligned} \tag{3}$$

where z_1 and z_2 denote the new state variables. Now by using the preceding equation, one can obtain the normal form of (1) as follows:

$$\begin{aligned}\frac{dz_1}{dt} &= z_2,\\ \frac{dz_2}{dt} &= \frac{\omega_B}{2H}(u - \frac{EV}{X_d'}\sin(z_1) - \frac{D}{\omega_B}z_2),\\ y &= z_1\end{aligned} \tag{4}$$

where $u = P_m$ is the input signal and y is the output signal.

III. The Proposed Identification Scheme

Till now, the dynamic model of synchronous generators in a canonical form is obtained. In the sequel, by incorporating a modified version of high-gain observers, RLS technique, and genetic optimization algorithm, a robust high-gain observer-based identification scheme is developed for the estimation of state variables and physical parameters of the generator.

A. Modified High-gain Observer Design

In this subsection, a modified high-gain observer is employed so as to be able to estimate the required information. Then, the unknown parameters are estimated accurately by employing the RLS technique.

As the nonlinear term

$$f(z,u) = \frac{\omega_B}{2H}(u - \frac{EV}{X_d'}\sin(z_1) - \frac{D}{\omega_B}z_2)$$

on the right hand side of (4) consists of unknown parameters, robust or adaptive techniques should be employed to reconstruct the states of nonlinear system (4). On the other hand, it is well-known that high-gain observers provide promising estimations when employed in observing states of unknown systems in canonical forms [15], [20]. Therefore, the following second order high-gain observer can estimate the states of (4).

$$\begin{aligned}\frac{d\hat{z}_1}{dt} &= \hat{z}_2 + \frac{\alpha_1}{\epsilon}(y-\hat{y}),\\ \frac{d\hat{z}_2}{dt} &= \frac{\alpha_2}{\epsilon^2}(y-\hat{y}),\\ \hat{y} &= \hat{z}_1\end{aligned} \tag{5}$$

where α_1 and α_2 are chosen so that the roots of polynomial $R_1(s) = s^2 + \alpha_1 s + \alpha_2$ have negative real values and ϵ is a small positive constant.

Remark 1: Although one can show that system (5) can estimate the states of system (4) precisely, it cannot be guaranteed that $\dot{\hat{z}}_2$ will converge to $\dot{z}_2$. In another word, two different signals ($\dot{z}_2 \neq \dot{\hat{z}}_2$) may have the same intergrals ($z_2 = \hat{z}_2$). This issue is of a great importance, since the procedure of estimating the unknown parameters of the generator is based on accessibility of an accurate estimation of $\dot{z}_2$; hence the proposed identification approach will fail to give promising estimations if it uses the results of high-gain observer (5).

To overcome the aforementioned problem, let us consider the following system that has the same input u and output y as (4) does:

$$\begin{aligned} \frac{d\eta_1}{dt} &= \eta_2, \\ \frac{d\eta_2}{dt} &= \eta_3, \\ \frac{d\eta_3}{dt} &= \frac{d}{dt} f(\eta, u), \\ y &= \eta_1 \end{aligned} \tag{6}$$

As can be seen $\eta_1 = z_1$, $\eta_2 = z_2$, and $\eta_3 = \dot{z}_2$. Now let us use a modified version of observer (5) as follows:

$$\begin{aligned} \frac{d\hat{\eta}_1}{dt} &= \hat{\eta}_2 + \frac{\beta_1}{\epsilon}(y - \hat{y}), \\ \frac{d\hat{\eta}_2}{dt} &= \hat{\eta}_3 + \frac{\beta_2}{\epsilon^2}(y - \hat{y}), \\ \frac{d\hat{\eta}_3}{dt} &= \frac{\beta_3}{\epsilon^3}(y - \hat{y}), \\ \hat{y} &= \hat{\eta}_1 \end{aligned} \tag{7}$$

where the roots of $R_2(s) = s^3 + \beta_1 s^2 + \beta_2 s + \beta_3$ have negative real parts. It can be guaranteed that the estimation error $e_\eta = \eta - \hat{\eta}$ is equal to zero when ϵ goes to zero. So as to elucidate more on this premise, let us subtract (7) from (6) and write the observation error dynamic e_η as follows:

$$\begin{aligned} \frac{de_{\eta 1}}{dt} &= -\frac{\beta_1}{\epsilon} e_{\eta 1} + e_{\eta 2}, \\ \frac{de_{\eta 2}}{dt} &= -\frac{\beta_2}{\epsilon^2} e_{\eta 1} + \eta_3, \\ \frac{de_{\eta 3}}{dt} &= -\frac{\beta_3}{\epsilon^3} e_{\eta 1} + \frac{d}{dt} f(\eta, u). \end{aligned} \tag{8}$$

In the absence of uncertain nonlinear term $\frac{d}{dt} f(\eta, u)$, the asymptotic convergence of error e_η is achieved by selecting design parameters β_i and ϵ such that matrix

$$A = \begin{bmatrix} -\beta_1/\epsilon & 1 & 0 \\ -\beta_2/\epsilon^2 & 0 & 1 \\ -\beta_3/\epsilon^3 & 0 & 0 \end{bmatrix}$$

is Hurwitz. In the presence of the unknown nonlinear term, the destructive effects of this term on the observation error dynamics should be eliminated. To put it in general words, the transfer function from the unknown nonlinear term to error dynamics should be equal to zero. This transfer function can be obtained by performing some basic manipulations on (8), as follows:

$$\frac{E_\eta}{F_t} = \frac{1}{\epsilon^3 s^3 + \beta_1 \epsilon^2 s^2 + \beta_2 \epsilon s + \beta_3} \times \begin{bmatrix} \epsilon^3 \\ \epsilon^3 s + \beta_1 \epsilon^2 \\ \epsilon^3 s^2 + \beta_1 \epsilon^2 s + \beta_2 \epsilon \end{bmatrix}$$

where $F_t = L\left(\frac{df(\eta,u)}{dt}\right)$ and $L(.)$ denotes the Laplace transform. The preceding equation guarantees that by choosing sufficiently small values for ϵ, the effects of unknown nonlinear term on e_η will be vanished. Hence, observer (7) is robust against uncertainties and can provide accurate estimations of state variables $\eta_{1,2,3}$. In another word, $\lim_{t\to\infty} e_\eta(t) = 0$ as long as $\epsilon \to 0$.

The estimation of ω, i.e., $\hat{\omega}$, can be calculated by using $\hat{\eta}_2$, and $\hat{\eta}_3$ can also be utilized for estimating H and D. Towards this end, by using (2), (4), and considering the fact that $\hat{\eta}_3$ is an accurate estimation of $\dot{z}_2$, one can get:

$$\hat{\eta}_3 = \frac{\omega_B}{2H}(u - P - \frac{D}{\omega_B}\hat{\eta}_2). \tag{9}$$

From (9), one can see that $\hat{\eta}_3$ is linear with respect to unknown coefficients. Therefore, one has:

$$\hat{\eta}_3 = \begin{bmatrix} \omega_B(u - P) & -\hat{\eta}_2 \end{bmatrix} \begin{bmatrix} \frac{1}{2H} \\ \\ \frac{D}{2H} \end{bmatrix}. \tag{10}$$

According to the preceding equation a regression model has been successfully obtained which enables us to utilize RLS algorithm and procure estimation of H and D in (10).

B. Rotor Angle Estimation

In order to conclude the proposed identification methodology, it is required to estimate the last unkown parameter, i.e., X'_d. Moreover, note that the proposed framework employs $\delta - \theta$ as the output of (1). On the other hand, the only available measurements are PMU data; therefore the challenge of estimating δ should be handled effectively.

To estimate X'_d, one can utilize (2) and get,

$$Q = \frac{-V^2 + EV\cos\left(\sin^{-1}\left(\frac{PX'_d}{EV}\right)\right)}{X'_d}. \tag{11}$$

As can be seen from (11), Q is a nonlinear function of unknown parameter X'_d. Hence, one can consider the estimation of X'_d, $\hat{X}'_d$, as the solution of the following constrained optimization problem:

$$\begin{aligned} \arg\min_{\hat{X}'_d} \quad & \frac{1}{2}\left(Q - \hat{Q}\right)^2 \\ \text{subject to} \quad & \hat{Q} = \frac{-V^2 + EV\cos\left(\sin^{-1}\left(\frac{P\hat{X}'_d}{EV}\right)\right)}{\hat{X}'_d}. \end{aligned} \tag{12}$$

The optimization problem (12) can be solved using the GA. In order to improve the estimation, one can introduce the range of practical values of X'_d to the GA. Moreover, one can utilize the measurements of Q on a specific time interval instead of using it's measurements at a specific moment. Therefore, the modified optimization problem is:

$$\begin{aligned} \arg\min_{\hat{X}'_d} \quad & \frac{1}{2}\left(\underline{Q} - \underline{\hat{Q}}\right)^T \left(\underline{Q} - \underline{\hat{Q}}\right) \\ \text{subject to} \quad & \hat{Q}_i = \frac{-V_i^2 + EV_i\cos\left(\sin^{-1}\left(\frac{P_i\hat{X}'_d}{EV_i}\right)\right)}{\hat{X}'_d} \\ & X'_{d_{\min}} \le \hat{X}'_d \le X'_{d_{\max}}. \end{aligned} \tag{13}$$

where $\underline{Q}$ and $\underline{\hat{Q}}$ are the vector of measurements of Q and its estimation as follows:

$$\underline{Q} = \begin{bmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_n \end{bmatrix}, \underline{\hat{Q}} = \begin{bmatrix} \hat{Q}_1 \\ \hat{Q}_2 \\ \vdots \\ \hat{Q}_n \end{bmatrix}. \tag{14}$$

After calculating $\hat{X}'_d$ by solving (13), the estimation of δ, $\hat{\delta}$, can be obtained by using (2) as follows:

$$\hat{\delta} = \text{sgn}\left(\frac{P\hat{X}'_d}{EV}\right)\cos^{-1}\left(\frac{Q\hat{X}'_d + V^2}{EV}\right) + \theta. \tag{15}$$

Note that one can overcome the aforementioned challenge, by employing the obtained $\hat{\delta}$ and considering $y = \hat{\delta} - \theta$ as the input of modified high-gain observer (7).

C. The Proposed Algorithm

As stated in the preceding sections, the aim of this research is to estimate the states and unknown parameters of synchronous generators. The proposed algorithm that is based on a modified version of high-gain observers can be summarized in few steps. This section provides the steps of the proposed algorithm that one can utilize for implementation.

The following algorithm describes the required steps:

1) The estimation of X'_d is calculated by solving constrained optimization problem (13) and using the measurements of PMU.
2) The estimation of δ can be obtained from (15). In addition, one can get y by using $\hat{\delta}$, i.e., $y = \hat{\delta} - \theta$.
3) By employing the modified high-gain observer (7), $\hat{\eta}$ is found.
4) In order to find the estimation of H and D, regression model (10) is used and the parameters is estimated by the RLS algorithm.

Remark 2: Although the proposed observer can provide a precise estimation of system states by choosing sufficiently small design parameter ϵ, it suffers from picking phenomenon which is an inherent disadvantage of high-gain observers. In another word, selecting too small values for ϵ will yield much more overshoot/undershoot in the initial moments of estimations. In the case of observer-based control this inherent picking phenomenon is of great significance and should be handled effectively [21]; because this overshoot/undershoot will be transmitted to the system via controller which may lead it into instability. However, due to the fact that in the identification problems, the estimated states are not fed into a controller, one can choose arbitrarily small values for ϵ. Therefore, the value of ϵ does not have any destructive effects on the stability of the system.

Remark 3: Although the picking phenomenon of modified high-gain observer (7) does not have any effects on the stability of the system, it may cause a tardy convergence of the estimated physical parameters to the ideal ones. Because, the estimated states, which plays a prominent role in the convergence of the RLS algorithm, deviate from their actual values significantly in the initial moments. One solution to overcome this problem is to commence estimating physical parameters after a delay. Note that this delay can be roughly adjusted based on the eigenvalues of matrix A which determines the convergence rate of the proposed observer.

TABLE I: Parameters used in the generator model.

Parameter	Value (pu)
ω_0	0
ω_B	$2\pi \times 60$
H	6.5
P_m	0.8
E	1.08
V	1.4142
X'_d	0.375
θ	0
D	0.05

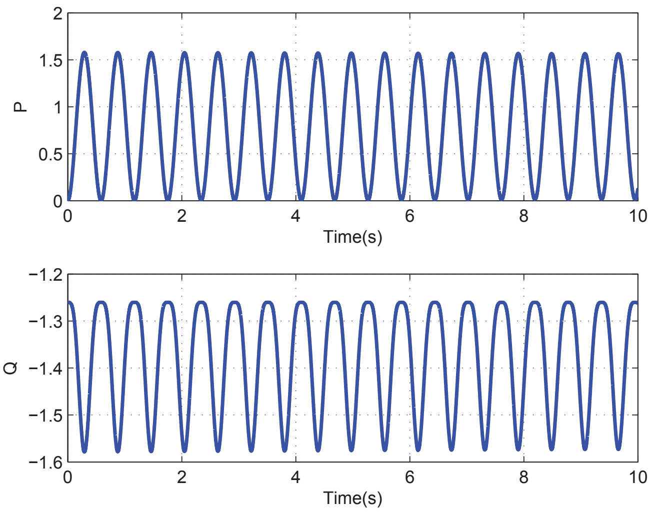

Fig. 1: Resulting P and G of generator simulation.

IV. Simulation Results

To test the fidelity of the proposed algorithm, this section provides a comparison between the proposed scheme and the well-known IEKF-based technique [22]. The IEKF-based method considers the unknown parameters as follows:

$$\begin{aligned} H_{k+1} &= H_k + \omega_1, \\ D_{k+1} &= D_k + \omega_2, \\ X'_{d,k+1} &= X'_{d,k} + \omega_3 \end{aligned} \tag{16}$$

where ω_i are the noise to represent un-modeled dynamics. Then (16) is augmented with the discrete form of (1) and the IEKF is employed to calculate the estimations.

The employed parameters for the simulation are listed in Table I [23], and P and Q are shown in Fig. 1.

In order to estimate X'_d, P and Q are utilized together with the following values as the minimum and maximum possible values of $\hat{X}'_d$ [1].

$$X'_{d_{\min}} = 0.14, X'_{d_{\max}} = 0.5 \tag{17}$$

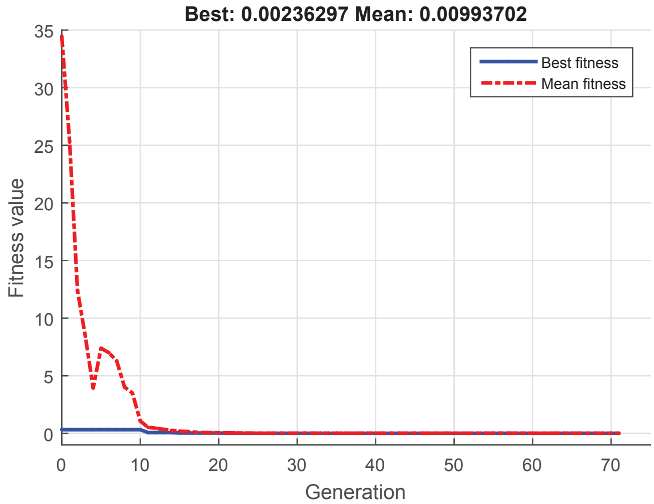

Fig. 2: Fitness vs Generation of the GA.

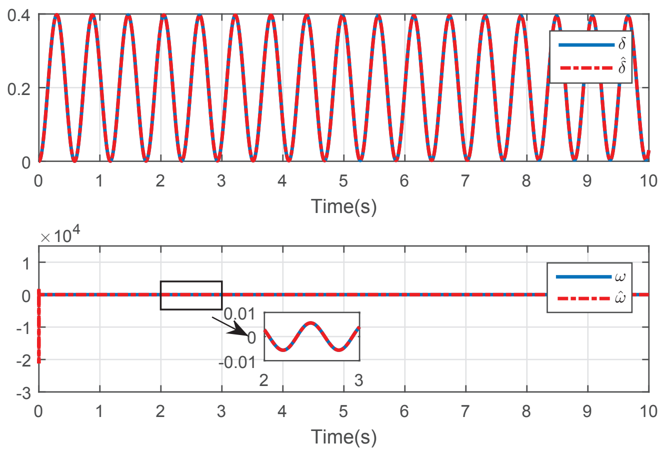

Fig. 3: Rotor angle δ, rotor speed ω, and their estimations, $\hat{\delta}$ and $\hat{\omega}$.

The computed values of fitness function (13) at each generation of the GA algorithm are depicted in Fig. 2, and the obtained estimation of X'_d is $\hat{X}'_d = 0.375$.

The states of synchronous generator and their estimations obtained by (15), $\hat{\delta}$, and modified high-gain observer (7), $\hat{\omega}$, are expressed in Fig. 3.

As can be seen in Fig. 3, there are some peaks in the initial estimation of ω, which is an inherent disadvantage of high-gain observers. As mentioned in Remark 3, the estimation process of the RLS algorithm is intiated after 1 second so as to avoid the affects of the peaking phenomenon on the estimation of D and H. The obtained estimation of D, $\hat{D}$, and H, $\hat{H}$, are shown in Fig. 4.

The estimated parameters using the IEKF-based method are depicted in Fig. 5. To summarize the performance of the simulation methods, the estimated parameters are reported in Table II.

From Table II, it can be seen that the proposed method

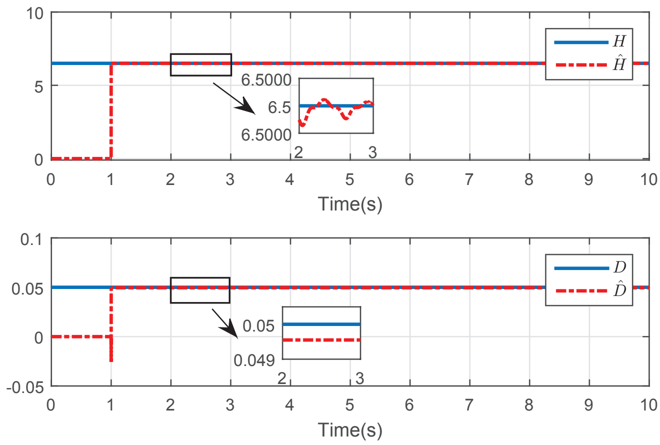

Fig. 4: Inertia constant H, damping coefficient D, and their estimations, $\hat{H}$ and $\hat{D}$.

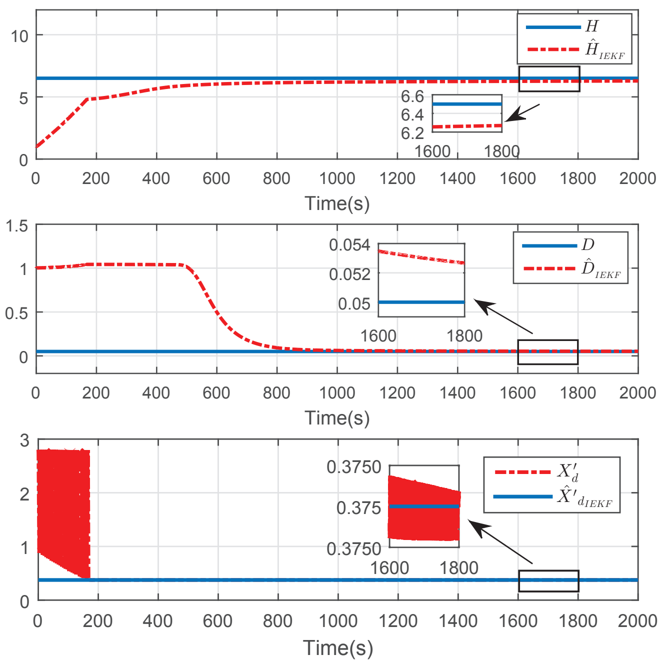

Fig. 5: Inertia constant H, damping coefficient D, internal impedance X'_d, and their IEKF estimations, $\hat{H}_{IEKF}$, $\hat{D}_{IEKF}$, and $\hat{X}'_{d_{IEKF}}$.

TABLE II: Physical parameters and their estimations.

Parameter	Estimated Value
H=6.5	$\hat{H} = 6.5$ $\hat{H}_{IEKF} = 6.2824$
D=0.05	$\hat{D} = 0.04955$ $\hat{D}_{IEKF} = 0.0521$
X'_d=0.375	$\hat{X}'_d = 0.375$ $\hat{X}'_{d_{IEKF}} = 0.375$

can estimate the parameters more accurately. Furthermore, by comparing Fig. 4 and Fig. 5, one can observe that the proposed approach converges in a shorter time than the IEKF-based method does.

V. Conclusions

This paper illustrated a systematic technique for state and parameter estimation of synchronous generators using PMU data. The well-known genetic optimization technique was employed to obtain an approximation of unknown parameter X_d'. Subsequently, a modified version of high-gain observers was utilized to reconstruct precisely the system states as well as to remove destructive effects of uncertainties. The RLS technique was later employed to estimate other physical parameters, i.e., H, D. The comparisons between the traditional schemes and the proposed one have been also presented throughout simulations. The simulation results demonstrated that the proposed methodology not only yields a smaller observation and identification errors, but also converges so rapidly, which are in commensurate with theoritical discussions.

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