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Original Article

An Improved Unscented Kalman Filter Algorithm for Dynamic Systems Parameters Estimation

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Abstract

The high capabilities of unscented Kalman filter (UKF) for estimating the state variables of a dynamic system have led to its use for parameter estimation as well. To use the UKF to estimate the unknown parameters of a dynamic system, the parameters generally be assumed in the form of virtual state variables. This paper first shows that this assumption causes some serious problems. Then, trying to solve the problem, a modified UKF algorithm will be presented. In the proposed version of the UKF algorithm, unlike the traditional one, the whole of the measurement signal samples is used as input in each stage of the estimation process. Eventually, using the proposed algorithm, the parameters of a turbine-governor system as a typical dynamic system are estimated and the efficacy of the method is investigated. The results depict that the proposed method overcomes the shortcomings of the conventional method and shows high efficiency and better performance.

Keyword*s*- Unscented Kalman Filter, Parameter Estimation, Turbine-Governor

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1. INTRODUCTION

Power systems stability studies largely depend on model and parameter information of grid components such as generators, transmission lines, power system stabilizers, etc. [1]. Incorrect information in the decision-making process has many adverse effects on network planning and operation. In addition, the lack of information about the model and its parameters may force electrical engineers to make conservative decisions which can lead to non-optimal assets utilization [2].

The absence of technical data in equipment documentation, changes in some parameters at the time of system commissioning, as well as the replacement and depreciation of equipment make it inevitable to identify the dynamic parameters of system components [3-6]. There are various methods for the identification of system parameters. Optimization methods based on heuristic algorithms and Kalman filter (KFs) based algorithms are examples of these methods. In [7-10], the former methods such as Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) have been presented. These methods provide different sets of values for the parameters to match the measured and estimated signals. However, the goal of parameter estimation is to find the exact value of parameters currently set on the system (some parameters may be changed and re-adjusted by operators during the operational period).

The unscented Kalman filter (UKF) has been also used for state estimation problems [11-14]. The method can also be utilized to estimate system parameters. This is done by changing the state estimation problem to the combined parameter and state estimation problem. Although the conventional UKF has many advantages for the estimation of state variables of nonlinear systems, its accuracy, and stability are reduced in cases where it is used for the identification of system parameters. To do this, several methods have been presented in [15-18] that try to increase the accuracy in both state estimation and parameter identification problems. However, there will always be two major challenges in parameter identification with the UKF method.

- Assuming the unknown system parameters as state variables makes the problem more complicated.
- The number of state variables increases with the addition of unknown parameters, while due to some economic limitations, the number of measurement signals cannot be increased.

These challenges make solving the estimation problem more difficult and sometimes even may lead to the non-convergence of the estimation process. In this paper, an attempt has been made to propose a solution for a better estimate of dynamic systems parameters by the UKF. Accordingly, a major modification is applied to the UKF algorithm. A standard turbine-governor system of TGOV1 type is chosen as a test system to describe the effectiveness of the proposed method. The major novelties of the paper are as follows:

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- The proposed method is actually an evolutionary method with the difference that its evolution principles do not have random behavior like heuristic algorithms. It is based on KF rules and relations and enjoys all the KF method advantages.
- The proposed method can be a useful alternative to the conventional UKF method with better performance for parameters identification.
- The proposed idea looks similar to a smoothing approach whose practical result is to filter out estimates with little physical meaning that normally arise when the number of state-variables is increased.

The rest of the paper is organized as follows: Section 2 represents the description of the UKF method. In section 3, the UKF method is used for estimating the unknown parameters of a typical dynamic system. Section 4 examines the potentials of the UKF method, analyzes its deficiencies, and subsequently represents an improved version of the UKF algorithm. In section 5, the efficacy of the proposed method is investigated. The conclusion will be the last section of this paper.

2. State estimation with Kalman filter

Recently, Kalman filtering-based methods have been employed for the state estimation of dynamic systems. These methods can also be used for parameter estimation. This is performed by adding the vector of unknown parameters to the system state variables [19]. For several decades, EKF has been the most common type of Kalman filter in nonlinear systems estimation problems [20]. For systems with a high degree of nonlinearity, EKF does not show good accuracy and stability [21]. According to the limitations of the EKF, the UKF was proposed to estimate the state variables of nonlinear dynamic systems. Unlike the EKF, which approximates nonlinear state equations through the linearization process, the UKF uses a set of well-chosen sample points (SPs) to represent the distribution function of state variables. Alongside the high approximation accuracy, the UKF avoids heavy Jacobian matrix computations and simplifies the implantation of the algorithm [14]. It is worth noting that, other methods such as the cubature Kalman filter (CKF) have also been presented for state estimation of nonlinear dynamic systems, whose major difference with the conventional UKF is in the method of choosing the SPs and calculating weight coefficients [22].

Below, the UKF method and its usage for both state and parameter estimation of non-linear dynamic systems are discussed. The behavior of a non-linear dynamic system can be modeled using continuous-time dynamic equations as follows:

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

where, $\boldsymbol{x}(t)$ represents the state variable vector, $\boldsymbol{y}(t)$ denotes the vector of output variables (measurement vector), $\boldsymbol{u}(t)$ shows the vector of input variables, $\boldsymbol{v}(t)$ indicates the process noise vector with the covariance value of $\mathbf{Q}$ which can also include the modeling error of the system, $\boldsymbol{w}(t)$ represents the measurement noise vector with the covariance value $\boldsymbol{R}$, and f and h indicates the non-linear functions. If Δt assumed as the time step, equation (1) can be written in a discrete form as follows:

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

where $\boldsymbol{x}_k$ indicates the state variables vector of the discrete system with a specific mean and covariance value. UKF is a recursive algorithm and includes three stages: estimating the SPs and calculating the weight coefficients, prediction stage, and correction stage.

2.1. Estimation of the SPs and calculation of the weight coefficients

An n-dimensional state vector $\boldsymbol{x}_k$ is considered a random variable vector with the mean value of $\hat{x}_{k,k}$ and covariance of $\boldsymbol{P}_{k,k}$. By knowing $\hat{x}_{k,k}$ and $\boldsymbol{P}_{k,k}$, $2n+1$ vectors (sample vectors) are determined using the following relations. These equations model the random nature of the state variable vector x_k with the mean value, $\hat{x}_{k,k}$, and the covariance matrix $P_{k,k}$.

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

where, $\left(\sqrt{(n+\lambda)\boldsymbol{P}_{k,k}}\right)_i$ represents the i_{th} element of the second order matrix $(n+\lambda)\boldsymbol{P}_{k,k}$, which is obtained through Cholesky decomposition [22]. The weighting factors of the covariance and the mean values, u_c^0 and u_m^0, are calculated as follow [13].

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

λ indicates the scaling parameter which is calculated as $\lambda=\alpha^2(n+\sigma)-n$. α, m and β are constant positive values that can be used for adjusting KF. α is usually chosen between 0 and 1 so that the predicted covariance is positive and the covariance mean value has good accuracy. The optimal value of β is equal to 2. σ stands for the deviation of sample points from the mean value [13].

2.2. Prediction stage

In this stage, the chosen SPs ($x_{k,k}^i$) are incorporated into the dynamic equations of the system and, the new sample points ($x_{k+1,k}^i$) are obtained [13]. The new sample points as well as their mean ($\hat{x}_{k+1,k}$) and covariance ($\boldsymbol{P}_{xk+1,k}$) are calculated as follows:

$$x^i_{k+1,k} = f\left(x^i_{k,k}, u_k, w_k\right) \quad i= 1,2,3, \dots ,2n+1 \tag{5}$$

$$\hat{x}_{k+1,k} = \sum_{i=0}^{2n} u_m^i x^i_{k+1,k} \tag{6}$$

$$\boldsymbol{P}_{xk+1,k} = \sum_{i=1}^{2n} u_c^i \left(x^i_{k+1,k} - \hat{x}_{k+1,k}\right)\left(x^i_{k+1,k} - \hat{x}_{k+1,k}\right)^T + \boldsymbol{Q}_K \tag{7}$$

Then, the SPs obtained from equation (5) are incorporated into the measurement equation (8), and the measurement sample point vector is predicted. The predicted measurement values ($\gamma^i_{k+1,k}$), their mean ($\hat{\gamma}_{k+1,k}$) and covariance ($\boldsymbol{P}_{\gamma_{k+1,k}}$), as well as the cross-covariance ($\boldsymbol{P}_{x\gamma_{k+1,k}}$) of the SPs of the state variable ($x^i_{k+1,k}$) and SPs of measurement ($\gamma^i_{k+1,k}$) are calculated as follows:

$$\gamma^i_{k+1,k} = h\left(x^i_{k+1,k}, u_{k+1}, v_{k+1}\right) \tag{8}$$

$$\hat{\gamma}_{k+1,k} = \sum_{i=0}^{2n} u_m^i \gamma^i_{k+1,k} \tag{9}$$

$$\boldsymbol{P}_{\gamma_{k+1,k}} = \sum_{i=1}^{2n} u_c^i \left(\gamma^i_{k+1,k} - \hat{\gamma}_{k+1,k}\right)\left(\gamma^i_{k+1,k} - \hat{\gamma}_{k+1,k}\right)^T + \boldsymbol{R}_K \tag{10}$$

$$\boldsymbol{P}_{x\gamma_{k+1,k}} = \sum_{i=1}^{2n} u_c^i \left(x^i_{k+1,k} - \hat{x}_{k+1,k}\right)\left(\gamma^i_{k+1,k} - \hat{\gamma}_{k+1,k}\right)^T \tag{11}$$

Note that k is the counter of the UKF algorithm iterations and i is the counter of the number of SPs. $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$ are the covariance of process and signal noise in iteration k, respectively.

2.3. Correction stage

At this stage, the estimation values obtained in the previous stage are corrected using the actual measured values of the system output vector. The relevant equations are shown below:

$$\boldsymbol{K}_{k+1} = \frac{\boldsymbol{P}_{x\gamma_{k+1,k}}}{\boldsymbol{P}_{\gamma_{k+1,k}}} \tag{12}$$

$$\hat{x}_{k+1,k+1} = \hat{x}_{k+1,k} + \boldsymbol{K}_{k+1}\left[Y_{k+1} - \hat{\gamma}_{k+1,k}\right] \tag{13}$$

$$\boldsymbol{P}_{k+1,k+1} = \boldsymbol{P}_{xk+1,k} - \boldsymbol{K}_{K+1}\boldsymbol{P}_{\gamma_{k+1,k}}\boldsymbol{K}^T_{k+1} \tag{14}$$

where $\boldsymbol{K}_{k+1}$ is the gain of the UKF, Y_{k+1} is the measurement value and $\boldsymbol{P}_{k+1,k+1}$ and $\hat{x}_{k+1,k+1}$ are the corrected covariance and mean values, respectively. In the continuation of the algorithm, $\hat{x}_{k+1,k+1}$ and $P_{k+1,k+1}$ are used instead of $\hat{x}_{k,k}$ and $P_{k,k}$, respectively.

3. Parameter Estimation by the UKF Method

The state estimation process can also be employed for parameter identification. This section examines the procedure of the UKF to estimate the parameters of a dynamic system.

A standard turbine-governor system of TGOV1 type (Fig. 1) is chosen as a test system to describe the method.

3.1. Modification of the system dynamic equations

To utilize the UKF method to identify the unknown parameters of a dynamic system, these parameters must be defined in the form of state variables (virtual state variables) [19]. In doing this, several equations (the number of which is equal to the unknown parameters) are added to the system equations. So, dynamic system equations (equation 2) are changed as follows:

$$\begin{aligned} \boldsymbol{x}_k &= \boldsymbol{x}_{k-1} + f[\boldsymbol{x}_{k-1}, \boldsymbol{M}_{k-1}, \boldsymbol{u}_{k-1}]\Delta t + \boldsymbol{v}_{k-1} \\ \boldsymbol{M}_k &= \boldsymbol{M}_{k-1} + \boldsymbol{v}_{k-1} \\ \boldsymbol{y}_k &= h[\boldsymbol{x}_k, \boldsymbol{M}_k, \boldsymbol{u}_k, \boldsymbol{v}_k] + \boldsymbol{w}_k \end{aligned} \tag{15}$$

where, $\boldsymbol{M}_k$ is the vector of unknown parameters.

3.2. Estimation the TGOV1 turbine-governor system parameters

In traditional power plants, the turbine-governor system controls the kinetic energy of fuel (gas or steam) for a pre-specified value of active power generation. The turbine-governor system controls the fuel valves based on the power reference value and changes in the grid electrical frequency. One of the well-known standard models of the turbine-governor system, which is used for modeling steam power plants, is the TGOV1 model shown in Fig. 1. This model includes the turbine-governor droop (R), the main steam control valve movement and its time constant and bounds (T_g, V_{MAX}, V_{MIN}) and, a single lead-lag block (T_a/T_b) that shows the time-constants associated with steam movement through the reheater and turbine [23]. This system controls the position of the control valve (within a certain range) as well as its opening and closing rate to finally control the output mechanical power based on changes in the grid frequency and the reference power.

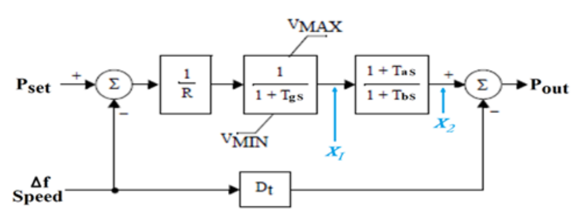


Fig. 1. The TGOV1 steam turbine model

The TGOV1 model has two state variables and four constant parameters. The state variables include the position of the control valve x_1 and the intermediate state variable x_2. The system parameters include R, T_g and T_a, T_b. These parameters should be estimated by the UKF method by considering them as virtual state variables. Note that, the input signal (including the load reference and frequency changes) is assumed as a known value, and the output power is available and measured. The system differential equations are now as follows:

$$\begin{cases} \frac{dx_1}{dt} = \frac{\frac{u}{R} - x_1}{T_g} \\ \frac{dx_2}{dt} = \frac{x_1(1-\frac{Ta}{Tb}) - x_2}{T_b} \\ y = x_2 + \frac{T_a}{T_b}x_1 \\ \frac{dR}{dt} = 0 \\ \frac{dT_g}{dt} = 0 \\ \frac{dT_a}{dt} = 0 \\ \frac{dT_b}{dt} = 0 \end{cases} \tag{16}$$

To use the UKF estimator, equation (16) should be discretized. In this paper, the sampling frequency is considered as 10 Hz (T_s=100 ms). Then we have:

$$\begin{gathered} x_1(k) = x_1(k-1) + T_s\frac{\frac{u(k)}{R(k-1)} - x_1(k-1)}{T_g(k-1)} + w_1(k) \\ x_2(k) = \frac{T_s}{T_b}\frac{1-\frac{T_a}{T_b}}{3}x_1(k-1) + \left(1-\frac{T_s}{T_b}\right)x_2(k-1) + w_2(k) \\ y(k) = x_2(k) + \frac{T_a}{T_b}x_1(k) \\ R(k) = R(k-1) + w_3(k) \\ T_g(k) = T_g(k-1) + w_4(k) \\ T_a(k) = T_a(k-1) + w_5(k) \\ T_b(k) = T_b(k-1) + w_6(k) \end{gathered} \tag{17}$$

$w_i(k)(i = 1{:}6)$ represent the noises of the system indicating some pseudo-noise uncertainties in the system equations whose covariance matrix has been shown by **Q**. The covariance matrices have been considered as follows (the values are selected by trial and error):

$$\begin{aligned} \boldsymbol{P}_x &= 0.2 * diag([15,1,1,1,1,1,1]) \\ \boldsymbol{Q} &= 10^{-7}P_x \end{aligned} \tag{18}$$

Since R is in the denominator of one of the equations, its inverse value ($\frac{1}{R}$) is estimated for simplicity. Estimation of the system parameters is performed for simultaneous estimation of four parameters and two states in two scenarios. In the first scenario, the turbine output power (P_{out}) is assumed as the only measured signal. In the second scenario, in addition to that, the control valve position (x_1) is also considered as a measurement signal. The actual and the initial guessed values of the parameters have been shown in equations (19) and (20), respectively.

$$\left[\frac{1}{R}, T_a, T_b, T_g\right] = [20, 1, 3 ,2] \tag{19}$$

$$\left[\frac{1}{R}, T_a, T_b, T_g\right] = [15, 2, 3, 5] \tag{20}$$

To perform the estimation process, a step function shown in Fig. 2 has been applied to the system as the deviation of grid frequency (Δf) while the reference power (P_{set}) is constant and assumed to be 0.035pu.

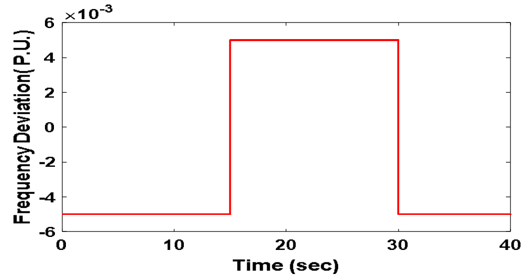


Fig. 2. The system input disturbance

- ***Scenario I***: *The output power is the only measured signal*

The preliminary simulations show that without considering the parameters limitations, the estimation process is not performed well and the estimated values are far from the actual values. More investigations show that with the increasing of T_a/T_b (which is a differential coefficient in the system), the noise sensitivity of the estimation process increases and tends toward instability. Accordingly, the following limitation is applied to the value of T_a/T_b.

$$\frac{T_a}{T_b} < 5 \tag{21}$$

By applying equation (21), the estimation process converged, that is the estimated output matches the measured output. The estimated parameters are as follows:

$$[\mathrm{R}, T_a, T_b, T_g] = [0.051, 2.2, 5.1, 3.8] \tag{22}$$

According to the estimation results, none of the parameters can be correctly identified by considering the output active power as the only measured signal.

- ***Scenario II***: *The governor and the turbine output powers are considered as the measured data*

In this scenario, in addition to the output power, the governor's output (x_1) is also considered as a measured signal. The results show that the estimation process is converged and the estimated signals match well the measured ones (Fig. 3).

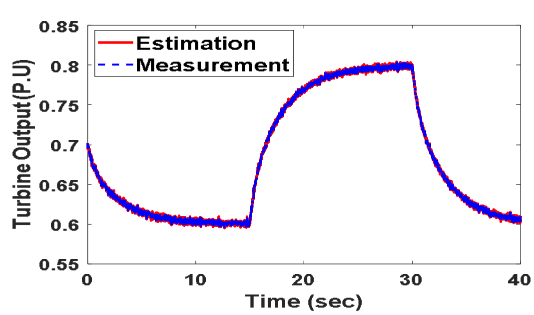


Fig. 3. Comparing the measured and estimated outputs

The estimated parameters are also presented in Table 1. As can be seen, despite the good agreement between the measured and estimated signals, the estimated parameters are still far from their correct values. However, the estimated parameters in this scenario are closer to the true values than in scenario I.

TABLE 1. Results of estimating the parameters of the TGOV1 system with one and two measured signals

Method	unknown parameters				Average estimation error %
	R	T_a	T_b	T_g	
Actual value	0.05	1	3	2	-
Estimation by One measured signal	0.051	2.2	5.1	3.8	70
Estimation by Two measured signals	0.0495	2.14	5.27	2.55	54

4. THE IMPROVED VERSION OF THE UKF METHOD FOR PARAMETER ESTIMATION

As shown in the previous section, the UKF does not show good accuracy for estimating the parameters of the TGOV1 system. In general, the following reasons can be listed:

- *A large number of state variables (including real and virtual state variables) against a small number of measured signals*: According to the results, despite the agreement between the measured signal and its estimate, when using only one measured signal, all parameters deviate significantly from their actual values. By adding a second measured signal, the estimation accuracy is improved, but there is still a large error. Note that due to some economic limitations, the number of measured signals cannot be increased.

- *Assuming the system parameters as virtual state variables:* In the estimation process, the system parameters are modeled as state variables, which are dynamic quantities, while in reality their value is constant. Accordingly, the estimated parameters are changed during the estimation process.

To solve the abovementioned problems and get better results, a modified version of the UKF algorithm is proposed. As mentioned, the state estimation process is usually an online process and the system state variables are recursively estimated using the measured signals in each time step (each iteration). Indeed, the traditional UKF algorithm is run at each time step and the instantaneous value of the system state variables is estimated using the measurement values on that time step. But parameter estimation is naturally an offline process and all measurement data in the entire observation period can be utilized to estimate the system parameters. So, in the proposed version of the UKF algorithm, the whole of the measurement signal samples is used as input in each stage of the estimation process. By doing this, throughout the entire simulation time i.e. within the entire period in which the measured signals exist, the unknown parameters are considered constant.

To this end, consider the dynamic system of Fig. 4a. For parameter estimation, a new system (shown in Fig. 4b) is introduced. The inputs of the proposed system include the estimated parameters (EP), input signals of the original system, and the measurement signals. The output of the system is also the integral of the square error between the measured signal and its corresponding signal obtained from the simulation of the system with the estimated parameters. It is expected that the output of the squared error integral will always be zero. This output will be assumed as the estimated output signal and will be compared with a new virtual measurement signal whose value is always zero in each step of the UKF algorithm. These parameters are estimated for the next stage using the UKF algorithm and applied to the input of the new system.

The following nonlinear equation can be written for the new system:

$$\hat{y}_{new} = F(\boldsymbol{EP}, u(t), y_{measured}(t)) \tag{23}$$

In the proposed algorithm, $\hat{y}_{new}$ (which is a scalar value, not a vector) is calculated within the entire period in which the measured signals exist. Similar to equation (15), the dynamic equations of the proposed system are as follows:

$$\begin{aligned} \boldsymbol{xnew}_k &= F(\boldsymbol{EP}_{k-1}, u(t), y_{measured}(t)) + \boldsymbol{v}_{k-1} \\ \boldsymbol{EP}_k &= \boldsymbol{EP}_{k-1} + \boldsymbol{v}_{k-1} \\ ynew_k &= xnew_k + w_k \end{aligned} \tag{24}$$

According to equation (24), there is only one state variable in the proposed system, called $\boldsymbol{xnew}$ which has a nonlinear relationship with the estimated parameters, inputs, and measured signals. Further, as mentioned above, for the new system, a new virtual measurement signal has been defined and its value is always zero. This zero signal must be continuously compared with the estimated output. Indeed, equality between $\hat{y}_{new}$ and $ynew_k$ means $\hat{y}_{new} = 0$ and $\hat{y}(t) = y(t)_{measured}$ in the whole period. Consequently, the stages of the modified UKF algorithm are as follows:

- *Sigma points selection and calculation of the weight coefficients:*

The $n = m + 1$ dimensional state variables vector of $\boldsymbol{x}_k = [\boldsymbol{xnew}_k, \boldsymbol{EP}_k]_{1*n}$, is selected as a random variable vector with the mean value of $\hat{x}_{k,k}$ and covariance of $\boldsymbol{P}_{k,k}$. m represents the number of parameters to be estimated. By knowing the $\hat{x}_{k,k}$ and $\boldsymbol{P}_{k,k}$, $2n + 1$ of the sample vectors and their weight coefficients are generated according to the equations (3) and (4) as follows:

$$x_k^i = [xnew^i(k), EP(k)] \quad i = 1,2, \dots, 2n + 1 \tag{25}$$

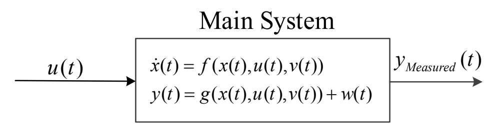
- *Prediction:*

At this stage, $2n+1$ sets of equations are put in the simulation model of the new proposed system in Fig. 4b, and then, for each set of parameters, $xnew^{i}{}_{k}$ (which is equal to $\hat{y}new^{i}{}_{k}$) is determined. Also, the vector of EP_k^i is specified based on equation (24). Using the obtained sample vectors $x_{k,k}^i = [xnew_k^i, EP_k^i]$, their mean and covariance matrices are also determined using equations (6) and (7). Finally, the average value of the measurement samples $\gamma_{k+1,k}^i$ (the predicted measurement), their covariance $P_{\gamma_{k+1,k}}$ and cross-covariance $P_{x\gamma_{k+1,k}}$ are calculated using equations (9) to (11).

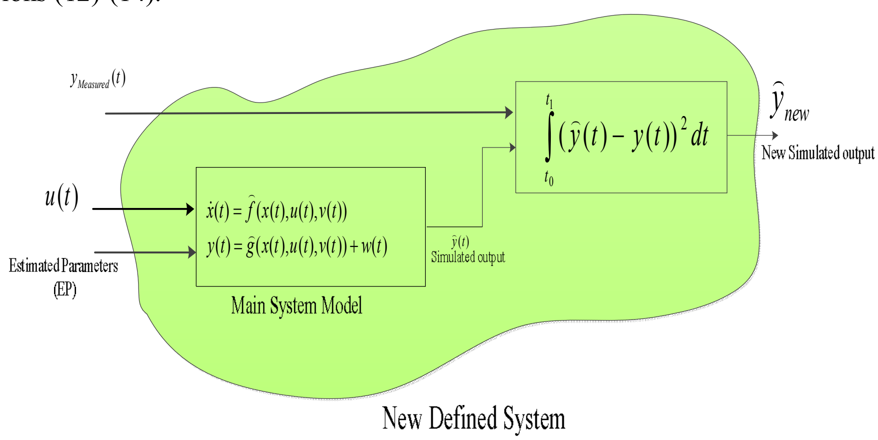
- *Correction:*

At this stage, knowing $ynew_k = 0$, the estimation values obtained in the prediction stage are corrected based on equations (12)-(14).

The three stages of the modified version of the UKF algorithm continue until the value of the newly estimated output tends to the measured value. In the proposed algorithm, each stage (k) is the simulation of the system in the time interval in which the measured signal has been recorded. Since in this period, the value of the parameters does not change and is assumed to be constant, so the problem related to the dynamic assumption of parameters is solved.



(a)



(b)

Fig. 4. (a) The original (main) system, (b) The proposed system

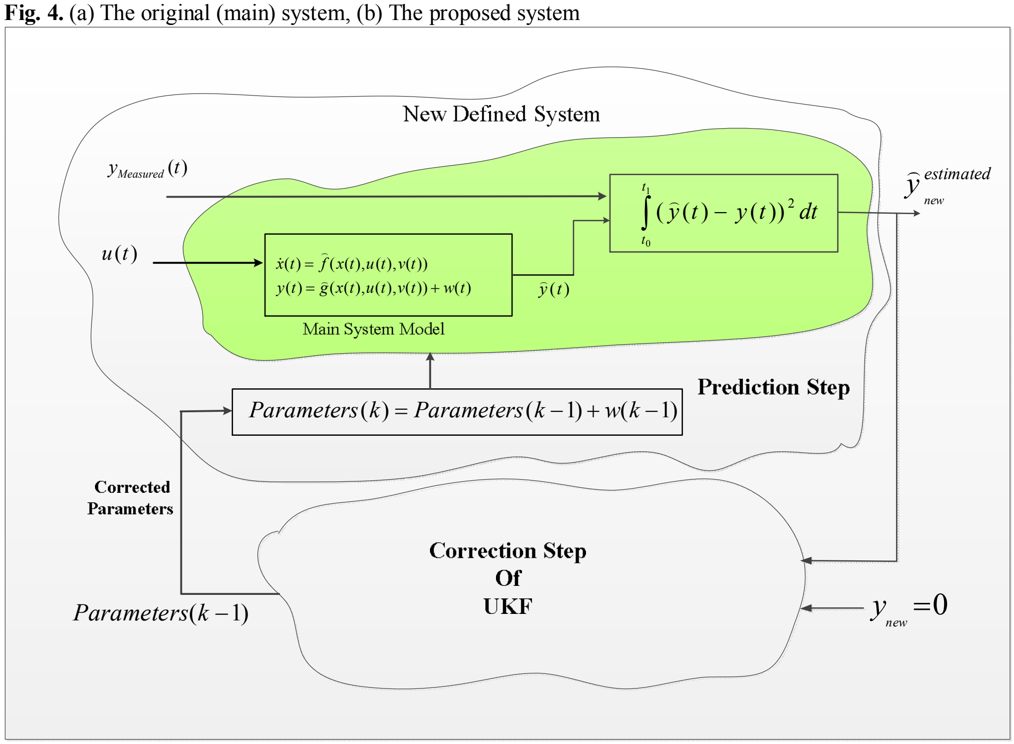


Fig. 5. The overall view of the improved UKF method

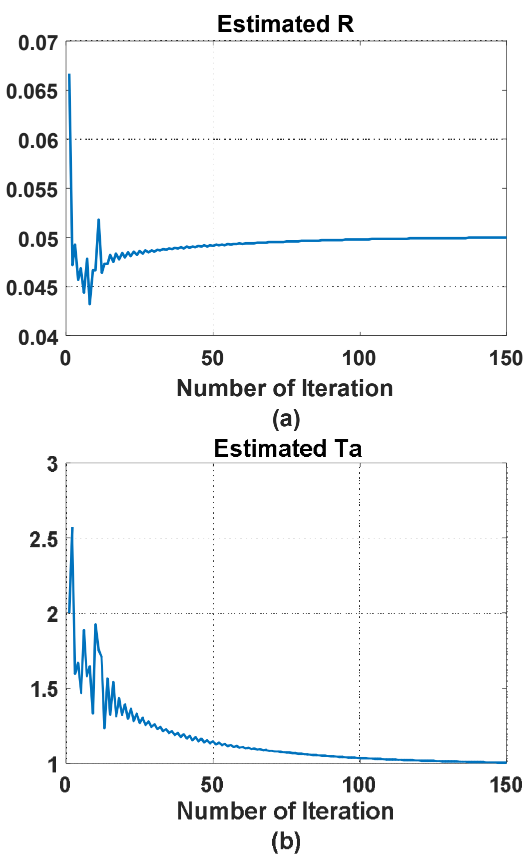
This results in higher accuracy and precision in the estimation process. Fig. 5 demonstrates the general overview of the improved UKF algorithm.

5. TEST OF THE PROPOSED METHOD

In this section, the efficacy of the proposed method for estimating the parameters of the TGOV1 Turbine-governor system is examined by Matlab-Simulink software. It is assumed that the only measured signal is the turbine output power ($y_{measured}(t) = P_m(t)$). The initial values of parameters have been considered similar to the conventional UKF method (equation (18)). The results of the estimation process are shown in Table 2 and Fig. 6. As can be seen, despite the assumption of only one measured signal, the parameters of the governor system are well identified. The results prove the effectiveness of the proposed method. It is clear that with more measured signals, much better results will be obtained.

Table 2. Results of estimating the parameters of TGOV1 system with the proposed method

Method	unknown parameters				Average estimation error %
	R	T_a	T_b	T_g	
Actual value	0.05	1	3	2	-
Proposed Method	0.0499	1.007	3.02	1.912	1.47



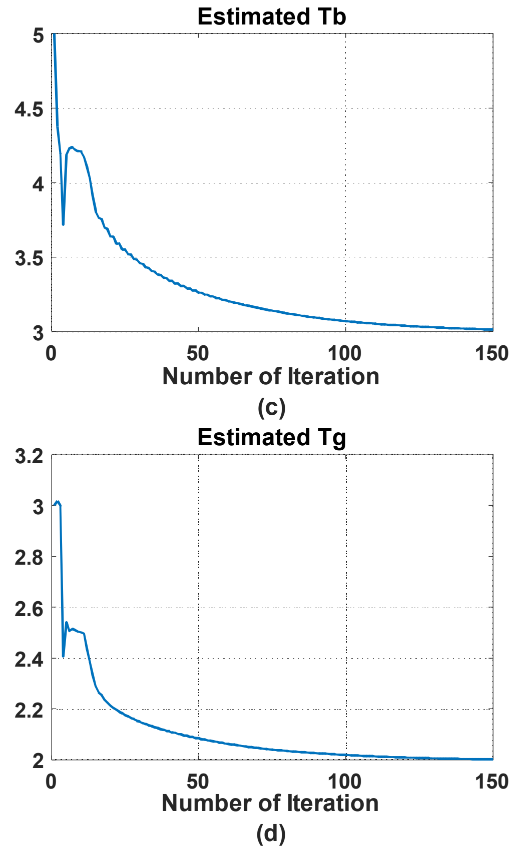


Fig. 6. The estimated parameters

6. CONCLUSION

Parameter estimation plays a significant role in modeling the behavior of dynamic systems under different operational conditions. The development of a suitable method for estimating dynamic system parameters can be very challenging. Various KF-based methods have been proposed for both state variables and parameter estimation so far. Nevertheless, an examination of its efficiency in parameter estimation problems reveals some shortcomings in the performance of these methods. Accordingly, in this paper, by changing the point of view to system modeling, an improved version of the UKF-based method was presented. The proposed idea looks similar to a smoothing approach whose practical result is to filter out (in the mean sense) estimates with little physical meaning that normally arise when the number of state variables is increased, which ultimately might lead the filter to diverge. The proposed approach overcomes the shortcomings of the conventional method and shows high efficiency in parameter estimation of a TGOV1 Turbine-governor system as a case study. Although the focus of the paper is on the UKF and parameter estimation of a turbine-governor system, the proposed method can be applied to any dynamic system and all types of Kalman filters.

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