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Original Article

Excitation System Parameters Estimation by Different Input Signals and Various Kalman Filters

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Abstract

he excitation system is one of the most crucial components of a power plant. Knowing the exact parameters of the excitation system and their changes over time is essential for efficient and accurate power system dynamic studies. In this paper, the parameters of a typical and well-known type of an excitation system are estimated using different types of Kalman filter, including unscented Kalman filter (UKF), spherical-simplex Kalman filter (SS-UKF), and cubature Kalman filter (CKF). Efficacy of these Kalman filter methods in excitation system parameters estimation problem is investigated under three different planned and unplanned events as the input of the methods. The planned disturbances will be internal type (a reference voltage step) and external type (unit transformer tap changing) whereas the unplanned disturbance is caused by power grid events (neighbour generator outage). Comparison is done between the simulation results and experimental ones and the best appropriate approach is selected.

Keywords: Excitation system, parameters identification, Kalman filter

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1. INTRODUCTION

In terms of operation and control, power grid is the largest and most difficult man-made system [1]. Several hundred generators send their power to interconnected transmission and distribution networks and thousands of electrical loads are consuming the power. Therefore, knowing how the power system reacts after a small or a large disturbance and determination of network stability limits are the main concerns of power grid researchers, engineers, and operators [1].

Stability studies largely depend on model and parameter information of power plant components such as generator, excitation system, governor, power system stabilizer (PSS) and etc. Use of inaccurate information in the decision-making process has great undesirable effects on the network operation and planning. Furthermore, lack of information about the model and its parameters forces the power engineers to make conservative decisions in power system operation. This can lead to non-optimal using of equipment and assets [2]. Lack of technical information in power plant documents, existence of typical information about a number of parameters, change in parameters during commissioning and operation, and replacement and depreciation of power plant equipment are sufficient to justify using the parameters' estimation and identification methods, which are to be employed in stability studies [3].

In [4, 5], the effect of system models and their parameters are stated in some power system studies. One of the most important control systems of a power plant is the excitation system that so far less attention has been paid to its various identification aspects. In addition to terminal voltage control under normal conditions, excitation system has a significant effect on maintaining the unit's stability in transient conditions. Besides, unlike the generator parameters, which usually remain unchanged during operation time until maintenance is performed, the plant operator can change excitation system parameters in various conditions. Generally, three types of test are used for identification process: offline tests, open circuit tests and on-line tests [6].

Performing offline and open circuit tests requires disconnecting a unit from the grid and may have a high risk for damaging of equipment. Furthermore, the

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power plant owner may lose the revenue from energy sales. Online tests can be performed during the generator operation, i.e. the conditions which are desirable for unit operators.

There are several methods to identify the parameters of a system. Among these, the methods based on intelligence algorithms and Kalman filter are found to be suitable for many cases. In [7-10], optimization methods based on intelligence algorithms - such as Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) were used for identification of parameters. These methods are able to obtain several different sets of parameters that based on those; the measured and estimated signals are in close agreement. However, the purpose of parameters identification is to find the exact parameters that have been set on the system and may be re-adjusted in operation time. In [11- 13], various types of Kalman filters are employed for identification process. Kalman filters have recursive nature and consequently they can be easily used in online identification problems. Furthermore, Kalman filters are less vulnerable to noise compared with the intelligence algorithm based identification methods [11].

Input selection is an important step in parameter identification process. This is a vital step for detecting all available modes in the system. Signals recorded by measurement devices as the inputs of the identification process can be obtained through planned or unplanned network disturbances. In [14] information of online planned disturbances (a step change in reference or a planned unit outage) and unplanned disturbances are used for parameters' validation and identification. The paper suggested step change to identify the parameters of excitation system and frequency variations for estimation of turbine and governor parameters.

Nowadays, by the development of phasor measurement units (PMUs) in power networks, use of unplanned inputs or network events' data on the identification process attracts more attention. In [15, 16], parameters identification was done by the network disturbances which have not caused unit instability. The authors stated that parameters identification in actual conditions is precisely what the network operator and planner deals with. In [17], the HV side frequency and 3-phase voltages signals that were measured by PMU are employed for identification. Due to several unknown parameters, a sensitivity analysis method was first done to extract the most effective parameters in the outputs. Then, the parameters were identified using trial-and-error method based on the author's knowledge about the system. In the research, the least square error method is employed for optimization. Reference [18, 19] proposed an online method called Hybrid Simulation too, in which actual measurements and simulation's data are combined to validate and identify the power system model and its parameters. The authors in [14, 15] stated that the major problem in identification by real events is to create pre-event conditions for the bulk power system. The authors introduced Hybrid Simulation as a way to avoid modeling of the whole network and creating the operation point of pre-event. The goal of this paper is to propose an identification approach based on hybrid simulation using Kalman filter for generator's excitation system parameters identification under online test conditions. The performances of three types of Kalman filter algorithms: unscented Kalman filter (UKF), spherical-simplex Kalman filter (SS-UKF), and cubature Kalman filter (CKF) in excitation system parameters identification is investigated. Furthermore, three types of disturbances are considered as input of identification process and the best type is chosen to determine the excitation system parameters. These algorithms are also verified by experimental tests, and the simulation and actual results are compared. Some practical issues encountered during parameter identification of excitation system parameters will also be discussed. The rest of article is organized as follows: Section 2 discusses identification concepts, and the identification methods based on Kalman filters. Section 3 introduces the simulated excitation system. Simulations and discussions and experimental tests are brought in section 4 and 5, and section 6 concludes the paper.

2. Identification method based on Kalman filter

Usually, filtering methods are used for system state estimation. If the parameter estimation problem turns to state estimation problem, then filtering methods can also be employed for parameter estimation. This process is carried out by adding the unknown parameter array to system equations [20].

If the dedicated models are uncertain and the measured signals are noisy, it has many advantages to use probability distribution function showing the states of a model. Parameter or state estimation is also an optimal way to extend the concept of probability distribution function over time. The Gaussian probability distribution function (GPDF) is commonly employed to indicate the model states, the processes, and the measurement noise. The GPDF can be described by a mean value and a covariance or standard deviation. Kalman filter (KF) optimally extends the mean and the covariance of a probability distribution function of a linear dynamic model state. For many decades, the most common way to use KF in nonlinear systems was Extended Kalman Filter (EKF) [21]. In EKF, Jacobean matrix is used for estimation. This matrix is the first-order approximation of the under study nonlinear process. EKF is valid when the linear approximation of a nonlinear dynamic system is available. In addition, the error caused by linearization has affected on actual mean value and covariance of distribution function as well as the filter performance. Therefore, for highly nonlinear models, the EKF does not provide high accuracy and stability [21, 22].

After the EKF, the UKF attracted the attention. Unlike EKF, which approximates the non-linear equations using linearization, the UKF employs the carefully selected sample points to show the distribution of state. These sample points, which is called sigma points (SPs), can capture accurately the correct mean value and covariance of Gaussian random variables. Along with the high accuracy of approximations, UKF avoids heavy calculations for Jacobean matrix construction in each step and this in turn simplifies the implementation of the algorithm [12].

The SS-UKF proposes another approach to select SPs, which reduces the number of points and increases computational stability by also decrease the running time of the algorithm in real-time applications [23]. In 2009, the CKF was proposed to step up the UKF performance using spherical-radial cubature rule [24]. The CKF uses an even number of sample points called cubature points (CPs) with equal weights. Indeed, the main difference between CKF and UKF can be described as follows: CKF directly follows the cubature rule, and its most important feature is that it does not have any free parameter while UKF introduces a non-zero scale parameter providing a non-zero center point which usually has more corresponding weight compared with the remaining SPs. Interestingly, if in UKF, the scaling parameters are set to zero, the set of SPs will be similar to the set of CPs and UKF algorithm is identical to CKF algorithm [25].

Before introducing the different stages of parameters identification by Kalman filter, it is necessary to note that, a continuous nonlinear dynamic system can be represented by the equations (1).

$$\begin{cases}\dot{\boldsymbol{x}}(t) = f[\boldsymbol{x}(t).\boldsymbol{u}(t).\boldsymbol{v}(t)] \\ \boldsymbol{y}(t) = h[\boldsymbol{x}(t).\boldsymbol{u}(t).\boldsymbol{v}(t)] + \boldsymbol{w}(t)\end{cases} \tag{1}$$

where, $\boldsymbol{x}(t)$ is the vector of state variables, $\boldsymbol{y}(t)$ is the vector of output variables (vector of measurement), $\boldsymbol{u}(t)$ is the vector of input variables, $\boldsymbol{v}(t)$ is the noise vector of the process with covariance $\boldsymbol{Q}$, which can cover modeling error of the system, $\boldsymbol{w}(t)$ is the measurement vector with covariance $\boldsymbol{R}$, and f and h are transition matrices. If Δt assumes as the time sample, equation (1) can be rewritten in a discrete form as (2):

$$\begin{cases}\boldsymbol{x}_k = \boldsymbol{x}_{k-1} + f[\boldsymbol{x}_{k-1}.\boldsymbol{u}_{k-1}.\boldsymbol{v}_{k-1}]\Delta t \\ \boldsymbol{y}_k = h[\boldsymbol{x}_k.\boldsymbol{u}_k.\boldsymbol{v}_k] + \boldsymbol{w}_k\end{cases} \tag{2}$$

where, $\boldsymbol{x}_k$ is the vector of random variables with given mean and covariance values. The Kalman filter is a recursive algorithm predicting the conditional expectation of the state given all observations up to the current time. The prediction is being corrected at each time step by measurement information. The general steps of Kalman filter algorithms are as follows:

- ✓ Selection of sample points and calculation of weight coefficients,
- ✓ Prediction, and
- ✓ Correction of estimates.

The main difference of the three aforementioned algorithms (UKF, SS-UKF and CKF) is in Step 1.

2.1 Selection of sample points and calculation of weight coefficients

The main difference between the above-mentioned KF algorithms is in sample points and weight coefficient's selection, which are described below.

2.1.1. Estimation of sample points and calculation of weight coefficients in UKF

$\boldsymbol{x}_k$ is a n-dimensional state vector, which is estimated as a random variable vector using average value $\hat{x}_{k,k}$ and covariance $\boldsymbol{P}_{xk,k}$, and by aiding of $2n+1$ SPs. In each step of the algorithm, it is necessary to calculate SPs based on the previous step data. Furthermore, UKF uses weight coefficients for calculating the mean value and covariance of each step. One way for estimation of SPs and the corresponding weight coefficients is as follows:

$$\begin{cases}x_{k,k}^0 = \hat{x}_{k,k} \\ x_{k,k}^i = \hat{x}_{k,k} + \left(\sqrt{(n+\lambda)\boldsymbol{P}_{xk,k}}\right)_i \\ x_{k,k}^{i+n} = \hat{x}_{k,k} - \left(\sqrt{(n+\lambda)\boldsymbol{P}_{xk,k}}\right)_{i+n}\end{cases} \tag{3}$$
$$i = 1,2,\dots,n$$

$$\begin{cases}u_m^0 = \frac{\lambda}{(n+\lambda)} \\ u_c^0 = \frac{\lambda}{(n+\lambda)} + (1-\alpha^2+\beta) \\ u_m^i = u_c^i = \frac{\lambda}{2(n+\lambda)}\end{cases} \tag{4}$$
$$i = 1,2,\dots,2n$$

where, $\left(\sqrt{(n+\lambda)\boldsymbol{P}_{xk,k}}\right)_i$ is the i_{th} row or column of square root of the matrix $(n+\lambda)\boldsymbol{P}_{xk,k}$ and is obtained from Cholesky Decomposition [24]. λ is a scaling parameter equal to $\lambda = \alpha^2(n+k) - n$. α, k, and β are positive constant values, which can be used for tuning the filter. α is assumed between 0 and 1 and usually is chosen in a way that the predicted covariance being positive and the expectation of covariance had an appropriate accuracy.

To have Gaussian distribution function, the optimal value for β is two. k denotes the allowed distance between sample points and the mean value.

High values of k increase the distance between sample points and the mean value and reduce the weights of remote sample points. u_c , u_m are the weighting factors of covariance and mean value [12].

2.1.2. Estimation of sample points and calculation of weight coefficients in SS-UKF

Spherical UT uses $n+2$ spherical SPs and equal weight coefficients [23]. These spherical SPs are calculated by the following equation:

$$X^{(i)} = \bar{X} + (\sqrt{\boldsymbol{P}_{xk,k}}\sigma)_i \quad i = 0, \dots, n+1 \tag{5}$$

In the above equation, $(\sqrt{\boldsymbol{P}_{xk,k}})_i$ is the i_{th} row or column of square root of covariance matrix and σ_i is the i_{th} row of spherical SPs matrix, which is calculated using the following method:

a. Weighting factors:
Firstly, W_0 is assumed as (6) and the remaining weights are selected as (7).

$$0 < W_0 < 1 \tag{6}$$

$$W_i = \frac{1-W_0}{n+1} \qquad i = 1, \dots n+1 \tag{7}$$

In order to use the benefits of scaling, the previous weights can be scaled as (8). This reduces the effect of higher-order components. Finally, the weights of SPs can be modified as (9).

$$w_i = \begin{cases} 1 + \frac{(W_0 - 1)}{\alpha^2} & for \quad i = 0 \\ \frac{(W_i)}{\alpha^2} & for \quad i \neq 0 \end{cases} \tag{8}$$

$$\begin{aligned} u_c^0 &= w_0 + (1 - \alpha^2 + \beta) \\ u_m^0 &= w_0 \\ u_m^i &= u_c^i = w_i \end{aligned} \tag{9}$$

b. Spherical sigma point matrix

Now, the following single-component vectors are assumed as (10) and with an iterative process, the σ vectors can be obtained through the following steps, for j from 2 to n as shown in (11) [23].

$$\begin{aligned} \sigma_0^{(1)} &= 0 \\ \sigma_1^{(1)} &= \frac{-1}{\sqrt{2w^{(1)}}} \\ \sigma_2^{(1)} &= \frac{1}{\sqrt{2w^{(1)}}} \end{aligned} \tag{10}$$

$$\sigma_i^j = \begin{cases} \begin{bmatrix} \sigma_0^{j-1} \\ 0 \end{bmatrix} & for \;\; i = 0 \\ \begin{bmatrix} \sigma_i^{j-1} \\ \frac{-1}{\sqrt{j(j+1)w_1}} \end{bmatrix} & for \;\; i = 1, \dots, j \\ \begin{bmatrix} 0_{j-1} \\ \frac{j}{\sqrt{j(j+1)w_1}} \end{bmatrix} & for \;\; i = j+1 \end{cases} \tag{11}$$

For systems with few numbers of state variables, spherical transform shows a good numerical stability [23].

2.1.3. Estimation of sample points and calculation of weight coefficients in CKF

CPs are obtained from a third-degree spherical-radial rule, as shown in (12) and (13). The number of these points is twice of the number of state variables.

$$\begin{aligned} \xi_i &= \sqrt{n}[1]_i \\ u_c &= u_m = \frac{1}{2n} \end{aligned} \tag{12}$$

$$\begin{aligned} \boldsymbol{P}_{xk,k} &= \boldsymbol{S}_{k,k}\boldsymbol{S}_{k,k}^T \\ x_{k,k}^i &= \hat{x}_{k,k} + S_{k,k}\xi_i \\ i &= 1,2,\dots,2n \end{aligned} \tag{13}$$

2.2. Prediction step [12]

At this step, the sample points obtained in the previous step ($x_{k,k}^i$) are put in dynamic equations of the system and the new sample points of state variables ($x_{k+1,k}^i$) are determined. Subsequently, the mean ($\hat{x}_{k+1,k}$) and covariance values ($\boldsymbol{P}_{xk+1,k}$) of SPs are calculated as follows (14).

$$\begin{aligned} x_{k+1,k}^i &= f(x_{k,k}^i, u_k, w_k) \\ \hat{x}_{k+1,k} &= \sum_{i=0}^{2n} u_m^i x_{k+1,k}^i \\ \boldsymbol{P}_{xk+1,k} &= \sum_{i=1}^{2n} u_c^i (x_{k+1,k}^i - \hat{x}_{k+1,k})(x_{k+1,k}^i - \hat{x}_{k+1,k})^T + \mathbf{Q}_K \end{aligned} \tag{14}$$

SPs obtained from (14) are put into measurement equations to predict the new sample points of measurement. The predicted measurements points ($\gamma^{\mathrm{i}}_{\mathrm{k+1},k}$), their mean values ($\hat{\gamma}_{\mathrm{k+1},k}$), covariance ($\boldsymbol{P}_{\gamma_{k+1,k}}$) and cross-covariance ($\boldsymbol{P}_{x\gamma_{k+1,k}}$) are calculated using (15).

$$\begin{aligned}
\gamma^{\mathrm{i}}_{\mathrm{k+1},k} &= h\left(\mathrm{x}^{\mathrm{i}}_{\mathrm{k+1},k}, u_{k+1}, v_{k+1}\right) \\
\hat{\gamma}_{\mathrm{k+1},k} &= \sum_{i=0}^{2n} u^{i}_{m} \gamma^{\mathrm{i}}_{\mathrm{k+1},k} \\
\boldsymbol{P}_{\gamma_{k+1,k}} &= \sum_{i=1}^{2n} u^{i}_{c} \left(\gamma^{i}_{k+1,k} - \hat{\gamma}_{k+1,k}\right)\left(\gamma^{i}_{k+1,k} - \hat{\gamma}_{k+1,k}\right)^{T} + \mathbf{R}_{\mathrm{K}} \\
\boldsymbol{P}_{x\gamma_{k+1,k}} &= \sum_{i=1}^{2n} u^{i}_{c} \left(x^{i}_{k+1,k} - \hat{x}_{k+1,k}\right)\left(\gamma^{i}_{k+1,k} - \hat{\gamma}_{k+1,k}\right)^{T}
\end{aligned} \tag{15}$$

It should be noted that in CKF algorithm, after calculating the $\hat{\mathrm{x}}_{\mathrm{k+1},k}$ and $\boldsymbol{P}_{xk+1,k}$ from (14), the CPs of $(k+1)_{th}$ step are recalculated from (13) and then are put in (15). It is mention again that k is the counter of KF algorithm iterations and i is the counter of the number of cubature/sigma points. $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$ are the covariance of process and signal noise in step k.

2.3. Correction step

Due to availability of the actual measurement data, they can be used in estimates correction step as follows:

$$\begin{aligned}
\hat{x}_{k+1,k+1} &= \hat{x}_{k+1,k} + \boldsymbol{K}_{k+1}\left[Y_{k+1} - \hat{\gamma}_{\mathrm{k+1},k}\right] \\
\boldsymbol{P}_{xk+1,k+1} &= \boldsymbol{P}_{xk+1,k} - \boldsymbol{K}_{k+1}\boldsymbol{P}_{\gamma_{k+1,k}}\boldsymbol{K}^{T}_{k+1} \\
\boldsymbol{K}_{k+1} &= \frac{\boldsymbol{P}_{x\gamma_{k+1,k}}}{\boldsymbol{P}_{\gamma_{k+1,k}}}
\end{aligned} \tag{16}$$

Were Y_{k+1} is measurement value, $\boldsymbol{K}_{k+1}$ is the gain of KF and $\boldsymbol{P}_{xk+1,k+1}$ and $\hat{x}_{k+1,k+1}$ are corrected covariance and mean value respectively. The estimation algorithms are based on measurement data, and the sampling time is thus important and should be chosen such that it does not reduce the accuracy of the estimation.

Another important point to note is that process and measurement's noise, i.e. $\boldsymbol{Q}$ and $\boldsymbol{R}$ matrices, are calculated by trial and error. Some researchers believe that, due to the uncertain nature of system states; the process noise cannot be measured. Therefore, offline data can be used for calculating the process noise matrix. The initial value of $\boldsymbol{P}_x$ matrix is not important because the iterative process will correct the values of this matrix. In this paper, $\boldsymbol{Q}$ and $\boldsymbol{R}$ matrices are calculated using the Genetic Algorithm (GA). For this purpose, in addition to estimate unspecified parameters of the excitation system, measured signals are also re-estimated for total duration of estimation. The GA calculates the values of $\boldsymbol{Q}$ and $\mathbf{R}$ matrices in a way that measured and estimated signals be consistent with each other. The GA tries to fit the measured signal and it is estimated by using a least square error algorithm as a fitness function. The arrays of $\boldsymbol{Q}$ and $\boldsymbol{R}$ matrices are defined as the population in GA. At the end of the process, the best value of $\boldsymbol{Q}$ and $\boldsymbol{R}$ are selected for parameter estimation. Finally, the KF algorithm runs again with these optimized values to estimate parameters of the excitation system.

3. Excitation system model

With regard to the reference and the measured voltages, the excitation system controls the output of the exciter so that, in addition to maintaining the generator's terminal voltage; it shows a proper response in face of transient disturbances. From the power system point of view, the excitation system should help to control the terminal voltage efficiently and to enhance network stability. In order to improve the system stability, the excitation system must be able to respond quickly to disturbances and send an appropriate stabilization signal to damp the system oscillations.

In this paper, the studied power plant has a static excitation system type UNITROL 6800, manufactured by ABB. According to available documents in the power plant, it can be adapted as IEEE ST1A model [26]. This excitation system is mounted in a gas turbine of a combined-cycle power plant which is connected to substation through a power transformer. Fig. 1 shows the arrangement and load flow of power plant units. Fig. 2 and Table 1 depicts the ST1A model and its typical parameters respectively.

According to [26], in this type of excitation system, the time constant is very small and there is no need to use an AVR stabilizer. Therefore, in this analysis, it is assumed that T_a has a small value and K_f is equal to zero. Proper selection of T_{C1} and T_{B1} make it possible to increase the transient gain of the system. For this purpose, if needed, T_{C1} should be selected greater than T_{B1}. However, if there is no need for high transient gain, it is possible to select these values so that whose effects are ignorable. In this paper, these values are assumed zero. Since the generator operates in normal operating conditions and within the allowable ranges, there are usually no limiter's actions. Based on the aforementioned assumptions, the studied system can be represented as Fig. 3.

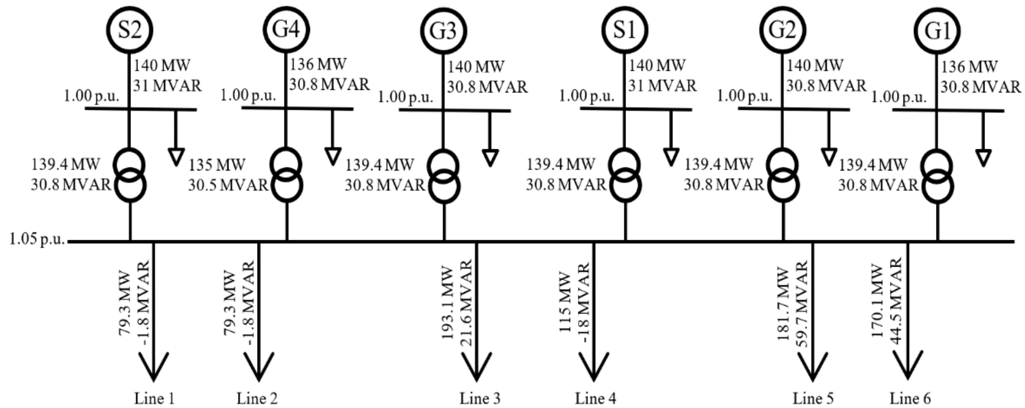

Fig. 1. ARRANGEMENT OF the UNITS OF THE POWER PLANT UNDER STUDY

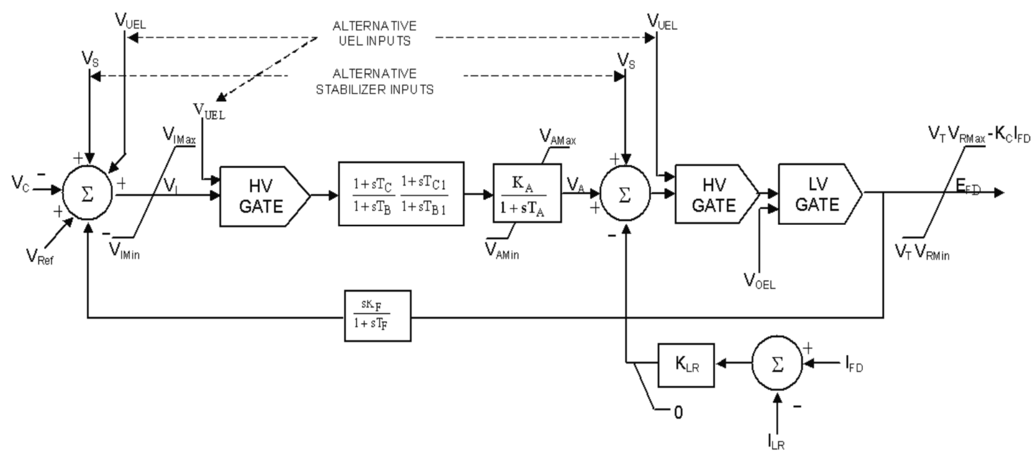

Fig. 2. ST1A EXCITATION SYSTEMS MODEL [26]

TABLE 1. SAMPLE VALUES OF PARAMETERS OF ST1A EXCITATION SYSTEM [26]

Exciter		
K_A = 100	T_{B1} = 0	V_{Imin} = -999
T_A = 0	V_{Rmax} = 7.8	K_F = 0
T_C = 1	V_{Rmin} = -6.7	T_F = 1 (not used)
T_B = 10	K_c = 0.08	K_{LR} = 0
T_{C1} = 0	V_{Imax} = 999	I_{LR} = 0 (not represent)

$$\begin{cases} V_{a_k} = V_{a_{k-1}} + \frac{\Delta t}{T_a}(k_a . V_{l_{k-1}} - V_{a_{k-1}}) \\ V_{t_k} = V_{t_{k-1}} + \frac{\Delta t}{T_t}(k_t . V_{a_{k-1}} - V_{t_{k-1}}) \\ V_{g_k} = V_{g_{k-1}} + \frac{\Delta t}{T_r}(k_r . V_{t_{k-1}} - V_{g_{k-1}}) \\ V_{l_k} = V_{l_{k-1}} + \frac{\Delta t}{T_b}(V_{ref_{k-1}} - V_{g_{k-1}} - \frac{T_c}{T_r}(k_r . V_{t_{k-1}} - V_{g_{k-1}}) - V_{l_{k-1}}) + \frac{T_c}{T_b}(V_{ref_k} - V_{ref_{k-1}}) \\ K_{a_k} = K_{a_{k-1}} \\ T_{a_k} = T_{a_{k-1}} \\ T_{b_k} = T_{b_{k-1}} \end{cases} \tag{17}$$

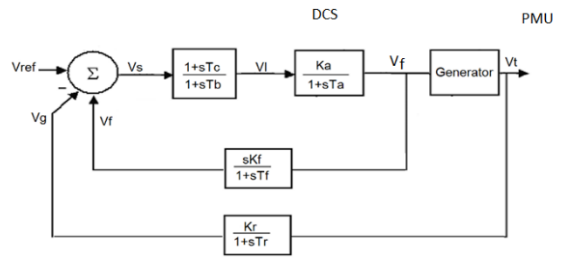

Fig. 3. THE GENERAL MODEL OF EXCITATION SYSTEM AND GENERATOR

In Fig. 3, T_c and T_b are the time constants of lead-lag block, K_a and T_a are the gain and the time constant of the exciter, K_f and T_f are the gain and the time constant of the excitation system stabilizer, and K_r and T_r are the gain and the time constant of the excitation system's voltage regulator. The generator model is also considered as a gain and a time constant (K_g and T_g). V_t shows the terminal voltage of generator, V_g is the generator voltage at the input of excitation system, V_s is the error, V_l and V_a are the input and output voltage of the exciter, respectively.
The system states vector will be selected as $x_k = [V_{a_k}, V_{t_k}, V_{g_k}, V_{l_k}]$. If the unknown parameters considered as state variables, these parameters can be estimated by KF algorithm too. Therefore, the final states vector will be $x_k = [V_{a_k}, V_{t_k}, V_{g_k}, V_{l_k}, K_{a_k}, T_{a_k}, T_{b_k}]$. Accordingly, the differential equations would be:
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4. SIMULATION AND DISCUSSION

The Iranian power grid is employed to evaluate the proposed algorithm. This grid has been simulated on the DIgSILENT software. Since generator parameters do not usually change during the operation time, their values are assumed as reported by the manufacturer. The power system stabilizer is considered to be off and the unit is connected to the grid, and the tests are performed online. Signals of excitation and generator terminal voltages are recorded with a sampling rate of 2.4 milliseconds by a fast recorder connected to the power plant DCS system. Online identification process usually uses the information obtained from planned disturbances or unplanned disturbances (network events). Step change in the reference voltage of excitation system and changes in the transformer tap position are the examples of planned disturbances. Neighbouring unit's trip is considered as network event that is unplanned and operational data. These disturbances are discussed below.

a. Change in reference voltage

Reference voltage changing is one of the most common disturbances, which is employed for parameters identification. It is commonly possible to make a sudden change in the reference voltage. In this paper, the reference voltage of the generator (G1) excitation system is stepped up to 1.02 per unit at t=5s, and then stepped down to 1 per unit at t=15s Fig. 4 represents the changes in the reference voltage and the response of the generator (G1).

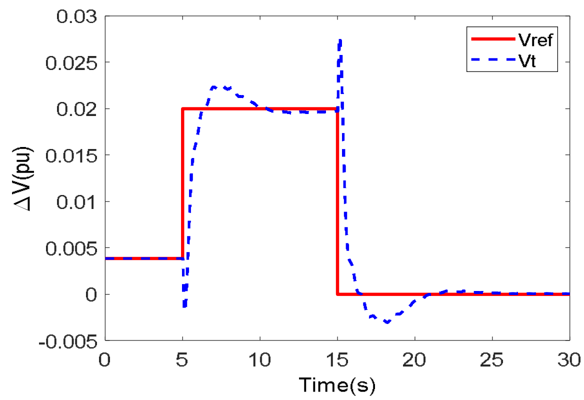


Fig. 4. CHANGE IN TERMINAL VOLTAGE OF GENERATOR AFFECTED BY A STEP CHANGE IN THE REFERENCE VOLTAGE

b. Changing the tap of unit transformer

Tap changing is one of the usual actions in the operation of the power plant. Fig. 5 shows changes in G1 terminal voltage where the transformer tap is moved up one step, and then returned to its previous position. As it can be seen, an impulse-like change is applied on the input of excitation system and thereafter, the system is stable.

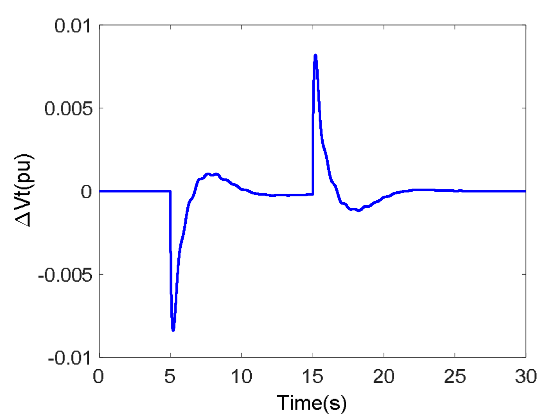


Fig. 5. CHANGES IN G1 TERMINAL VOLTAGE AFFECTED BY A CHANGE IN THE TRANSFORMER TAP

c. Trip of a neighbour unit

If it is not possible to carry out a planned disturbance, network event data (operational data) can be used for parameter identification. In this case, one of the units of the studied power plant suddenly trips and the recorded signals of G1 are used for identification. Fig. 6 shows changes of G1 terminal voltage affected by the trip of G2. As it can be seen, an impulse-like change is applied on the input of the excitation system and after some oscillations, the system returned to stable conditions

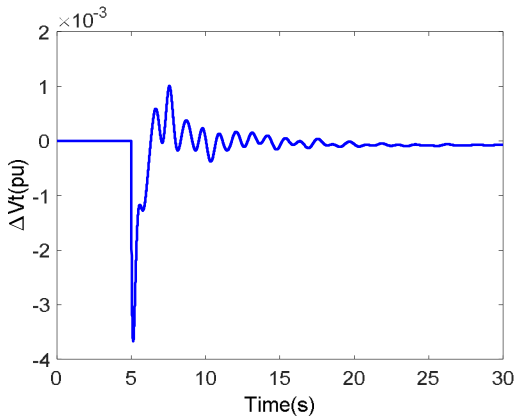


Fig. 6. CHANGING OF G1 TERMINAL VOLTAGE AFFECTED BY A NEIGHBOURED GENERATOR OUTAGE

The main purpose of this paper is performance evaluation and comparison of different types of Kalman filters in excitation system parameters identification. Accordingly, performances of these filters in identification of one or more parameters of an excitation system affected by the aforementioned disturbances are studied. Q and R matrices are selected by GA and are fixed further and do not change in different KF algorithms and different disturbances. It is clear that tuning the $Q$and R matrices, especially for each case will provide a better estimation for that case. The initial values of AVR parameters are selected based on the IEEE standard values.

4.1. Identification of parameter K_a

In the first step, the filters performance in identification of the gain parameter (K_a) is investigated. Fig. 2 presents K_a identification based on disturbances caused by change in the reference voltage, change in the transformer tap position, and the neighbour generator trip. As you can see in the figures, all three types of Kalman filters estimated an appropriate value for the parameter K_a. The disturbance caused by changing in the transformer tap provides more accurate value because the proximity of the signal to the impulse signal. The impulse signal contains all frequency components and excites all system modes. In G2 trip case, all three algorithms provide acceptable results.

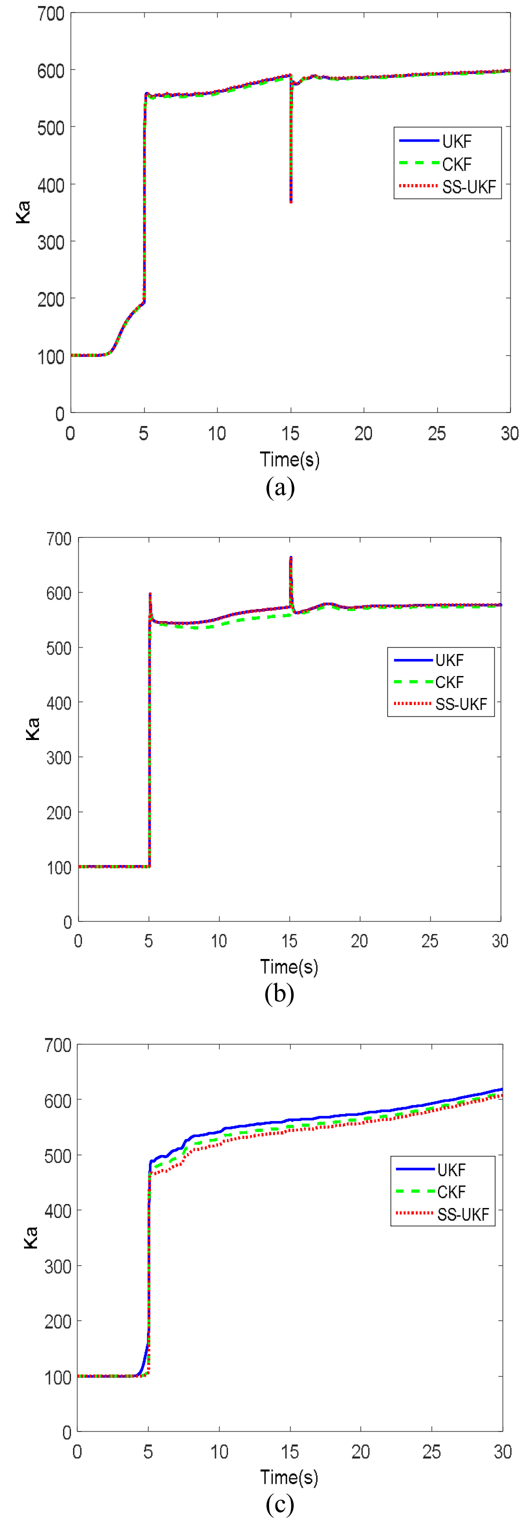
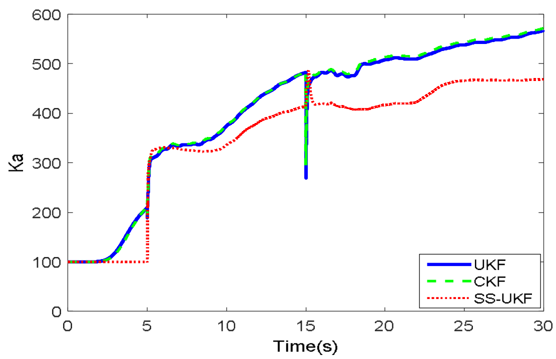


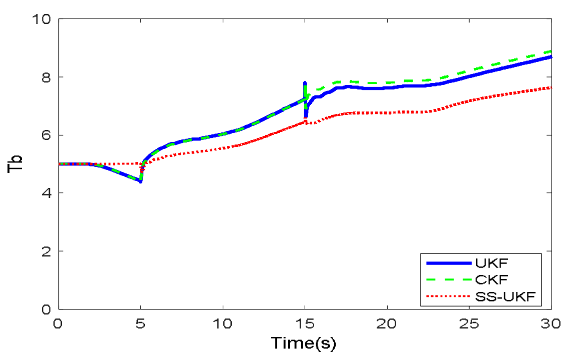
Fig. 7. ESTIMATED VALUE OF K_A IN A DIFFERENT DISTURBANCE (a: CHANGE IN REFERENCE VOLTAGE, b: TAP CHANGING, c: G2 OUTAGE)

4.2. Simultaneous Identification of Three Parameters: K_a, T_b, T_a

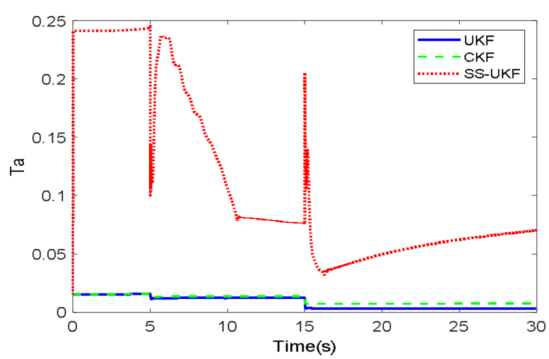
Identification of all three parameters of the excitation system is studied using described algorithms and disturbances. As shown in Fig. 8 to Fig. 10, SS-UKF algorithm cannot estimate an appropriate value of any parameters because of the number of the SPs and the order of the equation. Change in tap changer provides faster and more accurate responses than the other disturbances.



(a)



(b)



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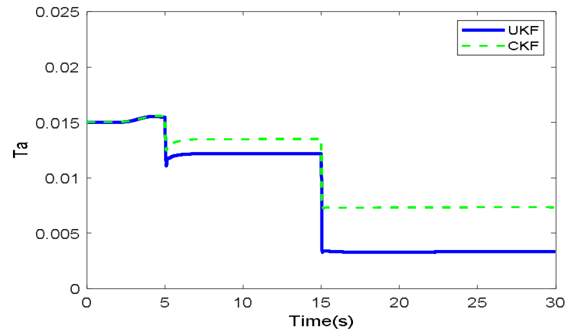


(d)

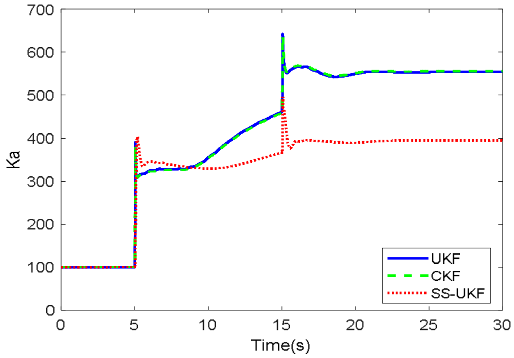
Fig. 8. ESTIMATED VALUE OF PARAMETERS IN A DISTURBANCE CAUSED BY STEP CHANGE IN REFERENCE VOLTAGE,
(a: K_a, b: T_b, c: T_a and d: T_a by UKF & CKF)

In the change of reference voltage case, T_a identification is not performed correctly and in comparison with the UKF and CKF algorithms, the CKF algorithm has less error. However, UKF provides a better result in transformer tap changer event. In the neighbour generator trip, UKF and CKF algorithms also converge to the appropriate values.

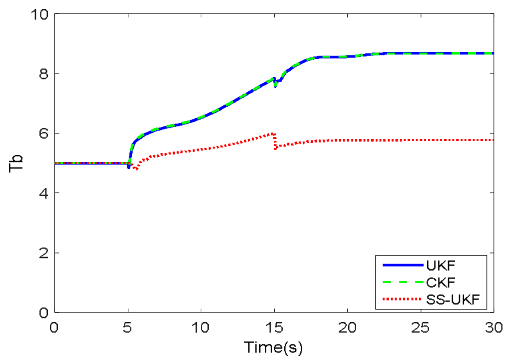
Table 2 shows the Excitation system parameters estimation by different input signals and various Kalman filters. According to the result and as discussed, tap changing provides more accurate results for excitation system parameters identification problem.

TABLE 2. ERROR OF DIFFERENT DISTURBANCES/METHOD IN EXCITATION PARAMETER ESTIMATION

Disturbance /Method	Step in reference voltage	Tap changing	Neighbor unit outage	Average error
UKF	0.29	0.03	0.066	0.11
CKF	0.22	0.04	0.08	0.13
Average error	0.25	0.0345	0.075	



(a)



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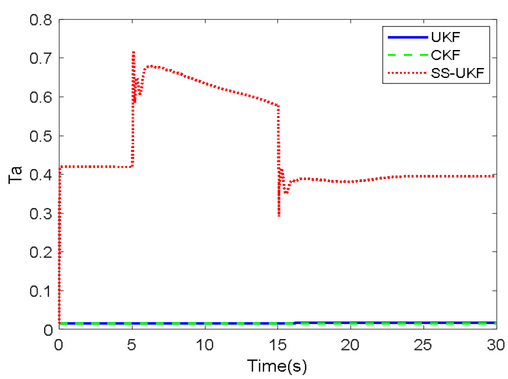
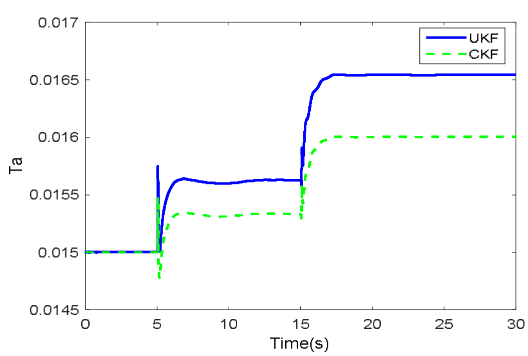
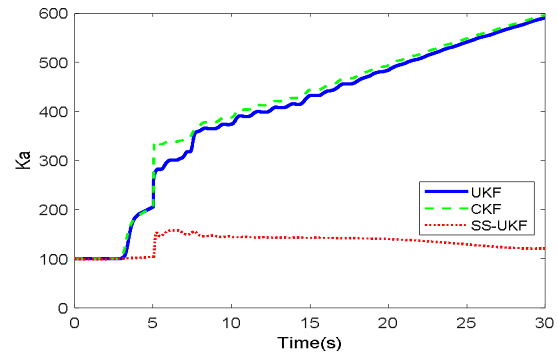


(c)

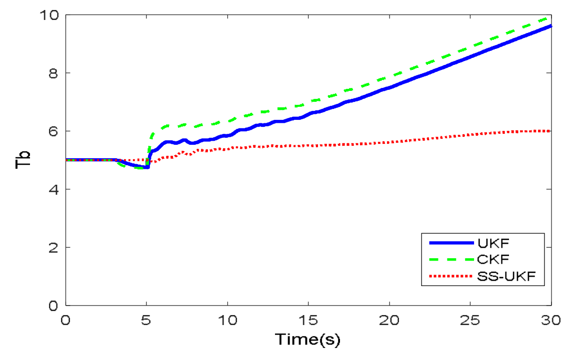


(d)

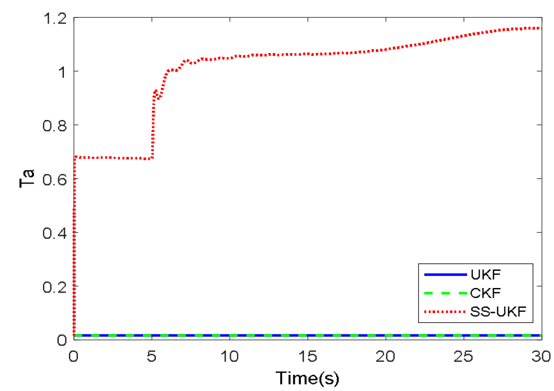
Fig. 9. ESTIMATED VALUE OF PARAMETERS IN A DISTURBANCE CAUSED BY TAP CHANGING, (a: K_a, b: T_b, c: T_a and d: T_a by UKF & CKF)



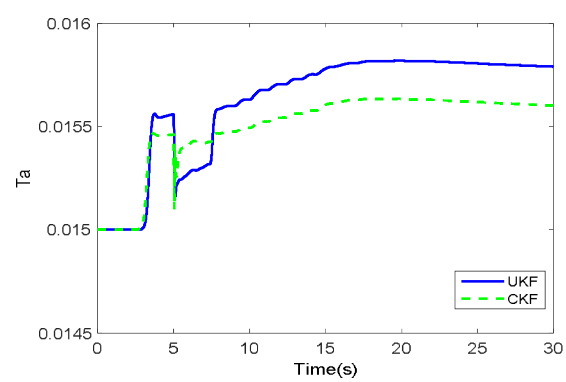
(a)



(b)



(c)



(d)

Fig. 10. ESTIMATED VALUE OF PARAMETERS IN A DISTURBANCE CAUSED BY TRIP OF G2, (a: K_a, b: T_b, c: T_a and d: T_a by UKF & CKF)

5. Real tests

In this section, UKF and CKF are applied on real case test results. Reference voltage of G2 in Fig. 1 test system, steps up 0.02 percent at t=4s and then steps down to the previous value at t=8s using the generator DCS system. To record the available signals a laptop was connected to the system by a Rj45 cable and recorded the available signals by rate of 2.4ms. Figure 11 shows change of the terminal voltage at this condition. This signal is employed to estimate the excitation parameters by KF algorithms. Because of the difference between the noise profiles of simulated and real signals, the matrix *R* is needed to calculate again. Fig. 12 shows the estimated parameters. The figure shows that UKF and CKF are able to estimate well the excitation parameters in real case too.

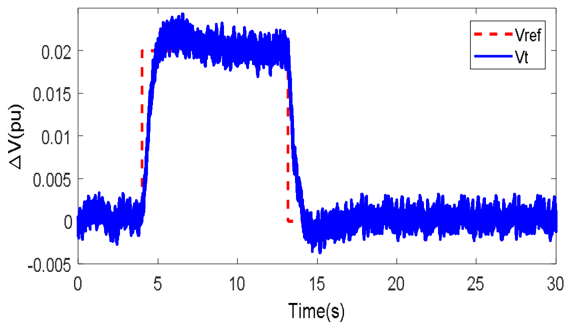


Fig. 11. Changing generator terminal voltage affected by a step change in the reference voltage

6. Conclusions

In this paper, the parameters of a generator excitation system are estimated with respect to three disturbances, including change in the reference voltage of excitation system, transformer tap changing and neighbour unit outage as inputs, using three types of Kalman filter including UKF, SS-UKF and CKF algorithms based on the simulation results.

All three disturbances and algorithms have a good response in the case of only one parameter estimation. However, when the number of estimated parameters is increased from one to three, the SS-UKF algorithm is not able to estimate correctly the excitation system parameters. Additionally, the disturbance caused by transformer tap changing provides more accurate estimation because of the similarity of the signal to the impulse signal. UKF and CKF were compared in Table 2. In addition, UKF and CKF are applied on real case test results by the reference voltage changing of the unit. Both filters are able to estimate well the excitation parameters.

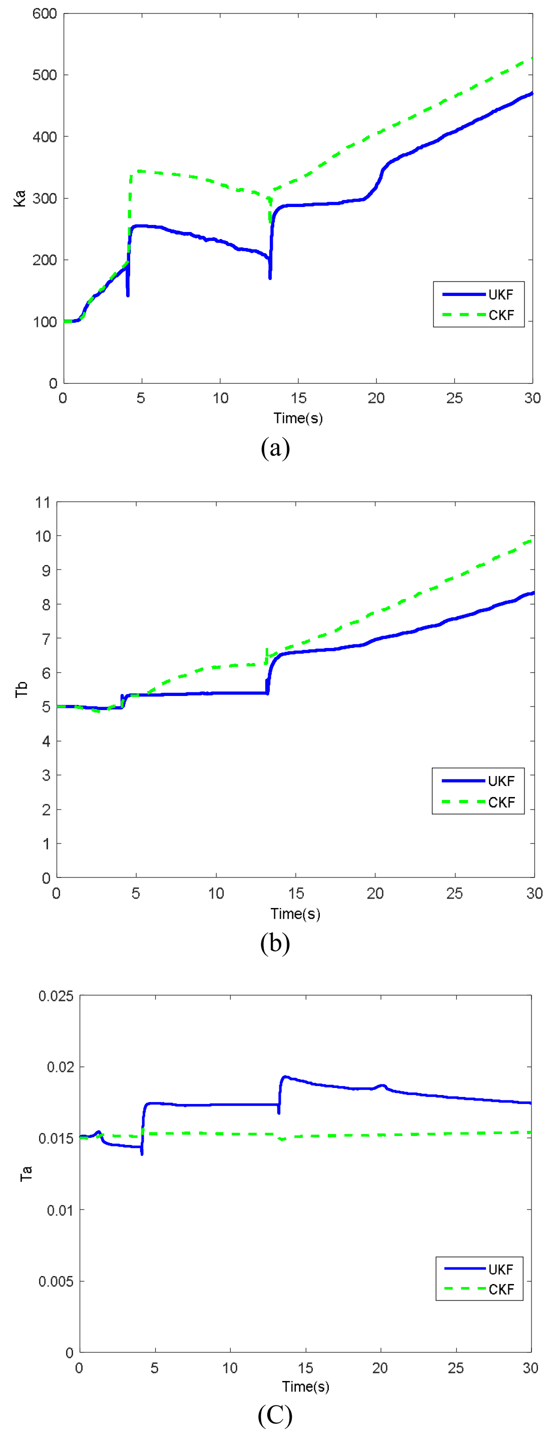


Fig. 12. Estimated parameters under real test, (a: K_a, b: T_b, c: T_a

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