

# State and Parameter Estimation of Photovoltaic Modules using Unscented Kalman Filters

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**Abstract.** This paper presents a parameter estimation technique for the circuit of a photovoltaic module. The proposed method is based on unscented Kalman filter for the joint estimation of the state variables and the parameters involved in the model equations, using external measurements only. A case study is presented where the obtained estimation errors remain lower than 3% in all cases. Additionally, three formulations of the Kalman filter are compared in terms of convergence and accuracy. This technique may contribute to the optimal operation of photovoltaic power plants and the maximization of the investor revenue.

**Key words.** unscented Kalman filter, parameter identification, state estimation, PV power plants.

## 1. Introduction

Renewable energy sources are becoming increasingly important due to the concern over global warming and fossil fuel reserves. Excluding hydro, wind and solar energies are the dominant sources. Particularly, photovoltaic (PV) systems installed power exceed 500 GW at the end of 2019. Only in the United States, solar PV has grown from being 0.1 % of the US electrical energy supply at the beginning of 2010 to 2.5 % by the end of the decade, [1].

The huge integration of alternate sources in electrical power systems (EPS) entails some technical challenges, such as the need of these intermittent power suppliers to contribute to voltage and frequency control, according to the existing grid codes.

In this context, it is important for grid operators to have a deep knowledge of the models describing the dynamic evolution of PV plants. These models are determined by the parameters involved in their equations. An accurate determination of these parameters may contribute to the correct operation and control of power systems with high PV penetration.

To approach the model parameter identification, [2]-[4] propose different analytical methods to calculate the parameters involved in a PV cell model. In these works, the parameter identification requires manufacturer information, which is supposed to be known and constant, even under changing operating or external conditions, such as snow and dust depositions on the PV panel. When this assumption is released, an alternative technique must be developed to obtain the parameter values.

A number of researches on dynamic state estimators (DSEs) based on Kalman filters (KFs) prove their accuracy in power systems with nonlinear dynamics, [5]-[6].

Among the different KF formulations, unscented Kalman filter (UKF) and extended Kalman filter (EKF), prove computational efficiency with synchronous machine dynamics, [7]. UKF has been used in different studies on state estimation in EPS, [8]. Parameter estimation is addressed in [9]-[10] for multi-machine power systems, using a set of internal measurements which are difficult to obtain in practice.

These difficulties are overcome in [11]-[12], where phasor measurement units (PMUs) are used for the parameter estimation.

Estimation techniques based on KFs are used in studies related to PV power generation. Short-circuit current estimation in a PV cell is approached in [13], while [14] proposes a method for the diagnosis of output power lowering in a PV array, which does not require high accuracy in the measurements. Maximum power point tracking (MPPT) is necessary in order to optimize the production of the PV power plant and the investor revenue. In this context, [15] and [16] propose MPPT techniques based on KFs, and [17] uses the UKF formulation with the same purpose.

This work presents a state and parameter joint estimation of a PV panel model. The proposed technique is based on the UKF formulation. To the authors' knowledge this is the first attempt to use KFs in the parameter estimation of a PV module, using a set of external measurements. The proposed method is also compared to other non-linear KF formulations, as the cubature KF (CKF), [18], and the ensemble KF (EnKF), [19].

The rest of the work is organized as follows. Section 2 formulates the equations in the algorithm of the DSE considered, i.e., UKF. The equations modeling the system under study are presented in Section 3. The implementation of the proposed UKF technique is described in Section 4, while Section 5 presents the estimation results with a scenario considered to test the accuracy of the estimator. Finally, the conclusions obtained of the estimation results presented are included in Section 6.

## 2. Unscented Kalman filter

Kalman Filter implementations involve a set of state equations, including the dynamic and the measurement equations. In the case of continuous-time, discrete-measurement, non-linear systems, these equations can be expressed as

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

$$\mathbf{z}(t_k) = \mathbf{g}(\mathbf{x}(t_k), \mathbf{u}(t_k)) + \mathbf{v}(t_k) \quad (2)$$

where  $\mathbf{x}(t)$  is the state vector,  $\mathbf{u}(t)$  the system input, and  $\mathbf{z}(t_k)$  the available measurements at instant  $t_k$ . The model and measurement noises,  $\mathbf{w}(t)$  and  $\mathbf{v}(t_k)$ , are assumed Gaussian processes with covariance matrices  $\mathbf{Q}$  and  $\mathbf{R}$ , respectively. The above equations have the following discrete counterparts:

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{w}_k \quad (3)$$

$$\mathbf{z}_k = \mathbf{g}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{v}_k \quad (4)$$

which are more appropriate for non-linear Kalman filtering techniques, like the EKF and UKF.

### A. Prediction Stage

For each iteration at instant  $k$ , a cloud of  $2L + 1$  vectors, called  $\sigma$ -points, is calculated from the estimated expected value of the state vector,  $\hat{\mathbf{x}}_{k-1}$  (dimension  $L$ ), and the covariance matrix of the state estimation error,  $\mathbf{P}_{k-1}$ , using the following expression, [20]:

$$\begin{cases} \mathbf{x}_{k-1}^0 = \hat{\mathbf{x}}_{k-1} \\ \mathbf{x}_{k-1}^i = \hat{\mathbf{x}}_{k-1} + \left[ \sqrt{(\mathbf{L} + \lambda)\mathbf{P}_{k-1}} \right]_i \\ \mathbf{x}_{k-1}^{i+L} = \hat{\mathbf{x}}_{k-1} - \left[ \sqrt{(\mathbf{L} + \lambda)\mathbf{P}_{k-1}} \right]_{i+L} \end{cases} \quad (5)$$

$$i = 1, \dots, L$$

where  $\left[ \sqrt{(\mathbf{L} + \lambda)\mathbf{P}_{k-1}} \right]_i$  is the  $i^{th}$  column of the matrix  $\sqrt{(\mathbf{L} + \lambda)\mathbf{P}_{k-1}}$ , and  $\lambda$  is a scaling factor calculated as

$$\lambda = \alpha^2(\mathbf{L} + \kappa) - L \quad (6)$$

with  $\alpha$  and  $\kappa$  being two filter parameters to be tuned.

Those  $\sigma$ -points are evaluated in (3) obtaining  $2L + 1$  resultant vectors,  $\mathbf{x}_k^{i-}$ , from which to obtain the *a priori* estimations  $\hat{\mathbf{x}}_k^-$  and  $\mathbf{P}_k^-$ :

$$\hat{\mathbf{x}}_k^- = \sum_{i=0}^{2L} \mathbf{W}_{mi} \mathbf{x}_k^{i-} \quad (7)$$

$$\mathbf{P}_k^- = \sum_{i=0}^{2L} \mathbf{W}_{ci} (\mathbf{x}_k^{i-} - \hat{\mathbf{x}}_k^-) (\mathbf{x}_k^{i-} - \hat{\mathbf{x}}_k^-)^T + \mathbf{Q}_k \quad (8)$$

where the weighting vectors  $\mathbf{W}_m$  and  $\mathbf{W}_c$  are calculated as follows:

$$\begin{cases} \mathbf{W}_{m0} = \frac{\lambda}{L + \lambda} \\ \mathbf{W}_{c0} = \frac{\lambda}{L + \lambda} + 1 - \alpha^2 + \beta \\ \mathbf{W}_{mi} = \mathbf{W}_{ci} = \frac{1}{2(L + \lambda)} \end{cases} \quad (9)$$

$$i = 1, \dots, 2L$$

and  $\beta$  is another tunable parameter.

### B. Correction Stage

On the basis of the *a priori* estimations, a new cloud of vectors is calculated,

$$\begin{cases} \mathbf{x}_k^{0-} = \hat{\mathbf{x}}_k^- \\ \mathbf{x}_k^{i-} = \hat{\mathbf{x}}_k^- + \left[ \sqrt{(\mathbf{L} + \lambda)\mathbf{P}_k^-} \right]_i \\ \mathbf{x}_k^{(i+L)-} = \hat{\mathbf{x}}_k^- - \left[ \sqrt{(\mathbf{L} + \lambda)\mathbf{P}_k^-} \right]_{i+L} \end{cases} \quad (10)$$

$$i = 1, \dots, L$$

and evaluated with the measurement function  $\mathbf{g}(\cdot)$  in (4) yielding

$$\mathbf{y}_k^{i-} = \mathbf{g}(\mathbf{x}_k^{i-}, \mathbf{u}_k) \quad (11)$$

$$i = 0, \dots, 2L$$

Those values are weighted using the vector  $\mathbf{W}_m$  defined in equation (9),

$$\hat{\mathbf{z}}_k^- = \sum_{i=0}^{2L} \mathbf{W}_{mi} \mathbf{y}_k^{i-} \quad (12)$$

Then, the covariance matrix of the measurement estimation error,  $\mathbf{P}_{zk}^-$ , and the cross-covariance matrix of state and measurements,  $\mathbf{P}_{xzk}^-$ , are obtained using the vector  $\mathbf{W}_c$ , as follows:

$$\mathbf{P}_{zk}^- = \sum_{i=0}^{2L} \mathbf{W}_{ci} (\mathbf{y}_k^{i-} - \hat{\mathbf{z}}_k^-) (\mathbf{y}_k^{i-} - \hat{\mathbf{z}}_k^-)^T + \mathbf{R}_k \quad (13)$$

$$\mathbf{P}_{xzk}^- = \sum_{i=0}^{2L} \mathbf{W}_{ci} (\mathbf{x}_k^{i-} - \hat{\mathbf{x}}_k^-) (\mathbf{y}_k^{i-} - \hat{\mathbf{z}}_k^-)^T \quad (14)$$

By using the *a priori* predictions at instant  $k$ , from (7)-(8) and (13)-(14), both the Kalman gain,  $\mathbf{K}_k$ , calculated as

$$\mathbf{K}_k = \mathbf{P}_{xzk}^- (\mathbf{P}_{zk}^-)^{-1} \quad (15)$$

and the respective *a posteriori* prediction can be obtained,

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{z}_k - \hat{\mathbf{z}}_k^-)^T \quad (16)$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}_k \mathbf{P}_{zk}^- \mathbf{K}_k^T \quad (17)$$

which are needed for the next algorithm iteration.

### 3. System Modeling

The proposed technique for the joint estimation of the state variables and parameters in the system under study requires a deep knowledge of the equations modeling the behavior of the PV panel. To approach this issue, this section presents the equations of the five-parameter model for the single-diode equivalent circuit of a PV module, [21], as shown in Fig. 1.

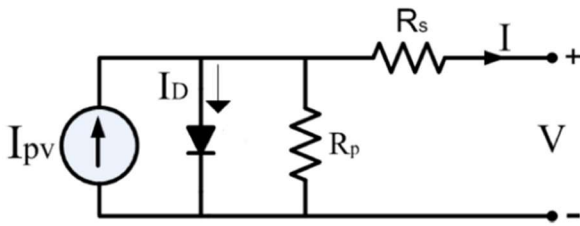


Fig. 1 Single-diode, five-parameter circuit for a PV module

The terminal current,  $I$ , is obtained using Kirchhoff's current law as follows:

$$I = I_{PV} - I_D - \frac{V + R_s I}{R_p} \quad (18)$$

where  $I_D$  is the current through the diode, represented by Shockley diode equation (19),

$$I_D = I_n \left( e^{\frac{q(V+R_s I)}{A \cdot N \cdot k \cdot T}} - 1 \right) \quad (19)$$

being,

$I_n$ : reverse bias saturation current of the diode.

$q$ : electron charge.

$V$ : terminal voltage of the PV system.

$R_s$ : series resistance.

$R_p$ : parallel resistance.

$A$ : diode ideality factor.

$N_s$ : number of cells connected in series per module.

$k$ : Boltzmann constant.

$T$ : temperature of the panel.

Regarding the current produced by the panel,  $I_{PV}$ , in equation (18), it is formulated as a function of the irradiance absorbed by the panel,  $G$ , and its temperature, yielding the following equation:

$$I_{PV} = \frac{G}{G^{ref}} \left( I_L^{ref} + \mu(T - T^{ref}) \right) \quad (20)$$

where each term is defined as:

$T^{ref}$ : reference temperature.

$G^{ref}$ : reference irradiance.

$I_L^{ref}$ : current produced under reference conditions.

$\mu$ : temperature coefficient.

Finally, the value of  $G$  depends on the solar irradiance,  $G_s$ , and a so-called panel absorption factor,  $\alpha$ , yielding the following expression:

$$G = \alpha \cdot G_s \quad (21)$$

### 4. Implementation of UKF

DSEs require the previous knowledge of the parameters involved in the model equations. Although these parameters usually have typical values, when these are not accurately known, or are modified because of changes in operating conditions, UKF can be used for a joint estimation of state variables and parameters, [22], so that an augmented state vector is defined as:

$$\mathbf{x}_a = [\mathbf{x}^T, \boldsymbol{\psi}^T]^T$$

with vector  $\mathbf{x}$  containing the state variables in the model considered for the UKF, and  $\boldsymbol{\psi}$  the model parameters. For the five-parameter model presented in section 3, the state vector  $\mathbf{x}$  is defined as:

$$\mathbf{x}^T = [V, G, T]$$

Regarding the model parameter vector,  $\boldsymbol{\psi}$ , it is composed by:

$$\boldsymbol{\psi}^T = [R_s, R_p, I_n, \mu, A, \alpha]$$

being the size of the augmented state vector  $L = 9$ . In the proposed implementation of the UKF, four variables are supposed to be obtained from the system under study, namely the terminal voltage,  $V$ , and current,  $I$ , the solar radiation,  $G_s$ , and the temperature,  $T$ . These magnitudes compose the measurement vector  $\mathbf{z}$ , as used in section 2,

$$\mathbf{z}_k^T = [I_k, V_k, G_{s,k}, T_k]$$

Note that the variables  $V$ ,  $G$  and  $T$  are typically taken as system inputs. However, with the proposed implementation of the UKF it is possible to deal with errors in these measurements, which would not be considered otherwise.

A smooth variation is assumed for the state vector  $\mathbf{x}$ , as a Gaussian random walk, given that the state variables are time dependent, but the variation is unknown. With this assumption, equation (3) is substituted by:

$$\mathbf{x}_{a,k} = \mathbf{x}_{a,k-1} + \mathbf{w}_k \quad (22)$$

Regarding the measurement function  $\mathbf{g}(\cdot)$  in equation (4), it is not possible to obtain an expression of the terminal current  $I$  from the model equations presented in section 3. The solution proposed in this work consists in solving the following implicit equation at each instant  $k$ ,

$$I_k = \frac{G_k}{G^{ref}} \left( I_L^{ref} + \mu_k (T_k - T^{ref}) \right) - I_{n,k} \left( e^{\frac{q(V_k + R_{s,k} I_k)}{A_k N_k T_k}} - 1 \right) - \frac{V_k + R_{s,k} I_k}{R_{p,k}}$$

This method may not be used with other KF formulations, like the EKF, as it requires the calculation of the Jacobian matrix of the measurement function. The expressions related to  $V_k$  and  $T_k$  are trivial, since they are state variables, while the solar radiation is obtained as:

$$G_{s,k} = \frac{G_k}{\alpha_k} \quad (23)$$

The UKF requires an initial estimation for  $x_a$ , which will be presented in section 5. Regarding the covariance of this initial estimation error, it is defined by a diagonal matrix, namely  $P_0 = \text{diag}([P_{x0}^T, P_{\psi0}^T])$ , where  $P_{x0}$ , corresponding to the state variables, has been defined as

$$P_{x0}^T = [10^{-4}, 10^{-4}, 10^{-4}]$$

and  $P_{\psi0}$ , related to the model parameters, yields

$$P_{\psi0}^T = [1, 1, 1, 1, 1, 1]$$

The UKF has been implemented considering  $\alpha = 10^{-4}$ ,  $\kappa = 3 - L$  and  $\beta = 2$ , following the results found in works on the influence of these scaling parameters in the estimation, [23]. The measurement noise covariance matrix  $R$  is taken as a diagonal matrix with  $R_{ii} = 10^{-4}$  for the terminal voltage and current, meaning a 1% standard deviation error, and  $R_{ii} = 10^{-2}$  for the solar radiation and the temperature, considering that the measurement errors for these variables are substantially higher.

Finally, the model noise covariance matrix  $Q$  is defined in this work as  $Q = \text{diag}([Q_x^T, Q_\psi^T])$ , where:

$$Q_x^T = [10^{-2}, 10^{-2}, 10^{-2}]$$

corresponds to the state variables, and

$$Q_\psi^T = [10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}]$$

to the model parameters.

The presented implementation is used in the case study presented in the next section, with no fine-tuning required.

## 5. Case Study

The performance of the proposed estimation technique is tested in this section. A five-parameter model has been considered for the simulation, given that the obtained measurements were similar to those extracted from a more complex model, [24], and in this manner, it is possible to count on simulation values for the model parameters to compare with the estimated ones. In the operating point considered, the reference conditions and the simulated values of the model parameters are summarized in Table I.

Table I. - Simulation values for the PV module

Variable	Unit	Value
$G^{ref}$	$W/m^2$	1000
$T^{ref}$	K	298
$I_L^{ref}$	A	6
$R_s$	$\Omega$	0.221
$R_p$	$\Omega$	415
$\mu$	A/K	0.0032
$A$	pu	1.5
$I_n$	A	$8.2 \cdot 10^{-6}$
$\alpha$	pu	0.8
$N_s$	-	54

For the terminal DC voltage  $V$  (system input,  $u$ ), a smooth evolution has been modeled, considering a Gaussian random walk with standard deviation  $R_w = 10^{-2}$ , as depicted in Fig. 2.

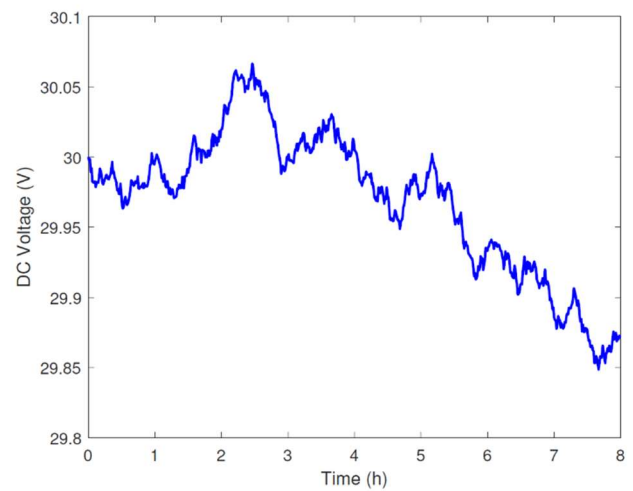


Fig. 2. Evolution of the DC terminal voltage.

The total simulation time is 8h, as it can be noticed from Fig. 2, while the sample period considered for the UKF implementation is  $\Delta t = 1$  min. Typical profiles have been taken for the solar radiation,  $G_s$ , and the module temperature  $T$ , as shown in Fig. 3, [25].

For the initial estimation of the augmented state vector,  $\hat{x}_{a0}$ , the corresponding initial measurements are considered for the state variables, while, regarding the parameter vector  $\psi$ , random initial values are used in the range of  $\pm 20\%$  to  $\pm 40\%$  of their values in the simulation. The performance of the proposed UKF algorithm resulted consistent in the estimation of the model parameters, as shown in Fig. 4, being the final estimated values summarized in Table II. For each parameter, the estimated value,  $\hat{x}_i$ , is represented jointly with a deviation equal to  $\hat{x}_i \pm 3\sqrt{P_{ii}}$ . Please note that the covariances tend to  $Q_{ii}$ , as it would be expected from an accurate estimation.

It is observed how most of the parameters evolve smoothly to values close to those taken in the simulation, with a maximum relative error under 3% in all cases, giving evidence of the good performance of the proposed technique.

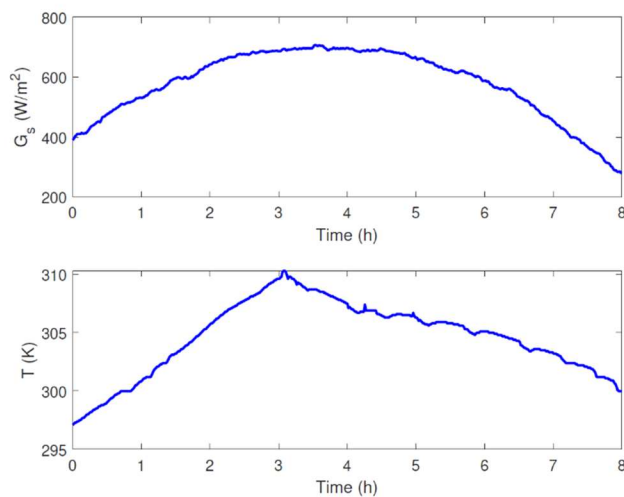


Fig. 3. Evolution of the solar radiation and cell temperature

Table II. - Relative error in the parameter estimation

Parameter	Units	Estimated Value	Error (%)
$R_s$	$\Omega$	0.219	0.91
$R_p$	$\Omega$	410.8	1.01
$A$	pu	1.458	2.80
$\mu$	A/K	0.00313	2.19
$I_n$	A	$8.32 \cdot 10^{-6}$	1.46
$\alpha$	pu	0.813	1.63

It can also be noticed how the convergence of the estimation is quick for all the parameters included in the UKF model, with a maximum time lower than 3 h in all cases. This time can be higher in other applications of the KF, particularly in those with a more complex model, [11].

To conclude this case study, the performance of the UKF is compared to other non-linear KF-based estimators, namely CKF and the EnKF. The estimation results obtained for the parallel resistance,  $R_p$ , are compared in Fig. 5 for the three KF formulations. It can be noticed how the accuracy of the UKF is slightly better than that of the CKF, while the EnKF scheme has shown convergence problems.

## 6. Conclusion

In this paper, an UKF implementation is proposed to jointly estimate the state variables and parameters of a PV cell model. The accuracy in the estimation of the terminal current has also been assessed for the considered five-parameter model.

The performance of three KF formulations have been compared, resulting on similar results for the UKF and CKF, while the EnKF scheme showed convergence issues. The main contribution of this work lies on the use of the UKF algorithm when the system model lacks a state function, as it is used in equation (1). The presented case study has shown that the proposed estimator yields accurate enough results in the parameter estimation, with a maximum relative error lower than 3%. The proposed identification technique may help with the plant management and the optimization of the economic benefit.

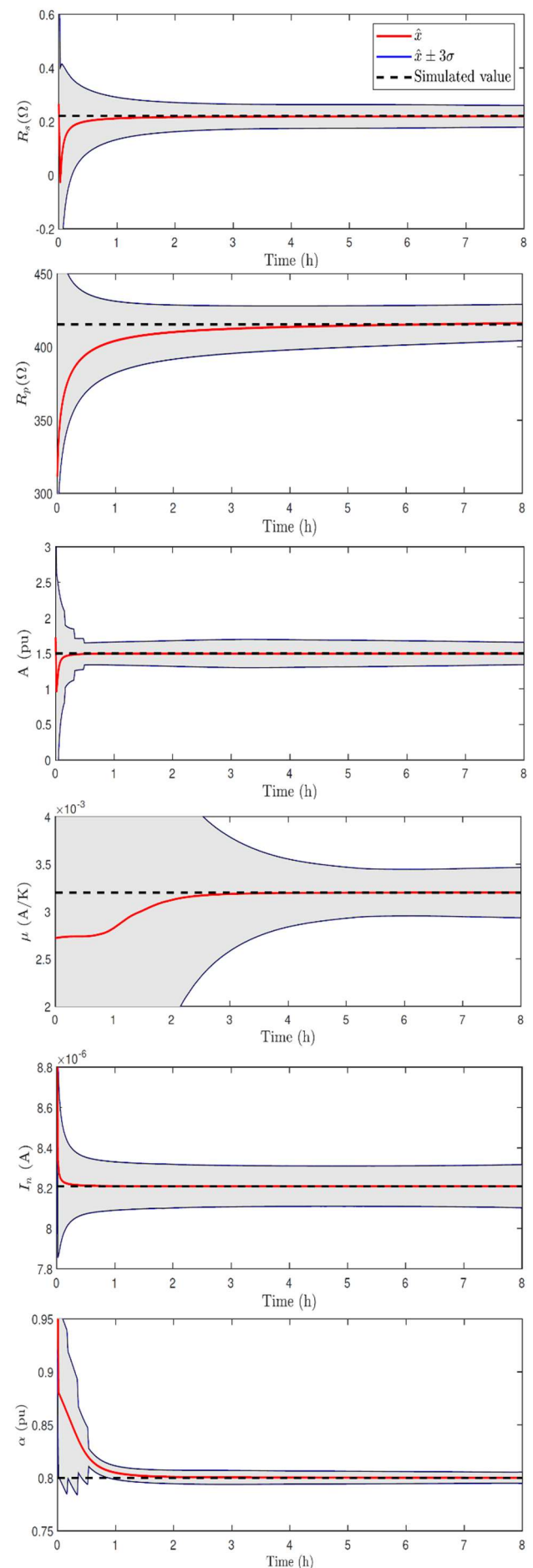


Fig. 4. Parameter estimation results



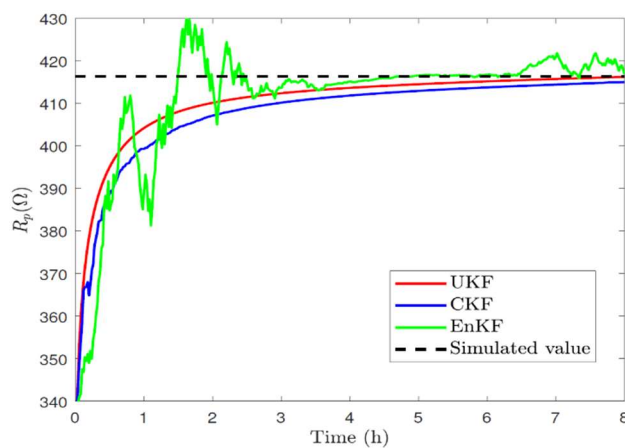


Fig. 5. Comparison of the estimation results for different KF formulations

## Acknowledgement

M. Á. González-Cagigal thanks the project HySGrid+ (CER-20191019) and the project FLEX-REN (P18-TP-3655) for the financial support.

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