Robust Kalman filter-based method for excitation system parameters identification using real measured data

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The excitation system is one of the most important components of a power plant. The network operator awareness of excitation system parameters is vital for accurate and efficient power system dynamic studies and optimal retuning. In this paper, the use of KFs for estimating generator excitation system parameters is proposed. The CKF is reformulated and developed for this purpose. A step disturbance in the reference voltage of the UNITROL 6800 excitation system -manufactured by ABB- is used to confirm the proposed method. The simulations are established based on a real case in Iran's grid, and the results are compared with the metaheuristics such as GA and PSO which have been widely employed in literature since now. The case studies indicate that the proposed method is more accurate and robust than the optimization algorithms, not only from mean value point of view but also from statistical point of view. Moreover, it is much more helpful to identify the parameters whose actual values are needed for optimal retuning.

keywords: *Parameter identification, Excitation system, Kalman filter, Metaheuristics.*

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NOMENCLATURE

Acronyms

PMU Phasor measurement unit
KF Kalman filter
AVR Automatic voltage regulator
CP Cubature point
PSS Power system stabilizer
GA Genetic algorithm
PSO Particle swarm optimization
PRBS Pseudo-random binary sequence
HMI Human-machine interface
EKF Extended Kalman filter
CKF Cubature Kalman filter
UKF Unscented Kalman filter

Matrices and vectors

$x(t)$ The vector of state variables
$u(t)$ The vector of input variables
$v(t)$ The noise vector of the process
$y(t)$ The vector of output variables (vector of measurement)
$w(t)$ The noise vector measurement signals
R, Q Covariance of process and signal noise
I Unit matrix
x The vector of random variables with given mean value and covariance (CPs vector)
p The error covariance matrix
X The square root error covariance matrix
A Submatrix of square root error covariance matrix
B Submatrix of square root error covariance matrix
$\widehat{x}_k$ The vector of CPs average values
y_k The vector of measurement points
$\widehat{y}_k$ Average of sample points of measurement
P_{xy}^k Cross covariance of CPs
P_{yy}^k The covariance of sample points of measurement
K_k The gain of CKF

Parameters and functions

f Transition function

h Transition function
Δt The sample time of signals
k The counter of KF algorithm iterations
n The number of state variables
ξ_i The i-th weight coefficient
U The standard step function
N The number of samples of measured signals
V_{ref} AVR reference voltage
V_f Excitation voltage
V_t Generator terminal voltage
V_g Feedbacked generator voltage in AVR
V_l The output signal of lead-lag compensator in AVR
K_a Gain of AVR
T_a Time constant of AVR
T_b Parameter of the lead-lag compensator
T_c Parameter of the lead-lag compensator
K_g The gain of the generator model
T_g Time constant of the generator model
K_r The gain of generator voltage feedback
T_r Time constant of generator voltage feedback
OF Objective function
V_{gk}^{Real} The k-th sample of the measured generator voltage signal
V_{gk}^{Sim} The k-th sample of the simulated generator voltage signal
x_m^{ij} The j-th component of i-th particle's position in m-th iteration of PSO
v_m^{ij} The j-th component of i-th particle's velocity in m-th iteration of PSO
w Inertia weight in PSO
c_1 Positive constant as a learning factor in PSO
c_2 Positive constant as a learning factor in PSO
$rand$ A random number within (0,1)
$x_{pbest,ij}^m$ The j-th component of i-th previous best particle's position in m-th iteration of PSO
$x_{gbest,ij}^m$ The j-th component of i-th global best particle's position in m-th iteration of PSO
r_m The mutation rate of GA
r_c Crossover rate of GA
N_{prn} Number of all the parents in GA
N_{prt} Number of all the particles in PSO

1. INTRODUCTION

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

During disturbances, numerous studies should be performed on the power system knowing the probable reactions of the power system and anticipating necessary measures to avoid critical situations. These studies need modeling of power systems and their components such as power plants. Dynamic study and simulation of power grid largely depend on equipment information of power plant components such as a generator, excitation system, governor, Power System Stabilizer (PSS) and etc. The use of inaccurate information in the decision-making process has great undesirable effects on network operation and planning.

Furthermore, the 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 no-optimal use of equipment and assets [2]. Lack of technical information in power plant documents, existence of typical information about a number of parameters, changes 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 dynamic studies [3].

In [4–6], the effect of systems 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. The network operator awareness of these parameter changes is vital to the success of dynamic studies. Due to the development of measuring devices and also introduction of new and more accurate estimation methods, it would be helpful to conduct more studies in the identification of excitation systems parameters. There are different methods to verify the model and to identify excitation system parameters. One of the most commonly used methods is to compare the simulated behavior of the system with its actual behavior after a disturbance event. Generally, there are three types of test to identify excitation system parameters [7, 8]:

- Offline test: In this test, the unit is out of service, and the excitation system is fed by an external power supply. The subsystems are separated from each other, and the tests are performed separately to find the transfer function of each section. After identification of each subsystem, a complete model is formed by combining the transfer functions. Then the model is verified as a closed-loop.
- Open circuit test: In this test, the generator is disconnected from the grid, and its speed and voltage are set to the nominal values. Open circuit test usually involves measuring the parameters of excitation system and generator in steady-state, dynamic tests of the closed-loop excitation system, and dynamic tests of limiters (by restricting the range of limitations).
- Online data-based test: In this test, the generator is connected to the grid and generates different active and reactive powers. Internal disturbances (such as a change in reference value of excitation voltage), external disturbances (such as changing the tap position in transformer or disconnecting a line), and information captured from grid actual events can be used in the identification process.

Performing offline and open circuit tests requires disconnecting a unit from the grid, and the power plant owner may lose the revenue from energy sales. In addition, though these tests may have a high risk for damaging equipment, they 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 the system under test. Among these, the methods based on heuristic algorithms, e.g. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used widely in the literature.

In [9–14], optimization methods based on metaheuristics were used for identification of excitation system parameters. In [9], the GA is employed for parameter identification of the excitation system, while an improved adaptive GA is used in [10]. The GA is also used in [11] for identifying the excitation system beside the synchronous generator parameters. The authors in [12] employ the GA to identify the parameters of the excitation system and synchronous generator of a steam power plant. In addition, the generator's excitation system is identified based on PSO algorithm in [13–15]. These metaheuristics are able to obtain several different sets of parameters, which based on those parameters the measured and estimated signals are in close agreement. In this way, the defined error as objective function is minimized and the algorithm is easily implemented. 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 the operation period. Therefore, the results of metaheuristic-based identification are not reliable for optimal re-tuning the parameters of the Automatic Voltage Regulator (AVR).

In addition to the employed method, the type of inputs is an important step in the 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 identification algorithms, can be obtained through the different kinds of disturbances. In [16] information of online planned disturbances (a step input in excitation system reference or a planned unit outage) and unplanned disturbances are used for parameters' validation and identification. This reference suggested step test data to identify the parameters of the excitation system and frequency variation's data for estimation of turbine and governor parameters.

In [9, 13, 17], the Pseudo-Random Binary Sequence (PRBS) signals were used as input in the identification process. PRBS signals are the most appropriate signals for parameter identification. However, due to lack of comprehensive use of the PRBS generators in practice, and also lack of permission to inject the signal at the reference voltage point/or other points on the excitation system in private power plants, using of PRBS signals in excitation system parameter's identification is very limited.

Nowadays, by the development of Phasor Measurement Units (PMUs) in power networks, the use of unplanned inputs or sudden network disturbance's data on the identification process attracts more attention. In [17, 18], the identification was done by the network's disturbances, which have not caused the unit instability. The authors stated that the parameter's identification in actual conditions is precisely what the network operator and planner deal with. In [19], the HV side frequency and 3-phase voltages signals that were measured by PMU are employed for identification. Amplitude and damping of oscillation have been considered as an indicative factor between measurement and simulation values mismatch. 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 a 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. In [16], some limitations in measurement, sampling rate and optimal location are announced as PMUs weak points. Furthermore, during a disturbance, the plant may be unavailable because of overhaul commitments, and the information will then be lost.

In [20, 21], an online method called Hybrid Simulation is proposed in which actual measurements and simulation data are combined to validate and identify the power system model and parameters. The authors in [17, 22] stated that the major problem in identification by real events is to create pre-event conditions for the bulk power system.

Overall the main challenges of excitation parameters identification in real conditions are summarized below:

- The actual tests are performed when the generator is connected to the electric grid i.e. online conditions; hence, the intensity and frequency of test disturbances are limited.
- There are some inaccessible points for signal measurement (especially in old power plants).
- The hardware-implemented parameters cannot be read via Human Machine Interface (HMI) even in modern excitation systems.
- Some parameters may be changed during a several-year operation; hence, the manufacturer documents are not completely reliable.
- There are several unknown parameters simultaneously for identification.
- There may be a number of candidate parameters sets, all of which minimize the overall error.

Consequently, it is required to use a powerful algorithm to overcome the above problems. In this paper, it is proposed to use the Kalman Filter (KF) for generator's excitation system parameter identification under online test conditions. The KF is commonly used for state estimation in power systems; however, it is reformulated and applied here for the excitation system parameter's identification. The proposed methodology is compared with the well-known metaheuristics considering a real case study in Iran. The novelties of this paper which distinguish it from the previous works are as follow:

- The KF is reformulated and used for the excitation system parameter's identification.
- The correlations between the AVR and exciter parameters are taken into account considering differential equations in a robust identification.
- The proposed method is compared with the well-known metaheuristics using statistical analysis.

The rest of the paper is organized as follows: Section 2 describes and formulates the proposed method based on Cubature Kalman Filter (CKF). The excitation system model and metaheuristic-based methods are presented in Sections 3 and 4, respectively. The case studies and simulation results are shown and discussed in Section 5. Finally, the concluding remarks are stated in Section 6.

2. IDENTIFICATION METHOD BASED ON KALMAN FILTER

KF is commonly used for state estimation in the power system [23–25], while it is used here for the excitation system parameter's identification. In this way, the unknown parameters are assumed as state variables along with the states of measuring signals. This process is carried out by adding the unknown parameter array to system equations. There are several types of KFs such as Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and CKF [26], all of which contains the following steps:

1. Selection of sample points and calculating the weight coefficients;
2. Prediction; and,
3. Correction of estimates.

The main difference between the aforementioned types of KF is in Step 1. In this paper, the CKF, as the newest version of KFs, is used for parameter identification. The CKF was proposed in 2009 to step up the UKF performance using spherical-radial cubature rule [27]. The CKF uses an even number of sample points called Cubature Points (CPs) with equal weights. These points are uniformly distributed on ellipses centered at the origin.

In order to employ the CKF for identification, it is firstly, required to define the nonlinear dynamic system equations, as shown in Eq. (1).

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

where the covariance of v(t) and w(t) are respectively represented with Q and R. It is noted that Q covers the modeling error of the system.

In real conditions, the measurement signals are discrete arrays. Hence, the continuous equations in Eq. (1) are rewritten in discrete form as follows:

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

Similar to the other types of KFs, the CKF is a recursive algorithm that predicts the conditional expectation of the states given all observations up to the current time. The measurement signals are used to correct the prediction at each time step.

The first step of KF, in fact, contains the initial calculations required for the next steps. In the beginning (when k=1), the error covariance is assumed to be an nn unit matrix, according to Eq. (3).

$$P^k_{xx,n\times n} = I_n \tag{3}$$

In addition, the weight coefficients are calculated using Eq. (4):

$$\xi_i = \frac{1}{2n}\sqrt{n}(-1)^{U\left(i-n-\frac{1}{2}\right)}, \quad i = 1,2,\ldots,2n \tag{4}$$

where the number of weight coefficients is twice of the number of state variables.

In the prediction process, firstly, the square root error covariance is calculated using the following equation:

$$\mathbf{X}^k_{n\times 2n} = \left[\mathbf{A}^k_{n\times n}|\mathbf{B}^k_{n\times n}\right] \tag{5}$$

where

$$\begin{aligned} \mathbf{A}^k_{n\times n} =& \hat{x}^k_{n\times 1}\mathbf{I}_{1\times n} + \xi_i \mathbf{P}^k_{xx,n\times n} \\ & i = 1,2,\ldots,n \end{aligned} \tag{6}$$

$$\begin{aligned} \mathbf{B}^k_{n\times n} =& \hat{x}^k_{n\times 1}\mathbf{I}_{1\times n} + \xi_i \mathbf{P}^k_{xx,n\times n} \\ & i = n, n+1,\ldots,2n \end{aligned} \tag{7}$$

Then, it is required to predict all the candidate state variables employing the dynamic model, which is obtained from the discrete state equations of the excitation system under study. Here, the set of state variables is a combination of recorded signals as well as the controller parameters.

For every state variable, there are $2n$ candidate states which are updated through this step. With respect to the predicted states i.e. updated states, the outputs of the system are determined using Eq. (8).

$$x^i_{k+1} = f\left(x^i_k, u_k, w_k\right), \quad i = 1,2,\ldots,2n \tag{8}$$

Afterward, considering the predicted outputs, it is feasible to calculate the related mean values and covariance according to Eqs. (9) and (10), respectively.

$$\hat{x}_k = \frac{1}{2n}\sum_{i=1}^{2n} x^i_k \tag{9}$$

$$\mathbf{P}^k_{xx,n\times n} = \sum_{i=1}^{2n}\frac{1}{2n}\left(x^i_k - \hat{x}_k\right)\left(x^i_k - \hat{x}_k\right)^{\mathrm{T}} + \mathbf{Q}_{k-1} \tag{10}$$

Due to the updated error covariance in Eq. (10), the square root error covariance is recalculated using Eqs. (5)-(7). Subsequently, the new measurement points are predictable according to the following equation:

$$y^i_k = h\left(x^i_k, u_k, v_k\right) \tag{11}$$

At the end of the prediction step, the mean value and covariance of the predicted measurements as well as their cross-covariance, sample points of state variables and measurements are estimated using Eqs. (12)-(14).

$$\hat{y}_k = \frac{1}{2n}\sum_{i=0}^{2n} y^i_k \tag{12}$$

$$\mathbf{P}^k_{yy,n\times n} = \sum_{i=1}^{2n}\frac{1}{2n}\left(y^i_k - \hat{y}_k\right)\left(y^i_k - \hat{y}_k\right)^{\mathrm{T}} + \mathbf{R}_k \tag{13}$$

$$\mathbf{P}^k_{xy,n\times n} = \sum_{i=1}^{2n}\frac{1}{2n}\left(x^i_k - \hat{x}_k\right)\left(y^i_k - \hat{y}_k\right)^{\mathrm{T}} \tag{14}$$

In the correction step, the estimated results can be improved thanks to the availability of the actual measurements. In this way, the outputs of Eqs. (13) and (14), i.e. P^k_{yy} and P^k_{xy}, are used to determine the Kalman gain in k-th iteration, as shown in Eq. (15).

$$\mathbf{K}_k = \mathbf{P}^k_{xy,n\times n}\left[\mathbf{P}^k_{yy,n\times n}\right]^{-1} \tag{15}$$

Finally, this gain is employed to update the estimated states and the covariance matrix, with respect to Eqs. (16) and (17), respectively.

$$\hat{\boldsymbol{x}}_{k+1} = \hat{\boldsymbol{x}}_k + \mathbf{K}_k\left[\boldsymbol{y}_k - \hat{\boldsymbol{y}}_k\right] \tag{16}$$

$$\mathbf{P}^{k+1}_{xx,n\times n} = \mathbf{P}^k_{xx,n\times n} - \mathbf{K}_k\mathbf{P}^k_{yy,n\times n}\left[\mathbf{K}_k\right]^{\mathrm{T}} \tag{17}$$

The prediction and correction steps are consecutively iterated for N times to converge to the final parameters. Another important point to note is that process and measurement's noise, i.e. $\mathbf{Q}$ and $\mathbf{R}$ 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

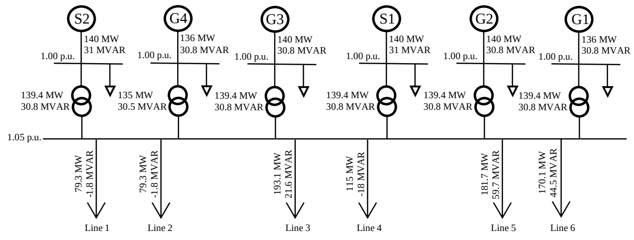

Fig. 1. The arrangement of combined cycle power plant's units under study.

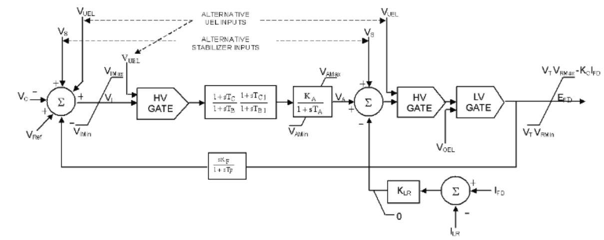

Fig. 2. ST1A excitation systems model.

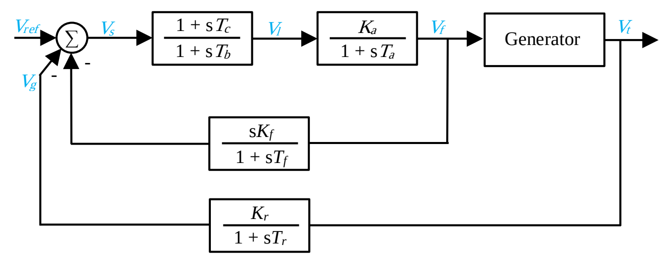

Fig. 3. Transfer function of the system under study.

data can be used for calculating the process noise matrix. The initial values of P_{xx} matrix is not important because the iterative process will correct the values of this matrix. In this paper, **Q** and **R** matrices are calculated using the 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 **Q** and **R** matrices in a way that measured and estimated signals are consistent with each other. The GA tries to fit the measured signal and it is estimated using a least-square error algorithm as a fitness function. The arrays of **Q** and **R** matrices are defined as the population in GA. At the end of the process, the best values of **Q** and **R** are selected for parameter estimation. Finally, the CKF algorithm runs again with these optimized values to estimate the 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 control the voltage of the generator efficiently and 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. In static excitation systems, the supply is taken from the generator itself through a step-down transformer whose primary is connected to the generator bus. The secondary winding supplies power to a controllable rectifier which provides the necessary field current to the rotor winding of the synchronous machine. The system has a fast transient response and provides excellent dynamic performance. This excitation system is mounted in a gas turbine of a combined-cycle power plant which is connected to a 230 kV substation through a power transformer. The rated apparent and active powers of every unit are 200 (MVA) and 160 (MW), respectively. Fig. 1 shows the arrangement and load flow of power plant units.

According to available documents in the power plant under study, the static excitation system namely UNITROL 6800, manufactured by ABB, can be adapted as IEEE ST1A model [28]. The ST1A model is presented in Fig. 2.

In this type of excitation system, the time constant is very small and there is no need to use an AVR stabilizer. Therefore, it can be 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 descriptions, the block diagram and actual parameters of the excitation system under study are presented in Fig. 3 and Table 1, respectively.

Table 1. The actual value of parameters of the system under study

Parameter	T_c	T_b	K_a	T_a
Value	1 (sec)	9.1667 (sec)	550	0.017 (sec)
Parameter	K_f	T_f	K_r	T_r
Value	0	1 (sec)	1	0.02

In this paper, three parameters including K_a, T_b, and T_a are assumed unknown, which must be estimated. The generator is considered as a first-order model with a gain and a time constant (i.e. K_g and T_g). V_t represents the terminal voltage of the generator, V_g is the generator voltage at the input of the excitation system, V_s denotes the error of voltage magnitude, V_l and V_f are the input and output voltage of the exciter, respectively.

The system states vector are selected as $x_k = [V_{fk} \quad V_{tk} \quad V_{gk} \quad V_{lk}]$. If unknown parameters are considered as state variables, these parameters can be estimated by KF algorithm, as well. Therefore, the final states vector will be $x_k = [V_{fk} \quad V_{tk} \quad V_{gk} \quad V_{lk} \quad K_{ak} \quad T_{ak} \quad T_{bk}]$.

According to the block diagram, system equations for updating/correction steps are as follows:

$$V_{f_{k+1}} = V_{f_k} + \frac{\Delta t}{T_a}\left(K_a \cdot V_{l_k} - V_{f_k}\right) \quad (18)$$

$$V_{t_{k+1}} = V_{t_k} + \frac{\Delta t}{T_g}\left(K_g \cdot V_{f_k} - V_{t_k}\right) \quad (19)$$

$$V_{g_{k+1}} = V_{g_k} + \frac{\Delta t}{T_r}\left(K_r \cdot V_{t_k} - V_{g_k}\right) \quad (20)$$

$$V_{l_{k+1}} = V_{l_k} + \frac{\Delta t}{T_b}\left(V_{ref_k} - V_{g_k} - \frac{T_c}{T_r}\left(K_r \cdot V_{t_k} - V_{g_k}\right) - V_l + \frac{T_c}{T_b}\left(V_{ref_{k+1}} - V_{ref_k}\right)\right) \quad (21)$$

$$K_{a_{k+1}} = K_{a_k} \quad (22)$$

$$T_{a_{k+1}} = T_{a_k} \quad (23)$$

$$T_{b_{k+1}} = T_{b_k} \quad (24)$$

As the controller parameters are fixed, those are the same in (*k+1*)-th and *k*-th step. So Eqs. (22)-(24) are added to transfer function as the state of the unknown parameters.

4. METAHEURISTIC-BASED METHODS

The metaheuristics are iterative optimization algorithms, which are used to minimize/maximize a predefined objective function. They search in candidate solution's space in stochastic manner with respect to the feedback of objective function calculation. In the use of metaheuristics for excitation system parameters identification, it is required to minimize the estimation error as the objective function. In this way, the error of simulated signal compared with the real recorded signal should be calculated. As the target signal is recorded in a discrete manner, the error, i.e. the objective function is defined considering recorded samples, as follows:

$$OF = \sum_{k=1}^{N}\left\{(V_{gk}^{\text{Real}} - V_{gk}^{Sim})^2\right\} \quad (25)$$

where V_{gk}^{Sim} is obtained from transfer function simulation (Fig. 2) considering the candidate parameters. In the following, the procedure of GA and PSO algorithms to manipulate the candidate parameters is described.

A. GA

The GA is a population-based algorithm that starts from an initial population containing random candidate parameters. The algorithm is based on three main operators mentioned below [29]:

1. Crossover;
2. Mutation; and,
3. Selection.

The crossover and mutation operators are used to create offspring form the old population i.e. parents. The objective function of new candidates, which are produced randomly considering the crossover and mutation rates, is calculated using Eq. (25). Then the new candidates are compared with the old solutions, so that, the most suitable solutions are selected to move to the next iteration. This process is iterated until the GA converges to a global or near-global optimum. The performance of GA is shown in Fig. 4. More details about GA can be found in [30]

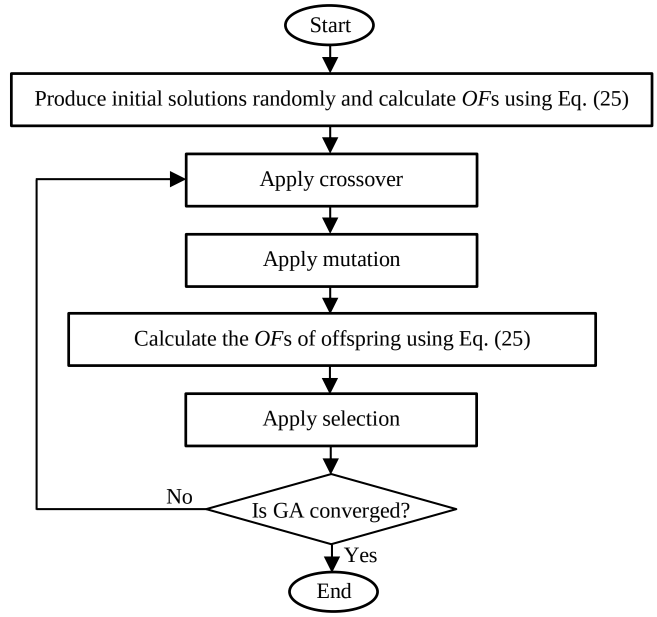

Fig. 4. Flowchart of GA to be used in parameter identification.

B. PSO

Similar to GA, the PSO is a population-based algorithm. Considering an initial population that is produced randomly, the candidate solutions are moved in the search space with a specified velocity. In every iteration, the position of particles i.e. candidate solutions is changed according to Eq. (26).

$$x_{ij}^{m+1} = x_{ij}^{m} + v_{ij}^{m+1} \quad (26)$$

The velocity of every particle i.e. candidate solution is updated with respect to its inertia, its own position, its previous best position and the global best position of population, as follows:

$$v_{ij}^{m+1} = w \times v_{ij}^{m} + c_1 \times \text{rand} \times \left(x_{pbest,ij}^{m} - x_{ij}^{m}\right) + c_2 \times rand \times \left(x_{gbest,j}^{m} - x_{ij}^{m}\right) \quad (27)$$

where the x_{pbest}^{m} and x_{gbest}^{m} are determined considering the objective function shown in Eq. (25). The constants c_1, c_2 and w are specified with respect to the literature. The performance of PSO is represented in Fig. **??**. More details about PSO can be found in [30].

The parameters of metaheuristics are initially set considering the recommendations in [29, 30], and then they are improved with trial and error. The final employed parameters of GA and PSO are shown in Table 2.

5. CASE STUDIES AND RESULTS

Iran's 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 PSS is considered to be off and the unit is connected to the grid, and the experiments are performed online. Online identification process usually uses the information

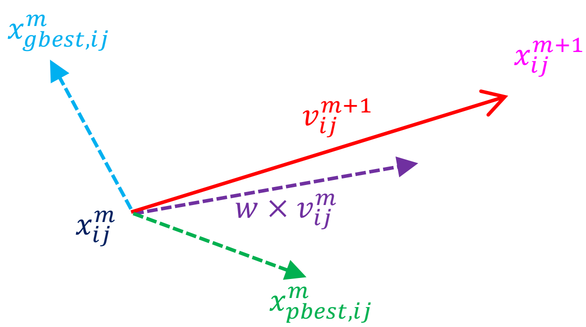

Fig. 5. Movement of particles in PSO algorithm.

Table 2. Parameters of metaheuristics for identification

Parameter	Value
r_m	0.33
r_c	0.5
N_{prn}	10
W	0.98
C_1	2
C_2	9
N_{prt}	10

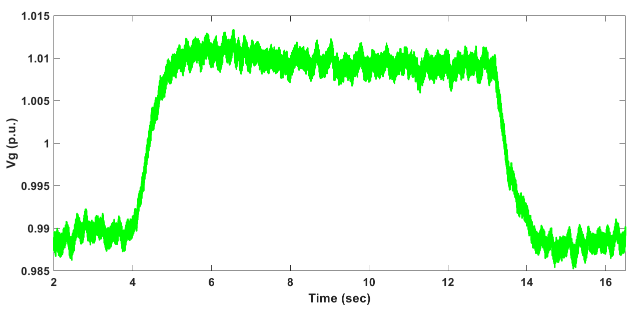

Fig. 6. The recorded signal i.e. V_g in power plant.

obtained from programmed disturbances or unplanned disturbances (network events). Changes in the reference voltage of the excitation system and changes in the transformer tap position are examples of programmed disturbances. On the other hand, the neighboring unit's trip is considered as an unplanned disturbance.

Change in reference voltage is one of the most common disturbances, which is employed for parameters identification. As mentioned before, it may be impossible to inject PRBS signal in all conditions or in all power plants, but in all systems, it is commonly possible to make a sudden change in the reference voltage. It should be noted that it is impossible to make step changes in the reference voltage in some old systems, and the change should be applied as a ramp with a high slope. In this paper, the standard step function is used for change in reference voltage. According to the test procedure, the 2% step change (increasing/decreasing) is applied to the reference voltage of AVR and the voltage of the generator is recorded as presented in Fig. **??**.

In order to record the accessible signal, a laptop was connected to the system using a Rj45 cable and the signal is recorded with the sample rate of 416.67 (Hz). This signal is employed to estimate the excitation parameters using CKF algorithm, and the results are shown in Fig. **??**. As can be seen, the main correction of parameters is established during step change in reference voltage, and finally, the estimation is converged in steady-state of the step response. In this case, the proposed method is capable to estimate the excitation parameters with the average error of 7.09%.

In order to specify the advantages of the proposed method, it is compared with the conventional methods in the literature, i.e. GA and PSO algorithms. The results of these metaheuristics for parameter identification are shown in Table 3, where the GA and PSO are run several times for the real case studied.

The GA and PSO give a wide range of different parameters in each run; so, it is not possible to achieve the real parameters. However, the proposed method is capable to obtain near actual parameters in only one run. The reason is that the GA and PSO, which are based on stochastic search, do not take into account the relations among the parameters; while the CKF considers the differential equations and parameter correlations in its identification procedure. Hence, the average error of CKF is much less than the average error of the GA and PSO, as shown in Fig. **??**.

Table 3. The extracted parameters using GA and PSO in 17 runs

GA			PSO		
K_a	T_b	T_a	K_a	T_b	T_a
136.8	4.3009	0.0011	556.1	18.2691	0.0019
105.5	3.274	0.0126	264.7	8.8441	0.0012
119.9	3.8835	0.004	523.5	17.3416	0.0014
375.4	12.5498	0.001	265.4	8.6834	0.0019
109	3.3453	0.0024	258.6	8.3454	0.0034
109.8	3.5256	0.001	263.2	8.7499	0.0006
153.7	5.0935	0.0011	263.3	8.6954	0.0029
174.3	5.6551	0.001	258.4	8.5228	0.0027
139.5	4.3598	0.0014	241.1	7.3964	0.0043
142.7	4.5699	0.0001	601.5	19.9965	0.0109
234.5	7.7378	0.0001	218.2	7.3402	0.012
196.9	6.5824	0.0001	271.7	9.0749	0.0001
180.2	5.889	0.0001	270.9	8.7437	0.0001
472.6	15.6211	0.0001	276.4	8.9418	0.0001
234.4	7.809	0.0003	276.1	9.29	0.0001
154.1	5.14	0.0001	248.7	8.1727	0.0044
182.8	6.1185	0.0001	261.3	8.9936	0.0022

In addition to the average error, the statistical properties of the GA, PSO and CKF are compared in Fig. **??**, where the box plots are used for clarification. As can be seen, the CKF is more precise than the GA and PSO, not only from mean value point of view, but also from variance and skewness perspective.

It is notable that the real parameters may not be obtained using GA and PSO, even if the objective function i.e. defined error in metaheuristics, is reached to zero. The reason is that the search space usually contains several global optimums which result in zero errors with different parameters, as shown typically in Fig. **??**. As the overall error minimization is the alone index of optimization algorithms to identify the parameters, this issue

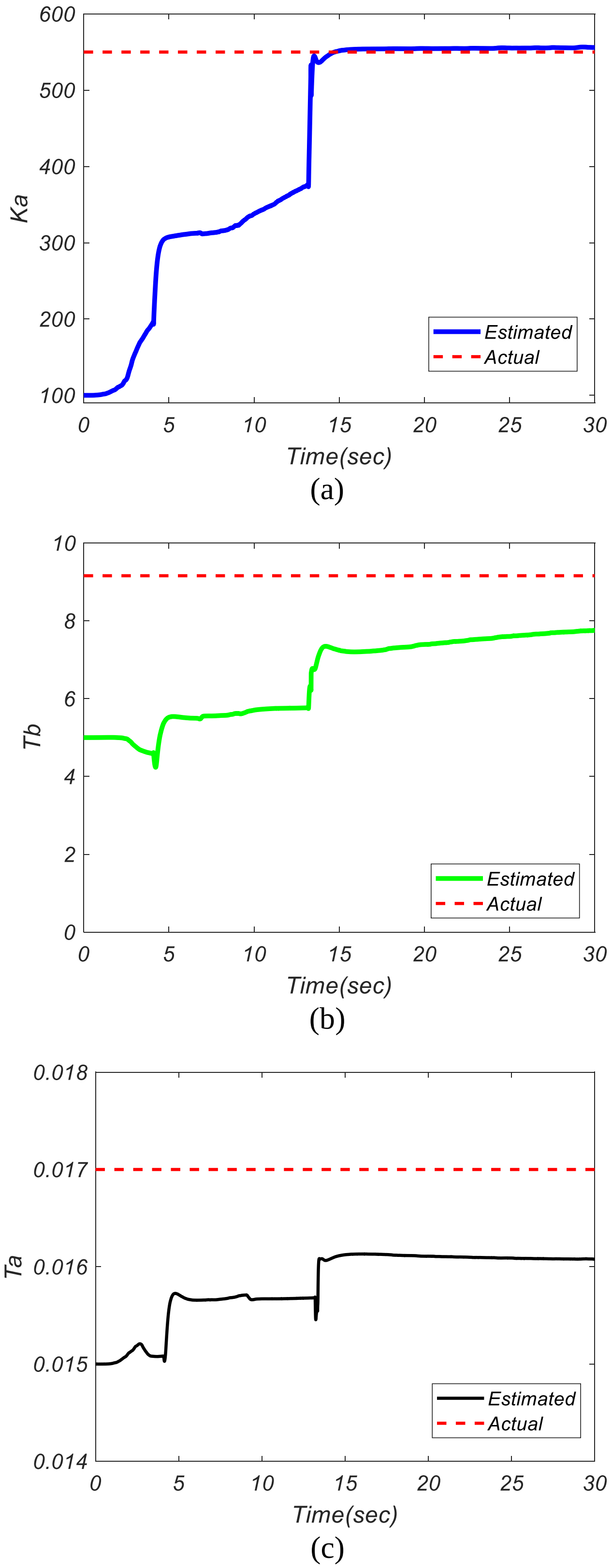

Fig. 7. Estimation trajectory of CKF in the real case for parameters (a) K_a, (b) T_b, and (c) T_a.

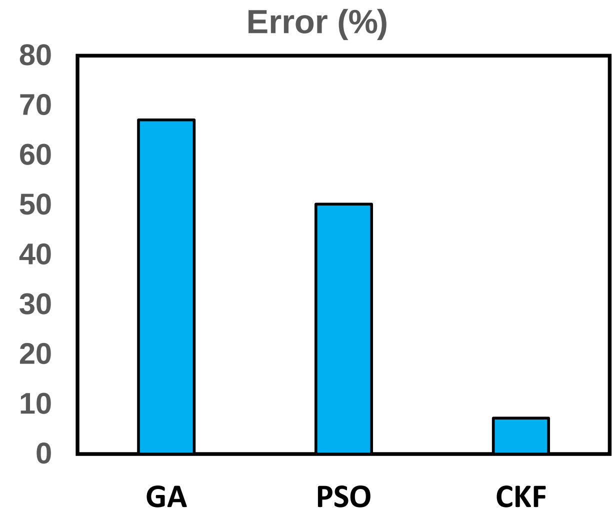

Fig. 8. Comparison of the average error of GA, PSO and CKF.

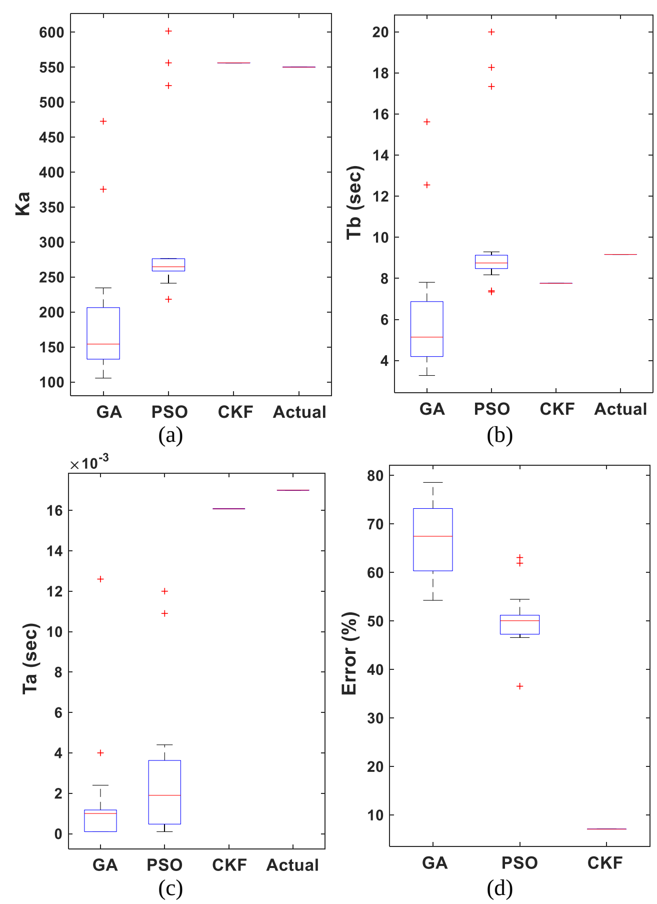

Fig. 9. The statistical presentation of the GA, PSO and CKF detailed results.

is more serious when the number of unknown parameters is increased, and the search space becomes more complex. Hence, it is necessary to develop the structure-based methods such as KFs for parameter's identification in real conditions.

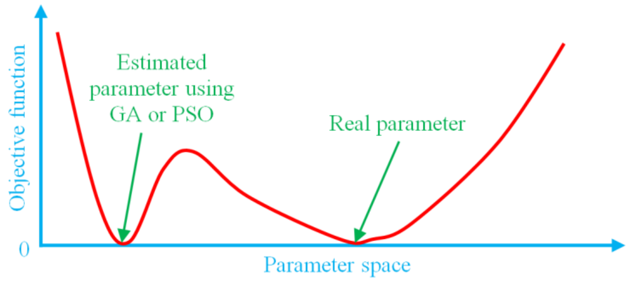

Fig. 10. A typical search space of GA and PSO for parameter identification.

6. CONCLUSIONS

In this paper, it is proposed to use KFs for identifying the excitation system parameters. In this way, the newest version of KFs, i.e. the CKF, is developed to handle the problem of parameter identification. In this situation, the unknown fixed parameters are taken into account as state variables. Consequently, the differential equations of transfer function are considered and rewritten to be used as a part of CKF formulation. As a real case study, the reference voltage step disturbance applied to UNITROL 6800 excitation system manufactured by ABB of a power plant in Iran electric grid is employed to verify the proposed algorithm. The simulation results show that the proposed method is capable to identify the unknown parameters with high accuracy. The advantage of the proposed method is that it results in a unique solution which is much more accurate than the conventionally used algorithms in literature e.g. GA and PSO. The case studied based on real recorded signals confirms that the proposed method is applicable. Unlike the metaheuristics, it is not based on stochastic variables, so it is robust especially when the actual value of parameters is required for the purpose of returning.

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