



Synchronous Generator Dual Estimation Using Sigma Points Kalman Filter

M. Zoghi, H. Yaghibi*

Faculty of Electrical and Computer Engineering, Semnan University, Semnan, Iran

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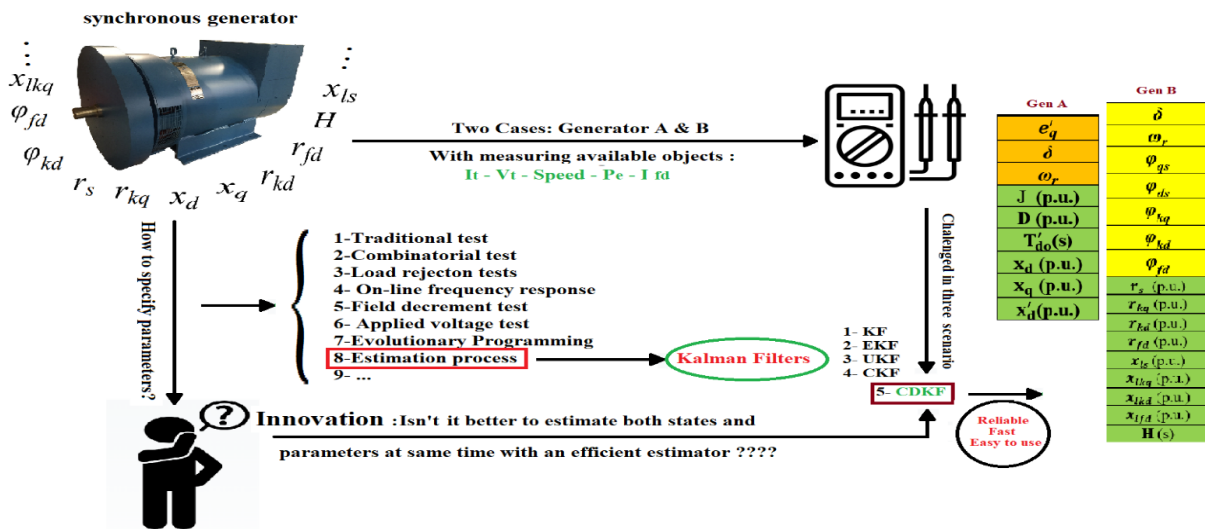
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ABSTRACT

In this article, the central difference Kalman filter (CDKF) has been used to estimate the parameters of two different models of synchronous generator (SG) in the presence of noise. It should be mentioned that there are different models of synchronous generators with different levels of accuracy for use in estimation algorithms. The estimation algorithm in this paper uses a smaller number of measurement inputs to estimate the states and unknown parameters for two exact models of the synchronous generator. The central difference Kalman filter (CDKF) is a member of the Kalman filter family, which, like the unscented Kalman filter (UKF), uses sigma points to model nonlinear equations. The differential Kalman filter (CDKF) provides better results than the unscented Kalman filter. In this research, by using two synchronous generator models with different parameters in three scenarios, the ability of the Kalman filter of the central difference is challenged, which shows that this method is very efficient and reliable.

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Graphical Abstract



1. INTRODUCTION

Today and after a long time, power grids are being spread and keeping the security issue feels more like it did

before. So we need comprehensive and efficient models for all components to work together in this set. One of the most important parts is the synchronous generator (SG). There are many kinds of models used for SGs, and each

*Corresponding Author Email: yaghibi@semnan.ac.ir (H. Yaghibi)

of these models contains some parameters, that their values are playing an important role in grid analysis. Usually, some of these parameters are specified by their manufacturers and assumed to be constant. However, some changes in power or terminal voltage may cause special operational point that needs to update these parameters.

The bases of the ways for determination of SG parameters in practical mode are discussed in literature (1-3) that used in many analysis. In addition, Mouni et al. (2) have conducted parameter estimation by applying a short circuit and least the square method, which may cause damage to the SG's structure. The other methods that are related to the direction of this research discussed by Chowdhury and Senroy (4) used five measuring quantities of SG and importing them in the unscented Kalman filter (UKF); although an example of estimating the state of a power system using the Kalman filter are given in literature (3) in a basic form. However, it is not possible to measure all these quantities at a low cost in practice. Appropriate estimation was made by Ghahremani and Kamwa (5) Ren et al. (6), for just dynamic states of SG with low order models and extended Kalman filter (EKF). Huang et al. (7) introduced fourth-order model parameters estimation with square root unscented Kalman filter (SRUKF) that they do not contain more details in comparison with high-order models of SGs. To fix this issue, Geraldi et al. (8) Zhao and Mili (9), Valverde et al. (10) estimated parameters or dynamic states with UKF. However, in UKF algorithms some coefficients need to be set accurately and may be necessary to fix them in other equations or different SG's types. For both parameter and state estimation, good results with a modified type of UKF to be achieved. Rouhani and Abur (11) dond parameter estimation for fully regulated SG, but uses a noncomplex model like two axes model with UKF. González-Cagigal et al.(12) , Li et al. (13) used cubature kalman filter (CKF) to estimate the dynamic state of SG in detailed. CKF algorithm for implementation needs a powerful computing platform, but can clearly say that the results of this filter are one of the most exact results, also the phasor measurement units (PMUs) are widely used in data acquisition of synchronous generator operation parameters, which can capture the dynamic response of generators. For many reasons it is hard to transmit gigantic volumes of data to the information center due to limited communication bandwidth, so to reduce communication pressure, an improved regularized particle filter (IRPF) is designed to guarantee the estimation performance by Bai et al. (14).

According to reviews, this research is the first analysis to challenge the CDKF performance in estimating both parameters and dynamic states for two different dynamic models. It should be noted that in this research, the estimation process will be implemented on SGs behaviour consisting of increasing excitation

voltage and input torque for generator A and instant short circuit for another generator (i.e. B). The measurements also used in this work is the easily accessible outputs of SG. Furthermore, the algorithm used has good stability, and even it does not need to specify parameters like UKF, and it is compatible with a wide range of dynamic equations. Also Using the CDKF filter in the hybrid form, where the discrete measurements are placed next to the continuous state equations that are known as HCDKF, and because discrete measurements are used, the answers are closer to reality.

The remaining parts of this work are organised as follows. Section 2 is allocated to describe and formulate the CDKF algorithm and after that in section 3 presents the models of SG used in the estimation process. Match the models with the CDKF algorithm for dual estimation described in section 4. Two study cases, including generators A and B with their details for testing the accuracy of the process, is presented in section 5. The conclusion and recommendation are obtained from the results presented in section 6.

2. CENTRAL DIFFERENCE KALMAN FILTER

The basis of all Kalman filter derivatives goes back to its linear type and is used to filter noisy data, produce nonobservable states and forecast future state (15). But for nonlinear states, these particle filters have the ability to estimate states with different tension that can be considered (16, 17). In nonlinear forms of this filter, the central difference Kalman filter (CDKF) is one of the exact forms with good results. For implementing this filter to SG's dynamic, a complete description of the states and measurements is required. Equations 1 and 2 represent the usual form of the states and measurement, Also, special attention should be paid to the discontinuity and continuity of these equations with respect to time, which will be explained more (18, 19).

$$\dot{x}(t) = f(x(t), u(t)) + v(t) \quad (1)$$

$$y(t_k) = h(x(t_k), u(t_k)) + n(t_k) \quad (2)$$

where $x(t)$ represents a state vector, $u(t)$ is the system input, and $v(t)$ is the process noise which is assumed to be Gaussian with covariance R_v . These values together form a continuous nonlinear function as f . In the second equation, $y(t_k)$ represents available measurement which is described by the function h . The measurement noise $n(t_k)$ is assumed to be Gaussian with the covariance R_n at instant t_k . Since this filter is supposed to be implemented on generator equations, a hybrid form of the filter should be mentioned. Generators like many nonlinear systems have continuous state equations and discrete measurement equation. Because sensors which record the measurements based on a sample time and finally

generate a data series with a specified step, so the measurement equation is modified as follows (20):

$$y_k = h(x_k, u_k) + n_k \quad (3)$$

If the EKF algorithm was used to estimate, Equation 1 should linearize and then enter into the process (21). However, in CDKF, the state equation evaluates in a continuous nonlinear form, that is based on Sterling's polynomial interpolation functions (16). This method is known for approximating nonlinear function and uses a finite number of the main function evaluations instead of analytical derivatives. For scalar form and if supposed that $g(x)$ is a nonlinear function with a random variable x and its mean \bar{x} , the 2nd order case is given by:

$$g(x) = g(\bar{x}) + \tilde{D}_{\Delta x} g + \frac{1}{2!} \tilde{D}^2_{\Delta x} g \quad (4)$$

where $\tilde{D}_{\Delta x} g$ is the first and $\tilde{D}^2_{\Delta x} g$ is the second-order central divided difference operators and given by:

$$\tilde{D}_{\Delta x} g = (x - \bar{x}) \frac{g(\bar{x}+h) - g(\bar{x}-h)}{2h} \quad (5)$$

$$\tilde{D}^2_{\Delta x} g = (x - \bar{x})^2 \frac{g(\bar{x}+h) + g(\bar{x}-h) - 2g(\bar{x})}{h^2} \quad (6)$$

h is known as interval length in these equations, except that, the derivatives are not analytically solved by extending the sterling formula to make a multi-dimensional mode. It's necessary to provide a new variable that is stochastically decoupled. So z can be expressed as Equation 7 and then put in a nonlinear function to create $\tilde{g}(z)$ in Equation 8.

$$z = S_x^{-1} x \quad (7)$$

$$\tilde{g}(z) = g(S_x z) = g(x) \quad (8)$$

where S_x is obtained from the Cholesky factorization of covariance matrix x called P_x . Furthermore, by putting this transformation in the sterling formula instead $\tilde{D}_{\Delta x} g$ & $\tilde{D}^2_{\Delta x} g$, it's easy to calculate mean, covariance and cross-covariance, which is summarized in two stages in the following. At first, it is necessary to specify initial values as below:

$$\hat{x}_0 = E[x_0] \quad (9)$$

$$P_{x0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T] \quad (10)$$

where \hat{x}_0 is the initial estimation or mean value for the first step and P_{x0} is the initial estimation covariance that can have a significant influenced on the estimation result.

2. 1. Time Update Time update in CDKF is similar to UKF and starts by specifying the number of sigma points which have $2L+1$ points for each instant k . L is the state space dimension or in other words, the number of states. \hat{x}_{k-1} is the previous value of estimation to calculate sigma points (x_{k-1}) as follows:

$$x_{k-1} = [\hat{x}_{k-1} \quad \hat{x}_{k-1} + h\sqrt{P_{x_{k-1}}} \quad \hat{x}_{k-1} - h\sqrt{P_{x_{k-1}}}] \quad (11)$$

Now it's time to propagate sigma points through a state equation that can obtain,

$$x_{k/k-1} = f(x_{k-1}, u_{k-1}) \quad (12)$$

Then, using these points to calculate a priori estimation of the mean (\hat{x}_k) and covariance (\hat{P}_{x_k}) as follows:

$$\hat{x}_k = \sum_{i=0}^{2L} w_i^{(m)} x_{i,k/k-1} \quad (13)$$

$$P_{x_k} = \sum_{i=1}^L [w_i^{(c1)} (x_{i,k/k-1} - \hat{x}_{k/k-1})^2 + w_i^{(c2)} (x_{i,k/k-1} + x_{i+L,k/k-1} - 2\hat{x}_{k/k-1})^2] + R_v \quad (14)$$

where $w_i^{(m)}$ is the weighting vector of mean and $w_i^{(c1)}$ & $w_i^{(c2)}$ are weighting vectors of covariance and calculated by Equation 15. In addition, the power of two in Equation 14 represents the outer product.

$$\begin{cases} w_0^{(m)} = \frac{h^2 - L}{h^2} \\ w_i^{(m)} = \frac{1}{2h^2} \quad i = 1, \dots, 2L \\ w_i^{(c1)} = \frac{1}{4h^2} \quad i = 1, \dots, 2L \\ w_i^{(c2)} = \frac{h^2 - 1}{4h^2} \quad i = 1, \dots, 2L \end{cases} \quad (15)$$

2. 2. Measurement Update In this stage, sigma points must be recalculated, but this time with prior estimation (\hat{x}_k) and its covariance (\hat{P}_{x_k}) that comes from the previous stage as follows:

$$x_{k/k-1}^* = [\hat{x}_k \quad \hat{x}_k + h\sqrt{P_{x_k}^-} \quad \hat{x}_k - h\sqrt{P_{x_k}^-}] \quad (16)$$

Then new sigma points ($x_{k/k-1}^*$) are propagated through measurement function as Equation 16.

$$y_{k/k-1} = h(x_{k/k-1}^*) \quad (17)$$

With the weights were calculated in Equation 15, mean (\hat{y}_k), covariance (p_{y_k}) and cross-covariance ($p_{x_k y_k}$) Can be easily found in Equation 18.

$$\begin{cases} \hat{y}_k = \sum_{i=0}^{2L} w_i^{(m)} y_{i,k/k-1} \\ \hat{P}_{y_k} = \sum_{i=1}^L [w_i^{(c1)} (y_{i,k/k-1} - \hat{y}_{k/k-1})^2 + w_i^{(c2)} (y_{i,k/k-1} + y_{i+L,k/k-1} - 2\hat{y}_{k/k-1})^2] + R_n \\ p_{x_k y_k} = \sqrt{w_1^{(c1)} P_{x_k}^-} [y_{1:k,k/k-1} - y_{1+1:2L,k/k-1}]^T \end{cases} \quad (18)$$

And in the last step, one of the filter's output that named Kalman gain (k) is calculated in Equation 19.

$$K_k = p_{x_k y_k} P_{y_k}^{-1} \quad (19)$$

Then the final results of the estimation process (\hat{x}_k) as a posterior estimation and its covariance (p_{x_k}) Can be obtained,

$$\hat{x}_k = \hat{x}_k + k_k (y_k - \hat{y}_k) \quad (20)$$

$$p_{x_k} = p_{x_k}^- - k_k p_{y_k}^- k_k^T (21)$$

where these values are the final estimation for the k th instant, and the first step for $k+1$ th.

3. SYNCHRONOUS GENERATOR MODELS

One of the most important parts in dual estimation is recognizing the dynamic model of the system under discussion. In this work, two models of SG are described that if not done correctly, can cause bad results. The third and seventh order model of SG presented in the next two sections.

3.1. Third-Order Dynamic Model The third-order model is the flexible and accessible model in the dynamic analysis (19, 22). It's not very detailed and to achieve the equations, some assumptions must be taken. For example, neglecting the dynamic changes of stator and damper windings, stator resistance is assumed to be zero and also rotor speed is considered to be equal with synchronous speed (1p.u.). However, using this model is favored in the filter and makes it, easy to estimate. The equations in this model consist of rotor angle (δ), rotor speed (ω) and transient internal voltage of the armature (e'_q) that are calculated as follows:

$$\dot{\delta} = \omega (22)$$

$$\dot{\omega} = \frac{1}{J} (T_m - T_e - D\omega) (23)$$

$$\dot{e}'_q = \frac{1}{T'_{do}} (E_{fd} - e'_q - (x_d - x'_d)i_d) (24)$$

To complete the above equations, mention the direct and quadrature current (i_d & i_q) and electrical torque (T_e) is required, which represent in Equations 25 to 27, respectively. Unknown parameters and states that should be estimated are discussed separately in the following sections.

$$i_d = \frac{e'_q - v \cos \delta}{x'_d} (25)$$

$$i_q = \frac{v \sin \delta}{x_q} (26)$$

$$T_e = P_e \cong \frac{v}{x'_d} e'_q \sin \delta + \frac{v^2}{2} \left(\frac{1}{x_q} \right) (27)$$

After determining the state equations, it's time to specify the measurement equations. There are many quantities in a generator that have a certain equation, but that's not enough alone. Quantities are selected, which can be easily measured. So in this work terminal current (i_t), terminal voltage (v_t), electrical power (p_e) and rotor speed (ω_r) are used. The following procedure can be followed to extract their equations. Equation 28, stator current is defined.

$$i_t = \sqrt{i_d^2 + i_q^2} (28)$$

For v_t , it's needed to calculate direct and quadrature voltage as follows:

$$v_d = \left(1 - \frac{x_e}{x_q}\right) v \sin \delta (29)$$

$$v_q = \left(1 - \frac{x_e}{x'_q}\right) v \cos \delta \frac{x_e e'_q}{x'_d} (30)$$

and then put them in Equation 31 to form the following equation.

$$v_t = \sqrt{v_d^2 + v_q^2} (31)$$

The Equations 23 and 27 can be used for ω_r and p_e respectively to establish a good connection between the states and measurement equations. In addition, this combination gives accurate results in the estimation process. All equations in this section are implemented on generator A and the details are given in the appendix.

3.2. Seventh-Order Dynamic Model The seventh-order model has more details than the third-order model. That is why implementing the estimation algorithm for this model is a challenging issue. There are five electrical equations and two mechanical equations in this model which form the dynamic states. Unlike the third-order model, the damper winding behavior is not neglected here. Krause et al. (23) is used to review these equations. The magnetic flux of the stator, rotor and damper windings are considered as electrical equations and written as follows:

$$\dot{\phi}_{qs} = \omega_b \left[v_q - \frac{\omega_r}{\omega_b} \phi_{ds} + \frac{r_s}{x_{ls}} (\phi_{mq} - \phi_{qs}) \right] (32)$$

$$\dot{\phi}_{ds} = \omega_b \left[v_d - \frac{\omega_r}{\omega_b} \phi_{qs} + \frac{r_s}{x_{ls}} (\phi_{md} - \phi_{ds}) \right] (33)$$

$$\dot{\phi}_{kq} = \omega_b \left[v_{kq} + \frac{r_{kq}}{x_{lkq}} (\phi_{md} - \phi_{kq}) \right] (34)$$

$$\dot{\phi}_{kd} = \omega_b \left[v_{kd} + \frac{r_{kd}}{x_{lkd}} (\phi_{md} - \phi_{kd}) \right] (35)$$

$$\dot{\phi}_{fd} = \omega_b \left[v_{fd} + \frac{r_{fd}}{x_{lfd}} (\phi_{md} - \phi_{fd}) \right] (36)$$

In coordinates transformation from abc to qdo the magnetic flux of the o axis (ϕ_{os}) becomes zero. ϕ_{md} and ϕ_{mq} are defined as middle variables to make writing equations easier and calculated as follows:

$$\begin{cases} \phi_{mq} = x_{aq} \left(\frac{\phi_{qs}}{x_{ls}} + \frac{\phi_{kq}}{x_{lkq}} \right) \\ \phi_{md} = x_{ad} \left(\frac{\phi_{ds}}{x_{ls}} + \frac{\phi_{kd}}{x_{lkd}} + \frac{\phi_{fd}}{x_{lfd}} \right) \\ x_{aq} = \left(\frac{1}{x_{mq}} + \frac{1}{x_{ls}} + \frac{1}{x_{lkq}} \right)^{-1} \\ x_{ad} = \left(\frac{1}{x_{md}} + \frac{1}{x_{ls}} + \frac{1}{x_{lkd}} + \frac{1}{x_{lfd}} \right)^{-1} \end{cases} (37)$$

and mechanical equations also calculated as:

$$\left(\frac{\dot{\omega}_r}{\omega_b}\right) = \frac{1}{2H} (T_L - T_e) \quad (38)$$

$$\dot{\delta} = \omega_b \left(\frac{\omega_r}{\omega_b} - 1\right) \quad (39)$$

where ω_b is the synchronous speed and equal to $2\pi f$. Now, and after completing the state equations, it is time to choose the measurable quantities.

In this model, rotor speed, field winding current (i_{fd}), stator voltage and current were chosen, and they are calculated according to Equations 39, 40, 28 and 31, respectively. Except that the direct and quadrature voltages are calculated with Equations 41 and 42.

$$i_{fd} = \frac{1}{x_{jfd}} (\phi_{fd} - \phi_{md}) \quad (40)$$

$$v_d = v \sin \delta - x_e i_q \quad (41)$$

$$v_q = v \cos \delta - x_e i_d \quad (42)$$

As it was reviewed, this model has seven states and nine parameters which should be estimated separately. These equations together, form the structure of generator B, which its real values for simulation are listed in the appendix.

4. IMPLEMENTATION OF CDKF

The CDKF is the most accurate filter among all sigma point Kalman filters and uses the Sterling interpolation formula. This filter has the computational complexity in the order of EKF but achieves a second or higher-order accuracy in the posterior mean and covariance which can be observed in some recent works (24). Any filter from sigma points filters or even a linear or nonlinear form of them can be used for state, parameter and dual estimation. However, for each of them, it is necessary to modify the base filter's structure. There are two approaches for dual estimation. One of them uses two filters that work together to estimate states and parameters. The other method uses just one filter, and the equations are written in such a way that states and parameters are estimated simultaneously. The second type is used in this work. Dual estimation has its difficulties; for example, González-Cagigal et al. (12) used two steps to estimate. In the first step, implement the algorithm on a simple model and then add other components and estimate whole parameters. However, in this work, the estimation process is implemented on complete forms of equations. Furthermore, to understand the structure of dual estimation in the form of a joint filter, Qi et al. (25) have used. According to the state equations from section (3), unknown states in third and seventh-order models of SG can be written as:

$$x_{(3th-order)}^T = [\delta, \omega_r, e'_q]$$

and

$$x_{(7th-order)}^T = [\varphi_{qs}, \varphi_{ds}, \varphi_{kq}, \varphi_{kd}, \varphi_{fd}, \omega_r, \delta]$$

respectively. In addition, the unknown parameters vector (w) for the mentioned models are

$$w_{(3th-order)}^T = [j, D, T'_{do}, x_d, x_q, x'_d]$$

and

$$w_{(7th-order)}^T = [r_s, r_{kq}, r_{kd}, r_{fd}, x_{ls}, x_{lkq}, x_{lkd}, x_{lfd}, H]$$

then the augmented vector of states and parameters ($x_{aug} = [x^T, w^T]^T$) must be formed, which is an important part of the estimation process. The size of the augment vector for the third-order model is $L_{(3th-order)} = 9$ and $L_{(7th-order)} = 16$ for the other. Now the augment vector should be replaced with the state vector in Equations 3 and 1 to perform the new structure as follows:

$$\begin{bmatrix} x_k \\ w_k \end{bmatrix} = \begin{bmatrix} f(x_k, u_k, w_k) \\ I w_k \end{bmatrix} \begin{bmatrix} v_k \\ r_k \end{bmatrix} \quad (43)$$

$$y_k = [I \quad 0 \quad \dots \quad 0] \begin{bmatrix} x_k \\ w_k \end{bmatrix} + n_k \quad (44)$$

where r_k is the parameters noise and depending on their equation, their values are set. For the measurement vector $y_{(3th-order)}^T = [\omega_r, I_s, v_d, p_e]$ is used for generator A and $y_{(7th-order)}^T = [\omega_r, I_s, v_d, i_f]$ is used for generator B, which their equations have already been specified. Finally, it should be noted that the input vector (u) consists of excitation voltage (v_f) and input torque (T_L) in case (1) and terminal voltage in case (2).

5. CASE STUDIES

CDKF algorithm is tested on generators A & B, which reviewed their equations in the previous sections. For measuring the output signals of generators, their structure was simulated in Matlab's code environment. To better determination of each case's details, two sections are considered.

5.1. Case1: Generator A As shown in Figure 1, generator A connected to an infinite bus in a steady state condition through a line with impedance $j0.2$ p.u. Generator outputs, which should enter to estimation process, are recorded by sensors at sample time $\Delta t = 1$ ms. They will be ready to use after the noise is added to them, which is shown in Figure 2. The additional noise has a Gaussian distribution with zero mean and standard deviation $R_n = 10^{-5}$.

The algorithm performance will be challenged in two changes. The first one is increasing the field voltage by 20% its real value at second 2, and after 10 seconds, the next change will happen with an increase of 2% in input

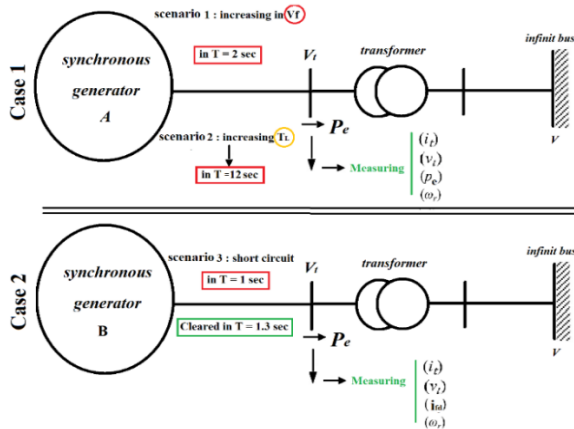


Figure 1. Structure of the system under study

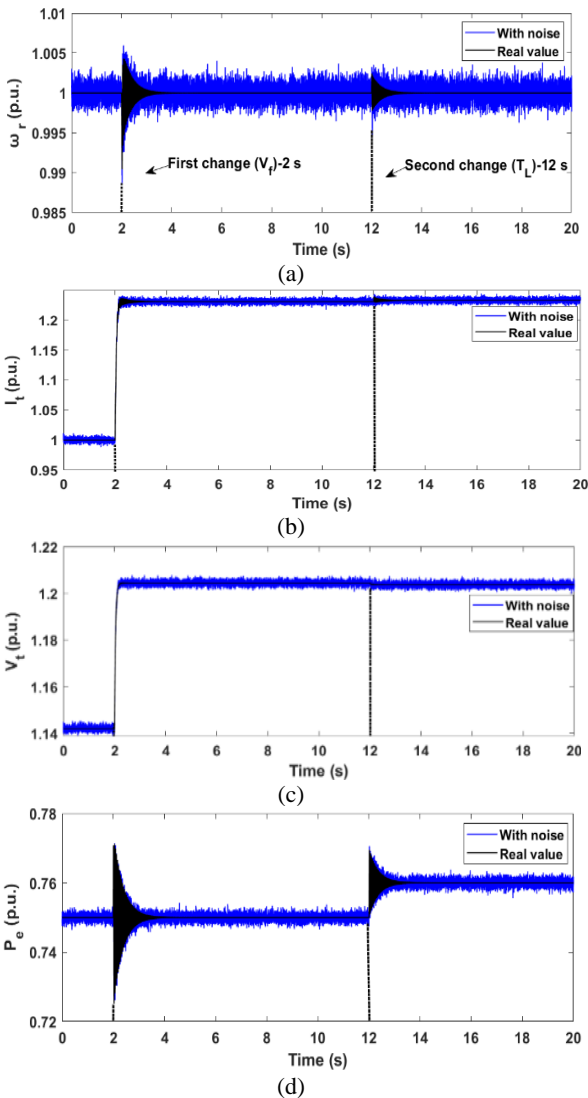


Figure 2. Diagrams of measurement changes for 20 seconds in generator A (a) Real and noisy values of rotor speed (b) Real and noisy values of terminal current (c) Real and noisy values of terminal voltage (d) Real and noisy values of electrical power

torque. Steady state calculation before changes take effect, listed in the appendix.

In this case, process noise (r_k) that being in state equations, is specified by its covariance matrix (Q_x) and also the parameter noise with covariance matrix (Q_w). These covariance matrixes combined each other as a diagonal form that, being ready for the dual estimation purpose as $Q_{CDKF} = \text{diag}(Q_x^T, Q_w^T)$. The usual value of Q_x in the UKF algorithm is 10^{-6} like Qi et al. (25), but in this work for better results, Q_{CDKF} consider as:

$$Q_{CDKF}^T = \text{diag}([10^{-6}, 10^{-6}, 10^{-7}, 10^{-5}, 10^{-5}, 10^{-6}, 10^{-5}, 10^{-5}])$$

The initial value of parameters is an important issue in the implementation algorithm. For this case, initial values are set at 80% and 130% of their real values, and for both of them, estimation results for states and parameters are shown in Figures 3, 4 and 5. Their results are named HCDKF, because the filter reformed for the SG's equations in hybrid structure and defined in section 2. In addition, the initial estimation error covariance, which indicates the confidence to the initial parameters is a diagonal matrix as:

$$P_{x_0}^T = \text{diag}([10^{-5}, 10^{-5}, 10^{-5}, 10^{-3}, 10^{-3}, 10^{-4}, 10^{-3}, 10^{-3}])$$

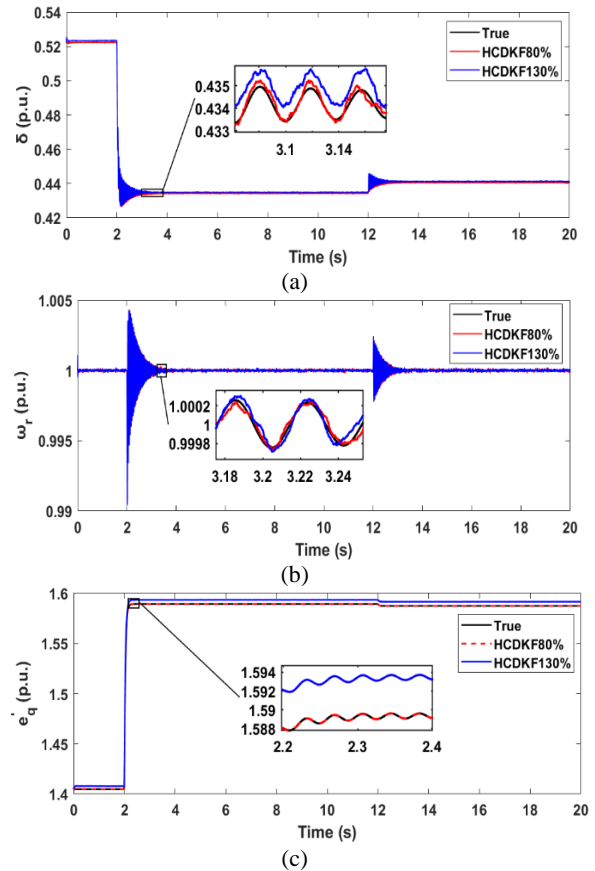


Figure 3. Diagrams of state estimations in generator A (a) Diagrams of true and estimated values of δ (b) Diagrams of true and estimated values of ω_r (c) Diagrams of true and estimated values of e'_q

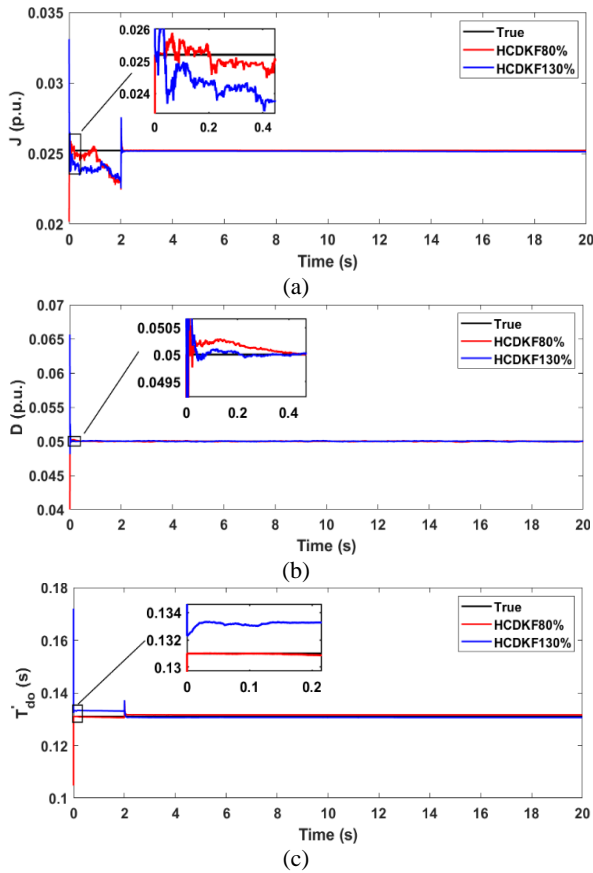


Figure 4. Diagrams of parameters estimation in generator A (a) Diagrams of true and estimated values of J (b) Diagrams of true and estimated values of D (c) Diagrams of true and estimated values of T'_{do}

For better comparison, the final estimated values in the second 20 are listed in Table 1. Two rows of this table are allocated to UKF estimation with similar noise to

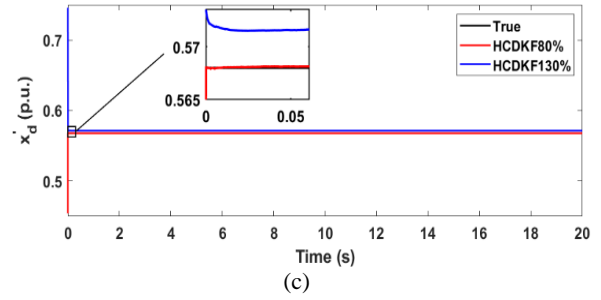
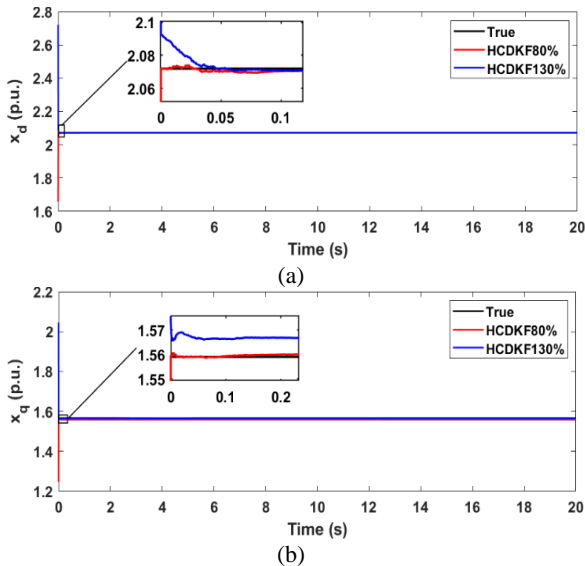


Figure 5. Diagrams parameter estimations in generator A (a) Diagrams of true and estimated values of x'_d (b) Diagrams of true and estimated values of x'_q (c) Diagrams of true and estimated values of x'_d

CDKF and tunable parameters $\alpha = (0.5)$, $\beta = (2)$ and $\kappa = (-6)$. The only tunable parameter in CDKF is h, which is equal to $\sqrt{3}$. The time duration (20 S) seems to be sufficient because the filter responses are being fixed. As it seen, estimation values are very close to the real values, also tracking states by the filter is admirable. On the other hand, to evaluate the estimation accuracy, relative errors for the last data in the filter's memory are calculated and listed in Table 2.

TABLE 1. Estimations of CDKF and UKF for generator A parameters in two initial conditions

| Parameters | Real values | CDKF estimations | | UKF estimations | |
|---------------|-------------|-------------------|--------------------|-------------------|--------------------|
| | | 80% initial valve | 130% initial value | 80% initial valve | 130% initial value |
| J (p.u.) | 0.0252 | 0.025193 | 0.0251217 | 0.025258 | 0.026209 |
| D (p.u.) | 0.05 | 0.049956 | 0.050007 | 0.050016 | 0.050336 |
| T'_{do} (s) | 0.1310 | 0.131622 | 0.130642 | 0.12787 | 0.126155 |
| x'_d (p.u.) | 2.072 | 2.07196 | 2.071871 | 2.07199 | 2.092736 |
| x'_q (p.u.) | 1.559 | 1.55959 | 1.56673 | 1.55335 | 1.56293 |
| x'_d (p.u.) | 0.568 | 0.568036 | 0.571634 | 0.56776 | 0.56858 |

TABLE 2. Relative errors for CDKF and UKF estimations in generator A with two initial conditions

| Parameters | CDKF relative errors (%) | | UKF relative errors (%) | |
|---------------|--------------------------|--------------------|-------------------------|--------------------|
| | 80% initial valve | 130% initial value | 80% initial valve | 130% initial value |
| J (p.u.) | 0.0253 | 0.3104 | 0.2337 | 4.004 |
| D (p.u.) | 0.08161 | 0.0159 | 0.0321 | 0.6735 |
| T'_{do} (s) | 0.4753 | 0.2727 | 2.3819 | 3.6981 |
| x'_d (p.u.) | 0.0015 | 0.062 | 3.53×10^{-5} | 1.0008 |
| x'_q (p.u.) | 0.0383 | 0.4961 | 0.3472 | 0.2525 |
| x'_d (p.u.) | 0.6440 | 0.6399 | 0.0409 | 0.1073 |

5. 2. Case2: Generator B For generator B, using the same connection to the grid as generator A, but the difference is that, in this case, a three-phase short circuit occurred at generator terminal in second 1 and cleared in 0.3 second later. Measurements change with the added noise to them showed in Figure 6. The noises have a Gaussian distribution with zero mean and standard deviation $R_n = 10^{-5}$.

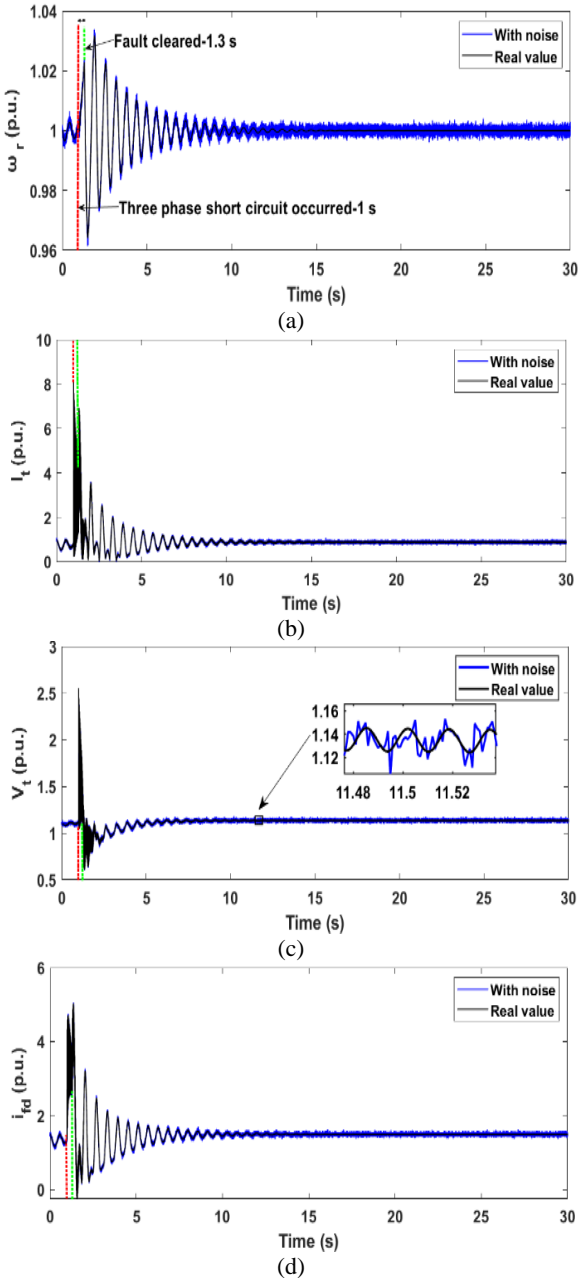


Figure 6. Diagrams of measurement changes for 30 seconds in generator B a) Real and noisy values of rotor speed b) Real and noisy values of terminal current c) Real and noisy values of terminal voltage d) Real and noisy values of filed current

Since this model has more details, the generator's operation is simulated for 30 seconds and filter should estimate states and parameters in this duration. Process and measurement noises are defined by 16×16 diagonal matrix (Q_{CDKF}) and in this case,

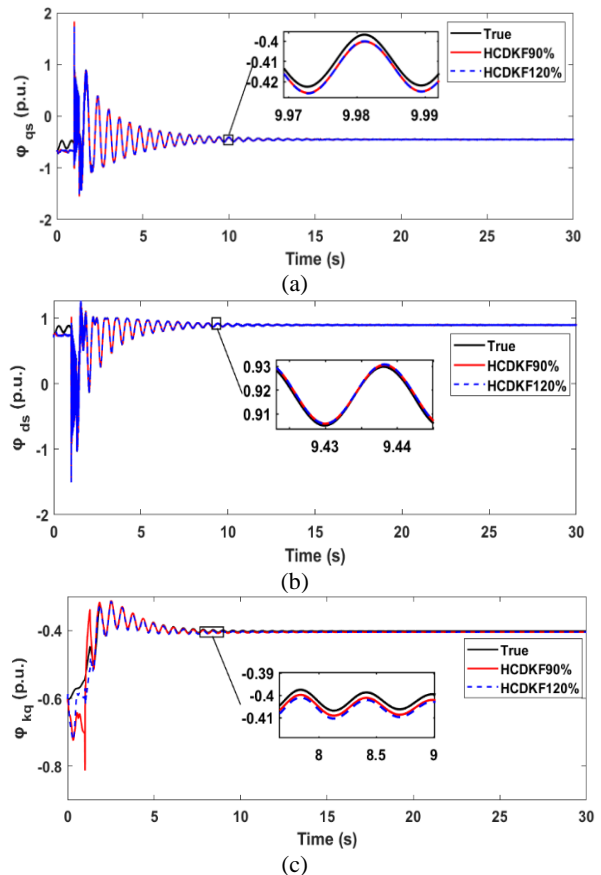
$$Q_{CDKF}^T = \text{diag} ([10^{-6}, 10^{-5}, 10^{-5}, 10^{-5}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-7}, 10^{-8}, 10^{-7}, 10^{-8}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-7}])$$

The initial values of parameters set 90% and 120% of their real values and the covariance error of the initial estimation (P_{x0}) defines as:

$$P_{x0}^T = \text{diag} ([10^{-6}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-6}, 10^{-4}, 10^4, 10^4, 10^4, 10^4, 10^4, 10^4, 10^4, 10^4])$$

with these values for noise and initial objects, as mentioned above, Figures 7 and 8 show the states and parameter estimation with both initial values of parameters. And Figures 9 and 10 show the performance of the filter to estimate the parameters. The result figures for this model, which are estimated by only four measurements signal are very acceptable.

The last estimation in 30 seconds for CDKF with $h = \sqrt{3}$ and for UKF with $\alpha = (1), \beta = (2)$ and $\kappa = (-13)$ with similar noises to the CDKF process are listed in Table 3. For better comparison, relative and definite errors are



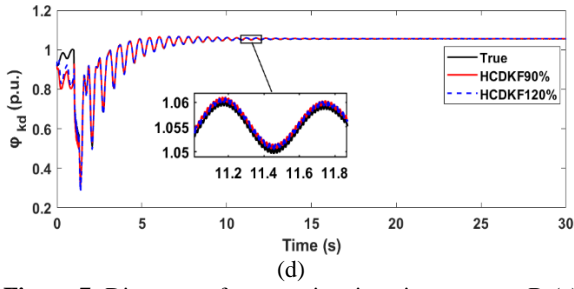


Figure 7. Diagrams of state estimations in generator B (a) Diagrams of true and estimated values of φ_{qs} (b) Diagrams of true and estimated values of φ_{ds} (c) Diagrams of true and estimated values of φ_{kq} (d) Diagrams of true and estimated values of φ_{kd}

presented in Table 4; which shows CDKF has done its job properly and in some parameters better than UKF

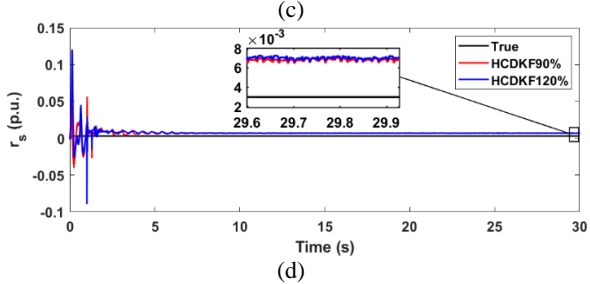
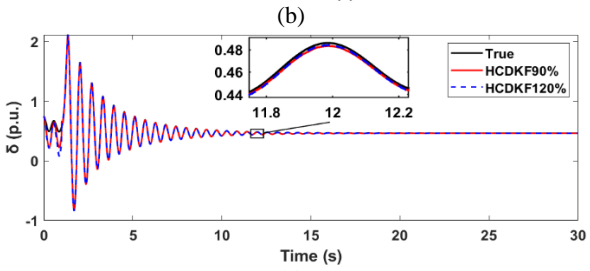
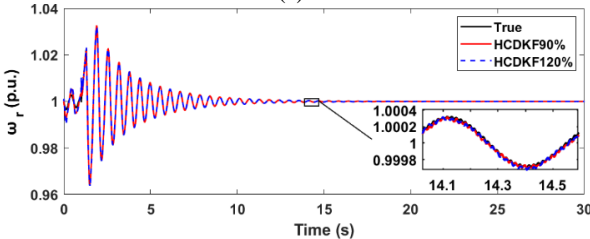
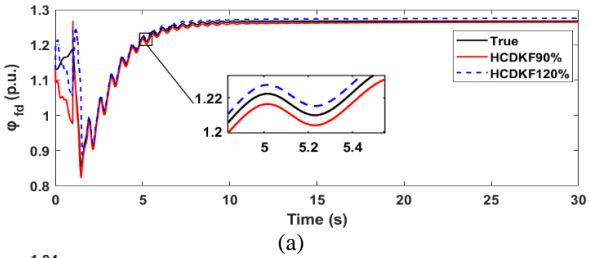


Figure 8. Diagrams of state and parameter estimations in generator B (a) Diagrams of true and estimated values of φ_{fd} (b) Diagrams of true and estimated values of ω_r (c) Diagrams of true and estimated values of δ (d) Diagrams of true and estimated values of r_s

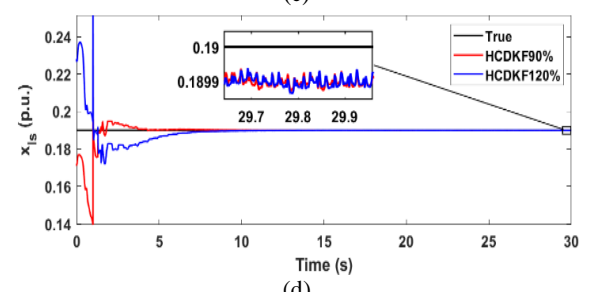
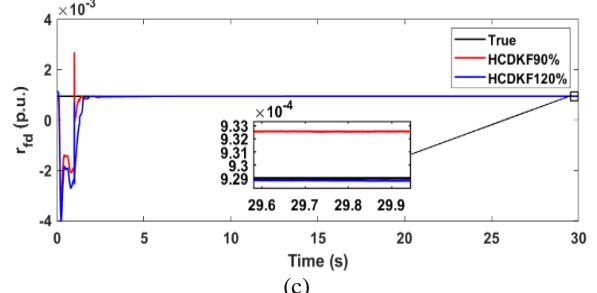
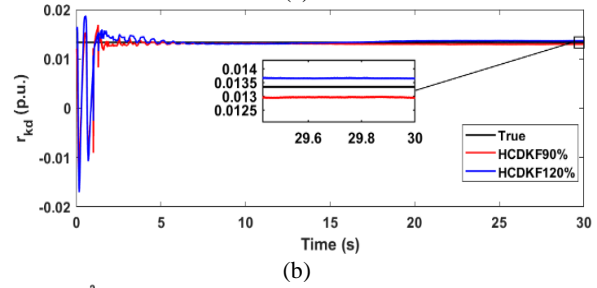
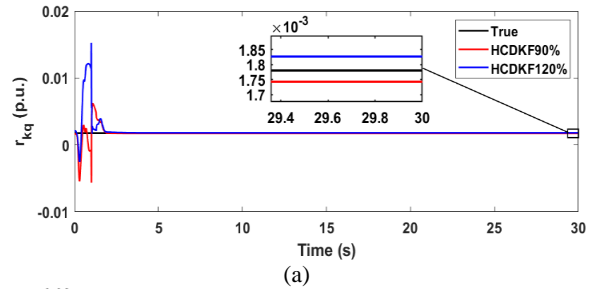
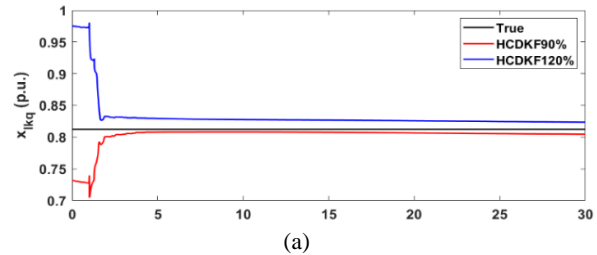


Figure 9. Diagrams of parameter estimations in generator B (a) Diagrams of true and estimated values of r_{kq} (b) Diagrams of true and estimated values of r_{kd} (c) Diagrams of true and estimated values of r_{fd} (d) Diagrams of true and estimated values of x_{1s}

except r_s . However, the important thing about the filter is the number of tunable parameters and its compatibility with many structures.



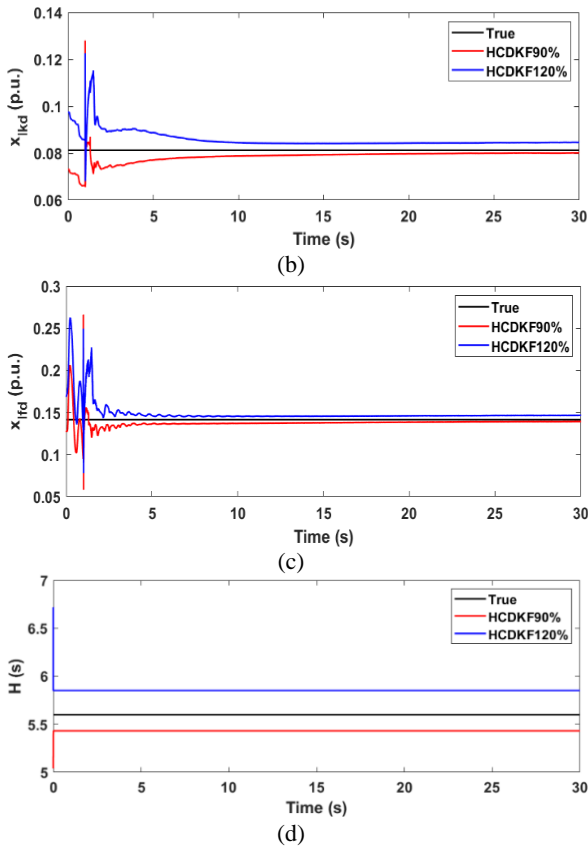


Figure 10. Diagrams of parameter estimations in generator B (a) Diagrams of true and estimated values of x_{ikd} (b) Diagrams of true and estimated values of x_{lkd} (c) Diagrams of true and estimated values of x_{lfd} (d) Diagrams of true and estimated values of H

Steady states equations and real values of generators A and B defined in Tables 5 and 6.

TABLE 3. Estimations of CDKF and UKF for generator B parameters in two initial conditions

| Parameters | Real values | CDKF estimations | | UKF estimations | |
|------------------|-------------|-------------------|--------------------|-------------------|--------------------|
| | | 90% initial valve | 120% initial value | 90% initial valve | 120% initial value |
| r_s (p.u.) | 0.003 | 0.00676 | 0.006953 | 0.0306 | 0.00287 |
| r_{kq} (p.u.) | 0.0178 | 0.001742 | 0.001826 | 0.001753 | 0.00167 |
| r_{kd} (p.u.) | 0.0133 | 0.012947 | 0.013647 | 0.013618 | 0.01267 |
| r_{fd} (p.u.) | 0.000929 | 0.000932 | 0.000928 | 0.000932 | 0.000893 |
| x_{ls} (p.u.) | 0.19 | 0.18988 | 0.189887 | 0.18989 | 0.18060 |
| x_{lkq} (p.u.) | 0.8125 | 0.80454 | 0.82359 | 0.8176 | 0.77187 |
| x_{lkd} (p.u.) | 0.08125 | 0.080166 | 0.08463 | 0.08320 | 0.07719 |
| x_{lfd} (p.u.) | 0.1414 | 0.139176 | 0.14650 | 0.14417 | 0.14037 |
| H (s) | 5.6 | 5.4320 | 5.8520 | 6.1600 | 5.3200 |

TABLE 4. Relative errors for CDKF and UKF estimations in generator B with two initial conditions

| Parameters | Real values | CDKF relative errors (%) | | UKF relative errors (%) | |
|------------------|-------------|--------------------------|--------------------|-------------------------|--------------------|
| | | 90% initial valve | 120% initial value | 90% initial valve | 120% initial value |
| r_s (p.u.) | 0.003 | 125.25 | 131.79 | 2.003 | 4.2141 |
| r_{kq} (p.u.) | 0.0178 | 2.1175 | 2.6159 | 1.447 | 5.6456 |
| r_{kd} (p.u.) | 0.0133 | 2.9508 | 2.3097 | 2.095 | 4.9994 |
| r_{fd} (p.u.) | 0.000929 | 0.3828 | 0.0204 | 0.3532 | 3.8986 |
| x_{ls} (p.u.) | 0.19 | 0.0610 | 0.0593 | 1.959 | 4.945 |
| x_{lkq} (p.u.) | 0.8125 | 0.9796 | 1.3652 | 1.997 | 4.9996 |
| x_{lkd} (p.u.) | 0.08125 | 1.3337 | 4.1670 | 2.067 | 4.9939 |
| x_{lfd} (p.u.) | 0.1414 | 1.5528 | 3.6079 | 0.0919 | 0.7246 |
| H (s) | 5.6 | 2.9997 | 4.5000 | 1.998 | 5.000 |

6.CONCLUSION

In this paper, a CDKF algorithm is implemented on two dynamic models of different generators, with the purpose of dual estimation of states and parameters.

Although many kinds of Kalman estimation algorithms EKF, UKF and CKF with different levels of accuracy tested on SG's equations. In each of them, some parameters have to be set. While in CDKF just by tuning one parameter can achieve good results the same as other methods. In addition, the 7-order model used in this work has 16 unknown states and parameters which are estimated only by four external measurements from accessible quantities of the generator.

The case studies have shown that the algorithm has acceptable accuracy in different working conditions and also in different initial values of parameters for the first step of estimation. Furthermore, in some parameters, it works better than UKF.

Also, due to the volume of equations and computational complexity of the CDKF algorithm, special attention can be paid to the implementation of this process on a low-cost and powerful computing platform such as PIC as future activities, and its results will be evaluated in the form of another research.

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8. APPENDIX

| | |
|--|--|
| <p>The main variables of 3-order model are:</p> <p>e'_q Transient internal voltage of armature δ Rotor angle ω_r Rotor speed E_{fd} The equivalent EMF in the excitation coil T_e Output electrical torque v_t Generator terminal voltage V Infinite bus voltage i_d, i_q Direct and quadrature axis stator currents T'_{do} Direct axis transient time constant x'_d Direct axis transient reactance J Rotor inertia D Damping factor x_d Direct axis reactance x_q Quadrature axis reactance</p> | <p>The main variables of 7-order model are:</p> <p>ϕ_{qs} Quadrature axis magnetic flux ϕ_{ds} Direct axis magnetic flux ϕ_{kq} Quadrature axis damper magnetic flux ϕ_{kd} Direct axis damper magnetic flux ϕ_{fd} Field winding magnetic flux i_{fd} Field winding current r_s Stator resistance r_{kq} Quadrature axis damper resistance r_{kd} Direct axis damper resistance r_{fd} Field winding resistance x_{ls} Stator leakage reactance x_{lkq} Quadrature axis damper leakage reactance x_{lkd} Direct axis damper leakage reactance x_{lfd} Field winding leakage reactance H Inertia constant v_q Quadrature axis voltage v_d Direct axis voltage v_{kq} Quadrature axis damper voltage v_{kd} Direct axis damper voltage v_{fd} Field winding voltage θ Generator voltage angle</p> |
|--|--|

TABLE 5. Generator A [20]

| Real values | Steady state calculations |
|-------------------------------------|--|
| $\omega_b = 120 \times \pi$ (rad/s) | $v = 1$ (p.u.) |
| $S = 1$ (p.u.) | $x_e = 0.2$ (p.u.) |
| $T_m = 0.8$ (p.u.) | $i_s = \frac{s}{v} = 1$ (p.u.) |
| $J = 0.0252$ (p.u.) | $\theta = \cos^{-1} \left(\frac{(T_m \cdot D \cdot I)}{s} \right) = 0.7227$ (p.u.) |
| $D = 0.05$ (p.u.) | $\delta = \tan^{-1} \left(\frac{x_q \times i_s \times \cos \theta}{v + x_q \times \sin \theta} \right) = 0.5223$ (p.u.) |
| $x'_d = 0.568$ (p.u.) | $\omega = 1$ (pu) |
| $x_d = 2.072$ (p.u.) | $E_{fd} = v \times \cos \delta + x_q \times i_s \times \sin(\delta + \theta) = 2.8297$ (p.u.) |
| $x_q = 1.559$ (p.u.) | $e'_q = v \times \cos \delta + x'_d \times i_s \times \sin(\delta + \theta) = 1.4048$ (p.u.) |
| $T'_{do} = 0.1310$ (s) | |

TABLE 6. Generator B [21]

| Real values | Steady state calculations |
|-------------------------------------|---|
| $S = 835 \times 1000000$ (VA) | $\theta = \cos^{-1}(PF) = 0.4510$ (p.u.) |
| $v_{LL} = 26000$ (v) | $v_{as} = 1$ (p.u.) |
| $v_s = \frac{v_{LL}}{\sqrt{3}}$ (v) | $i_{as} = \cos \theta - (\sin \theta \times I) i = 0.90 - 0.435 i$ (p.u.) |
| $PF = 0.9$ | $E_a = v_{as} + (r_s \times x_q \times I) i \times i_{as} = 1.787 + 1.618 i$ (p.u.) |
| $\omega_b = 377$ (rad/s) | $\delta = \angle(E_a) = 0.7359$ (p.u.) |
| $P = 2$ | $i_{ds} = -\sin(-\theta - \delta) = 0.9272$ (p.u.) |
| $H = 5.6$ (s) | $i_{qs} = \cos(-\theta - \delta) = 0.3745$ (p.u.) |
| $x_e = 0.2$ (p.u.) | $x_{md} = x_d + x_{ls} = 1.61$ (p.u.) |
| $r_s = 0.003$ (p.u.) | $x_{mq} = x_q + x_{ls} = 1.61$ (p.u.) |
| $x_{ls} = 0.19$ (p.u.) | $E_{fd} = E_a + (x_d - x_q) \times i_{ds} = 2.4114$ (p.u.) |
| $x_d = 1.8$ (p.u.) | $i_{fd} = \frac{E_{fd}}{x_{md}} = 1.4977$ (p.u.) |
| $r_{fd} = 0.000929$ (p.u.) | $i_{kq} = i_{kd} = i_{os} = 0$ (p.u.) |
| $x_{lfd} = 0.1414$ (p.u.) | $\phi_{qs} = -x_q \times i_{qs} + x_{mq} \times i_{kq} = -0.6741$ (p.u.) |
| $r_{kd} = 0.01334$ (p.u.) | $\phi_{ds} = -x_d \times i_{ds} + x_{md} \times i_{kd} + x_{md} \times i_{fd} = 0.7423$ (p.u.) |
| $x_{lkd} = 0.08125$ (p.u.) | $\phi_{kq} = x_{lkq} \times i_{kq} + x_{mq} \times (-i_{qs} + i_{kq}) = -0.6029$ (p.u.) |
| $x_q = 1.8$ (p.u.) | $\phi_{kd} = x_{lkd} \times i_{kd} + x_{md} \times (-i_{ds} + i_{fd} + i_{kd}) = 0.9185$ (p.u.) |
| $r_{kq} = 0.00178$ (p.u.) | $\phi_{fd} = x_{lfd} \times i_{fd} + x_{md} \times (-i_{ds} + i_{fd} + i_{kd}) = 0.1303$ (p.u.) |
| $x_{lkq} = 0.8125$ (p.u.) | $\omega_r = 1$ (p.u.) |
| | $T_m = \phi_{ds} \times i_{qs} - \phi_{qs} \times i_{ds} = 0.9030$ (p.u.) |

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Persian Abstract**چکیده**

در این مقاله، از فیلتر کالمن تفاضل مرکزی (CDKF) برای تخمین پارامترهای دو مدل مختلف ژنراتور سنکرون در شرایط وجود نویز استفاده شده است. قابل ذکر است که مدل های مختلفی از ژنراتور سنکرون با سطوح مختلف دقت برای استفاده در الگوریتم های تخمین وجود دارد. الگوریتم تخمین در این مقاله از تعداد کمتری ورودی جهت اندازه گیری برای تخمین حالت ها و پارامترهای ناشناس برای دو مدل دقیق از ژنراتور سنکرون استفاده می کند. فیلتر کالمن تفاضل مرکزی (CDKF)، از اعضای خانواده فیلترهای کالمن بوده که همانند فیلتر کالمن خنثی (UKF)، از نقاط سیگما برای مدل سازی معادلات غیر خطی استفاده می کند. فیلتر کالمن تفاضلی (CDKF) نتایج بهتری نسبت به فیلتر کالمن خنثی ارائه می دهد. در این تحقیق، با استفاده از دو مدل ژنراتور سنکرون با پارامترهای مختلف در سه سناریوی متفاوت، توانایی فیلتر کالمن تفاضل مرکزی به چالش کشیده می شود، که نشان می دهد این روش، بسیار کارا و قابل اطمینان است.
