

Identification of a Synchronous Generator Parameters Using Recursive Least Squares and Kalman Filter

Identificación de los parámetros de un generador síncrono mediante mínimos cuadrados recursivos y filtro de Kalman

Carlos F. Rengifo¹, Cristian Girón², Jhon Palechor³ y Diego A. Bravo M.⁴

Abstract

The comparison between recursive least squares (RLS) and Kalman filter (KF) is presented in this paper, both methods were adequate to estimate six parameters of a synchronous machine. The work focused on finding the operating conditions which the quality of the identification achieved with Kalman filter is better than recursive least squares. A linear model of the machine is used in order to considerate the currents and their derivatives as the system inputs while the three-phase voltage signals are the outputs. Furthermore two experiments with simulated and measured data were carried out, three operating scenarios and two variations of the algorithms respectively were considered. Despite the great similarity and good performance of both methods, it was found that Kalman filter slightly exceeded least squares due to the fact that it presented smaller oscillations in the estimated value of the parameters for any operating condition.

Keywords: identification, dynamic model, Kalman filter, recursive least squares

Resumen

En este artículo se presenta la comparación entre mínimos cuadrados recursivos (RLS) y filtro de Kalman (KF), ambos métodos fueron adecuados para estimar seis parámetros de una máquina síncrona. El trabajo se centró en encontrar las condiciones de funcionamiento en las que la calidad de la identificación lograda con el filtro de Kalman es mejor que los mínimos cuadrados recursivos. Se utiliza un modelo lineal de la máquina para considerar las corrientes y sus derivadas como entradas del sistema, mientras que las señales de tensión trifásica son las salidas. Además, se llevaron a cabo dos experimentos con datos simulados y medidos, se consideraron tres escenarios operativos y dos variaciones de los algoritmos respectivamente. A pesar de la gran similitud y buen desempeño de ambos métodos, se encontró que el filtro de Kalman excedía levemente los mínimos cuadrados debido a que presentaba menores oscilaciones en el valor estimado de los parámetros para cualquier condición de operación.

Palabras clave: identificación, modelo dinámico, filtro de Kalman, mínimos cuadrados recursivos

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¹Departamento de Electrónica, Instrumentación y Control. Universidad del Cauca, Popayán, Colombia.
Correo electrónico: caferen@unicauca.edu.co

²Departamento de Electrónica, Instrumentación y Control. Universidad del Cauca, Popayán, Colombia.
Correo electrónico: cristiangiron@unicauca.edu.co

³Departamento de Electrónica, Instrumentación y Control. Universidad del Cauca, Popayán, Colombia.
Correo electrónico: jhonpalechor@unicauca.edu.co

⁴Departamento de Física. Universidad del Cauca, Popayán, Colombia.
Correo electrónico: dibravo@unicauca.edu.co

1 Introduction

As the time goes by, identification of circuit and excitation parameters of synchronous generators has been approached from several perspectives that involve parametric estimation techniques and states, in order to find time constants, gains and limits which the generator operates either connected to the electrical network or off-line. These techniques could be classified into the categories of estimation by least squares and Kalman Filter. The modeling of both circuit parameters and excitation systems present in synchronous machines has a fundamental role in the stability of the power systems present in the national interconnected system. The reference [1] proposed practices with models of suitable excitation systems in stability studies for large-scale power systems such as the synchronous generator, while the generation of circuit parameters of the generator is contemplated in [2]. Owing to the idea of this research work is focused on estimating the parameters of a synchronous generator at laboratory scale, so it is taken as reference, [2].

In order to carry out the comparative study between the two techniques of identification machine parameters, it must be taken into account that the problem has been approached according to its different variants, on one side the researches carried out in [3, 4, 5, 6, 7, 8, 9], focus their job on estimate circuit parameters of the synchronous generator which have been object of abundant study. Whereas in [10, 11, 12, 13, 14, 15, 16], have been estimated excitation parameters by different techniques, and similarly there are variety of publications recorded. On the other hand, to obtain the estimation of either the circuit or excitation parameters of the synchronous generator, it is based on obtaining a model that depends on the nature of the machine used. This model can be linear as shown in [4, 5, 11, 10, 17, 14, 9], or no linear as used in [18, 6, 12, 7, 13, 8, 19, 16, 20]. Also, the various investigations in their phase of data collection used different types of measurements to carry out the parameters identification, these measurements were made using data time [18, 3, 4, 5, 6, 10, 7, 8, 17, 14, 21], frequency data [19, 15, 9], or with phasor measurement units (PMU) [11, 12, 13, 16, 20].

Identification techniques are essentially based on recursive and non-recursive estimation, they are distinguished because in first one the current estimation of the parameters is made based on a previous estimate. Whereas in certain practices it is opted to make a joint estimation between parameters and dynamic states of the system, as it usually happens in the studies where the technique used is the Kalman filter or any of its variations. In [18, 5, 10] recursive least squares was chosen as the method for estimating the synchronous generator parameters and [14] used nonlinear least squares, these methods generate few computational costs but yield high prediction if the noise affects the measurement. Other particular methods as Levenberg-Marquardt [19], output error method (OEM) [4] and error prediction [15] were carried out to estimate the machine parameters, or the case in [9] where the frequency and time response methods [8] were applied independently. In addition, some authors of recent studies carry out joint estimation of parameters and states using the unscented Kalman filter (UKF) technique [16, 13], extended Kalman filter (EKF) [12], or Kalman square root [7], these techniques start from a non-linear model and can estimate at most 5 parameters of the synchronous generator, while in [20] the unknown input Kalman filter (UIKF) only made the estimation of four dynamic states of the machine. Over the years, many research studies have resulted in synchronous generator models closer to the real model, however a detailed comparison between parameter estimation techniques has not been carried out to establish which of these offers the best results to obtain models and parameters in relation to the other techniques.

The article is structured as follows: section 2 describes the mathematical model of the generator, section 3 is dedicated to the recursive least squares and section 4 presents the Kalman filter algorithm, followed by the results presented in the section 5 and ending with the conclusion of the article in the section 6.

2 Synchronous generator model

First, it is presented the equivalent circuit of a synchronous generator in *abc* coordinates, where

$v_{a,b,c}$, $i_{a,b,c}$ and $\psi_{a,b,c}$ are respectively the winding voltage, current and linkage flux on armature, v_f , i_f ψ_f are the same but in the field. While L_a is the armature-phase inductance, L_{ab} is the armature phase-phase mutual inductance, L_m is the peak armature-phase to field-winding mutual inductance, L_f is the field-winding inductance, R_a is the armature phase resistance, R_f is the field-winding resistance and θ is the electrical angle between the magnetic axis of phase a and the magnetic axis of the field winding. Applying the voltage Kirchoff law to each electric circuit on Figure 1.

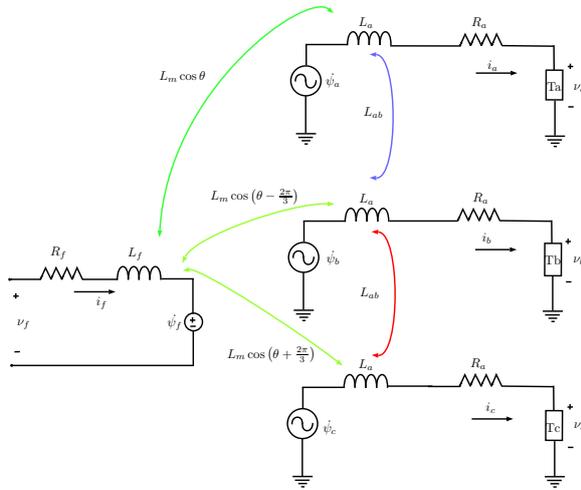


Figure 1. Equivalent circuit in abc coordinates.

$$\frac{d}{dt} \Psi_{abc} = V_{abc} - R_{abc} I_{abc} \quad (1)$$

where flux and current vectors can be associated as:

$$\Psi_{abc} = L_{abc}(\theta) I_{abc} \quad (2)$$

In the previous equations, the inductance matrix L_{abc} is time dependent, so it is necessary to apply Park transformation multiplying both sides of the equation (2) by a term that disappears the dependence. Thus the L_{abc} turns to L_{dq0} and this is the new equation with a state space representation:

$$\frac{d}{dt} I_{dq0} = L_{dq0}^{-1} V_{dq0} - L_{dq0}^{-1} [C L_{dq0} \omega + R_{abc}] I_{dq0} \quad (3)$$

where ω is rotor electrical angular velocity and C is a zeros matrix with $C_{1,2} = 1$ and $C_{2,1} = -1$, with a constant value of ω , the equation 3 could be written as voltage matrix applying Fourier transformation:

$$V_{dq0} = [L_{dq0} s + C L_{dq0} \omega + R_{abc}] I_{dq0}(s) \quad (4)$$

So the previous equation can be written as a impedance matrix

$$Z_{dq0} = L_{dq0} s + C L_{dq0} \omega + R_{abc} \quad (5)$$

3 Recursive least squares algorithm

Basic RLS algorithm seeks to minimize the squares of the prediction errors sum, by the following discrete representation of a dynamic system

$$y(k) = \phi(k)^T \theta + e(k) \quad (6)$$

according to equation (4) it defines the outputs and parameters vectors as:

$$\theta = \begin{bmatrix} R_a \\ R_f \\ L_a \\ L_{ab} \\ L_f \\ L_m \end{bmatrix}, \quad y(k) = \begin{bmatrix} v_d \\ v_q \\ v_0 \\ v_f \end{bmatrix} \quad (7)$$

and the regression matrix set as, see equation (14). Note that it was not necessary to use the discrete steps but in exchange derivatives of current signals in relation with the time must be calculated whereby the least squares method is used. These are the steps for designing a recursive least squares algorithm.

- Prediction error

$$e_p(k) = y(k) - \phi(k)^T \theta \quad (8)$$

- Gains vector

$$G(k) = P(k) \phi(k) [\lambda + \phi^T P(k) \phi(k)]^{-1} \quad (9)$$

where P is the covariance matrix that must be initialized when $k = 0$, thus:

$$P(0) = \alpha I, \quad \alpha \in [100, 1000] \quad (10)$$

meanwhile the forgetting factor is considered with a value close to one ($\lambda = 0.999$), which generates a slow convergence to the value of the parameters but greater immunity to noise.

- Covariance matrix in the step $k + 1$

$$P(k+1) = \frac{1}{\lambda} (I - G\phi^T) P(k) \quad (11)$$

- Update parameters

$$\theta(k+1) = \theta(k) + G(k)e_p(k) \quad (12)$$

4 Kalman filter algorithm

For this particular case was considered the following state space representation of a discrete system:

$$\begin{aligned} \theta_{k+1} &= \theta_k + W_k \\ v_k &= \phi \left(i, \frac{di}{dt} \right) \theta_k + Z_k \end{aligned} \quad (13)$$

where W is the random process noise and Z is the measurement noise. Kalman filter can accommodate parameters estimation by using the following equations

$$\phi(k)^T = \begin{bmatrix} i_d(k) & 0 & \frac{di_d}{dt}(k) - i_q(k)\omega & i_q(k)\omega - \frac{di_q}{dt}(k) & 0 & \sqrt{\frac{3}{2}} \frac{di_f}{dt}(k) \\ i_q(k) & 0 & \frac{di_q}{dt}(k) + i_d(k)\omega & -i_d(k)\omega - \frac{di_d}{dt}(k) & 0 & \sqrt{\frac{3}{2}} i_f(k)\omega \\ i_0(k) & 0 & \frac{di_0}{dt}(k) & 2 \frac{di_0}{dt}(k) & 0 & 0 \\ 0 & i_f(k) & 0 & 0 & \frac{di_f}{dt}(k) & \sqrt{\frac{3}{2}} \frac{di_d}{dt}(k) \end{bmatrix} \quad (14)$$

- *Prediction stage.*

Projection of the state:

$$\hat{x}_k = f(\hat{x}_{k-1}, h(\hat{x}_{k-1}, u_{k-1}), u_{k-1}, 0) \quad (15)$$

Projection of the covariance error:

$$\bar{P}_k = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \quad (16)$$

- *State correction.*

Kalman Gain

$$K_k = \bar{P}_k H_{z,k}^T [H_{z,k} \bar{P}_k H_{z,k}^T + Z_k R_k Z_k^T]^{-1} \quad (17)$$

State correction:

$$\hat{x}_k = \hat{x}_k + K_k [Z_k - h(\hat{x}_k, u_k, 0)] \quad (18)$$

Covariance error update

$$P_k = (I - K_k H_{z,k}) \bar{P}_k \quad (19)$$

Where:

- A_k y W_k : Jacobian process matrices in the step k .
- P_k : Covariance matrix of the state estimation error.
- Q_k : Covariance of process noise in the step k .
- $H_{z,k}$ y V_k : Are the Jacobian measurements in the step k .
- R_k : Covariance of measurement noise in the step k .

The value of process noise variance Q_k was set in zero, since there is a certain reliability that the parameters at the step $k + 1$ are equal at the step k due to the proposed model. Whereas the measurement noise variance is a identity matrix. Previous equations were implemented in MATLAB.

5 Results

Note that both methods require regression matrix (14) so they are very similar and only differ in their equations. Two experiments with simulated and real data were considered, for the first one it was designed a virtual generator model and one vector with random values of the parameters. In the other hand instead, current and voltage signals are measured from a laboratory machine with a acquisition data software.

5.1 Simulated data

The initial value of the parameters was set as zero and different values of white noise variance were added to the three-phase voltage and current signals in order to check the quality of the algorithms. Then the time convergence of the estimated parameters is shown.

Figure 2 shows great similarity between RLS and Kalman filter because of both estimate a closer value of real parameters, however recursive least squares (blue line) always present a more oscillatory time response than Kalman especially in the inductive parameters. Furthermore the estimated parameters with both algorithms are shown in the following table.

Resistance parameters unities are Ohms and inductive unities are mils-Henri. Note that Kalman filter has greater noise immunity due to considers this component in his equations and always recover a closer parameter value to real, on the contrary

Table 1. Estimated parameters with both methods with different values of white noise variance

Parameter	R_a	R_f	L_a	L_{ab}	L_f	L_m
Virtual	13	140	200	30	80	10
White noise variance = 0.01						
RLS	12.91	93.01	200.10	30.03	22.37	7.04
Kalman	12.96	94.53	199.72	29.71	67.43	6.95
White noise variance = 0.1						
RLS	12.34	24.34	200.65	30.39	-54.44	1.22
Kalman	12.37	22.46	199.22	29.19	30.39	1.61
White noise variance = 1						
RLS	8.21	4.28	197.54	28.62	-60.72	-0.04
Kalman	8.73	3.43	198.35	28.06	15.32	0.49
White noise variance = 2						
RLS	6.04	1.48	201.57	29.79	-71.58	-0.33
Kalman	6.27	1.23	202.99	30.12	16.52	0.66
White noise variance = 5						
RLS	3.39	0.73	200.77	28.06	-55.37	0.07
Kalman	3.52	0.88	200.95	27.37	16.37	0.17

recursive least squares quality decreases as white noise variance increases. Hence Kalman filter would be the best option.

5.2 Real data

A data acquisition of voltages, currents and rotor velocity with Arduino DUE was carried out in three different scenarios, 1000 samples was acquired and the sampling time was 100 micro-seconds. After processing the obtained signals the methods were compared. The machine must be connected as a engine because of the impedance equation (5) and all the the system will see as a load.

5.2.1 First scenario: Different values of v_f

A manual variation of the excitation machine voltage was made and the following fit between real and predicted signal was obtained. The example shows the results for $v_f = 20$ volts.

Figure 3 shows the performance of the algorithms to predict the three-phase signals, while the percentage of zero in the field voltage is due to the resolution of the sensor used in that channel since it fails to sense an AC induced voltage value in such a large DC component. Then it is presented the estimated parameters time convergence.

Here, the great similarity between the estimation methods because of the identified parameter value and their time signal evolution. Thus it is necessary to see the estimated parameters on different values of the field voltage. In the Table 2 it can appreciate how the quality of the identification with both methods decreases as the field voltage increases, that may due to the magnetic saturation in the iron structure of the machine, in low excitation voltages the algorithms be able to recover similar values of the machine parameters.

5.2.2 Second scenario: Line frequency = 50 Hertz

A variable frequency driver was connected in open loop with the machine in order to slow the line frequency down. It is worth to clarify that the delivered voltage signal by the driver is not sinusoidal hence the fit between signals is 0%. The estimated machine parameters are shown in the Table 3. Note that despite the aforementioned, the algorithms are able to estimate the value of some parameters since the magnitude of the three-phase voltage is maintained and the only variable that changes its value is the frequency.

Table 2. Comparison between the algorithms with different values of v_f

Recursive Least Squares						
v_f [v] Parameter	5	10	20	30	60	120
R_a [Ohms]	40.25	39.07	35.77	38.68	23.87	14.67
R_f [Ohms]	142.63	141.86	142.52	114.53	140.09	143.54
L_a [mH]	284.42	-31.32	7.59	44.08	-295.88	-92.03
L_{ab} [mH]	490.38	171.69	206.12	258.69	-146.83	37.87
L_f [mH]	-63.25	487.83	43.51	-33.79	-441.24	-1964.04
L_m [mH]	0.03	-0.06	0.02	0.13	-0.16	0.38
Kalman filter						
v_f [v] Param	5	10	20	30	60	120
R_a [Ohms]	40.87	39.02	35.79	38.69	23.64	14.89
R_f [Ohms]	142.60	142.44	142.56	114.53	139.70	141.70
L_a [mH]	191.70	33.49	45.63	121.74	-258.55	-167.92
L_{ab} [mH]	403.52	235.55	243.28	335.42	-109.84	-37.75
L_f [mH]	7.68	37.86	8.47	-22.24	10.74	-87.34
L_m [mH]	-0.01	0.01	0.01	0.03	-0.04	0.07

Table 3. Comparison between the estimated parameters, the machine operates with 50 [Hz]

Parameter	RLS	Kalman
R_a [Ohms]	16.99	13.39
R_f [Ohms]	141.88	141.79
L_a [mH]	-1018.41	204.15
L_{ab} [mH]	-936.69	294.46
L_f [mH]	-213.49	-149.67
L_m [mH]	0.03	-0.05

Table 4. Comparison between the estimated parameters, the machine carries a load

Parameter	RLS	Kalman
R_a [Ohms]	-11.77	-11.81
R_f [Ohms]	140.10	140.10
L_a [mH]	-112.32	-113.71
L_{ab} [mH]	28.67	27.81
L_f [mH]	13.62	0.31
L_m [mH]	0.02	0.00

5.2.3 Third scenario: The machine carries a load

An electro-dynamo is drawn by the motor through a belt. In the same way the acquisition data was carried out and sinusoidal signals of voltage and currents in three phase were obtained. Identified parameters are shown in the following table.

Definitely this scenario is not the appropriate to estimate the machine parameters due to the three-phase currents get a very large value and the rotor velocity slows down very much.

6 Conclusion

An alternative methodology was presented to model the synchronous generator to avoid discretization. Both designed algorithms in this work were very similar to estimate the synchronous machine parameters with low excitation voltages getting a great accuracy to the identified values. Kalman filter was slightly higher than RLS because of it considers noise model in the equations, hence the first one presented smaller oscillations in the convergence time figure of some estimated inductances.

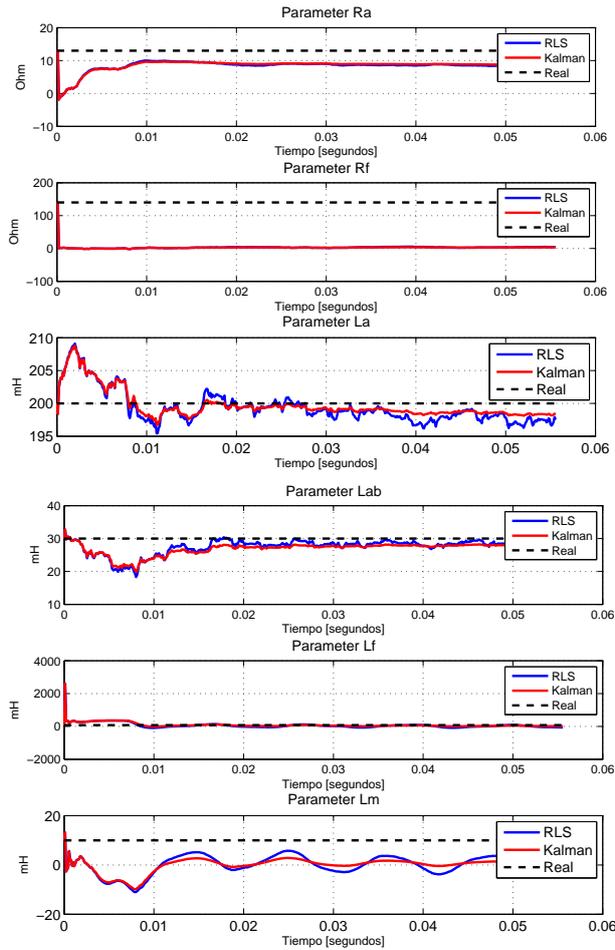


Figure 2. Convergence of the estimated parameters by the algorithms with 1 as the value of white noise variance.

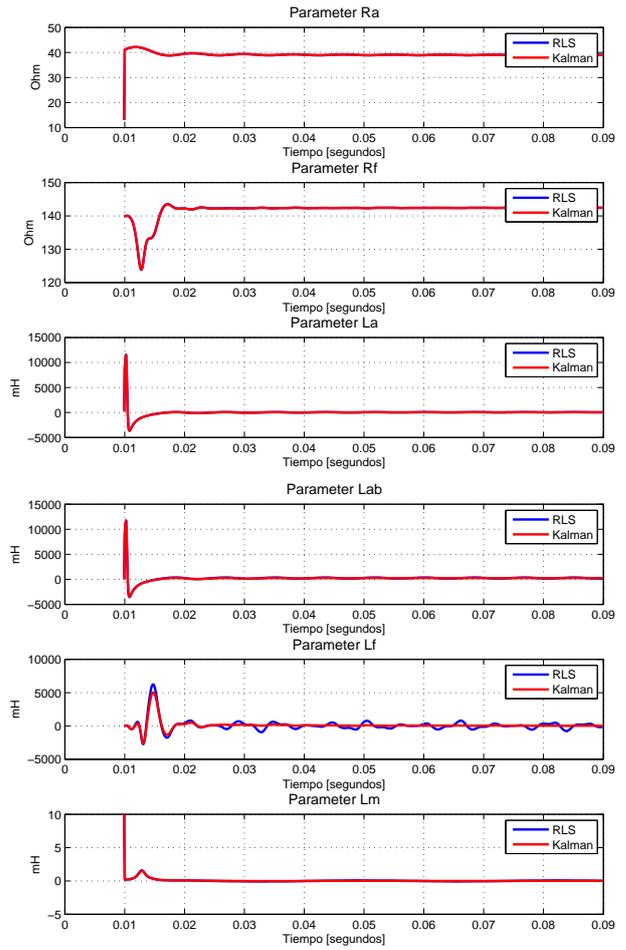


Figure 4. Time convergence of the estimated parameters, the machine operates with $v_f = 20$ volts.

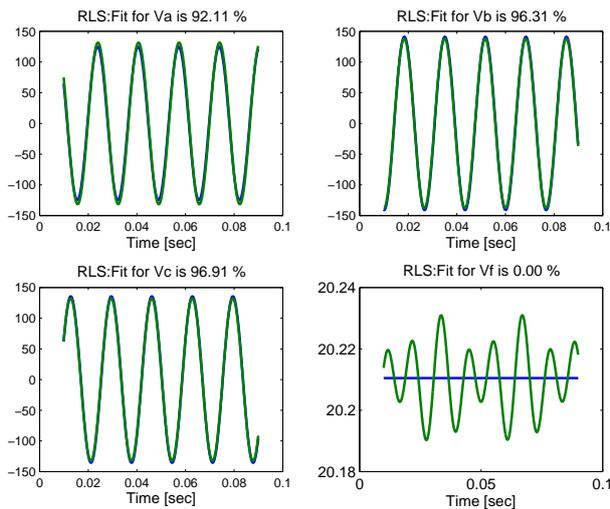


Figure 3. Fit between measured signal (blue) and predicted signal (green).

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