Identification and Tracking of Parameters for a Large Synchronous Generator

Final Project Report

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for a Large Synchronous Generator

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Executive Summary

The main project objective was to describe a method to identify synchronous machine parameters from on-line measurements and to develop a Graphical User Interface (GUI) application that is user friendly and self guiding to enable rapid estimation of desired parameters. In this way, possible fault conditions can be detected and corrective action can be undertaken. In addition, an algorithm was developed to enable detection and rejection of bad measurements thereby increasing the reliability of the results. The secondary project objectives included calculation of the error characteristics of the parameter estimates, development of a confidence index, study of which machine parameters can and cannot be estimated, and evaluation of alternative GUI features.

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1. Introduction

The power system state estimation problem has attracted the attention of many researchers. The main aim is to develop a technique to monitor the power system and to calculate some of the system states through other available data. Traditionally, synchronous machine parameters are obtained by off-line tests as described in IEEE Standards [1]. Several researchers between 1969 and 1971 developed methods to find additional parameter values based on the existing synchronous machine models by Dandeno [2], Schulz [3], and Dineley [4]. A contribution was made by Yu and Moussa in 1971 [5] who reported a systematic procedure to determine the parameters of the equivalent circuits of synchronous machines.

Off-line methods, however, are in most cases neither practical nor accurate. Decommiting a machine for parameter measuring is not economical for a utility especially if the specific machine is a base unit. Furthermore, under different loading conditions certain machine parameters may vary slightly and therefore off-line methods are not accurate enough for certain applications.

Interest in the field of synchronous machine parameter estimation arose in the late sixties. In the last fifteen years, this interest was enhanced by a number of researchers. Keyhani, who has conducted research on parameter estimation using a number of different techniques, has offered extensive literature on this topic. One of the methods used by Keyhani was the estimation of parameters from Standstill Frequency Response (SSFR) test data [6, 7]. In this approach, curve fitting techniques are used to derive the transfer functions of the d-axis and q-axis using available test data. The parameters of the model are then calculated from nonlinear equations, which relate the machine parameters and the time constants corresponding to the transfer functions [7]. Another method used by Keyhani was the identification of synchronous machine linear parameters from standstill step voltage input data [8]. Karayaka, Keyhani, Agrawal, Selin and Heydt in [9-11] concentrated on large synchronous utility generators to develop a procedure of parameter estimation from online measurements.

In [10], the authors present a method to estimate machine parameters using synthetic data as previously, but also real time operating data from a utility generator. This study showed that noise-corrupted data could be handled up to a certain point. Below a certain signal-to-noise ratio, estimation of machine parameters was not possible.

Estimation techniques such as state estimation, least squares and maximum likelihood are used in engineering applications interchangeably. For the purposes of this paper the mathematical model is desired to be transformed in a form realizable by a state estimation algorithm. State estimation is a process during which a number of unknown system state variables or parameters are assigned a value based on measurements from that system [12]. Schweppe [13] was one of the first to propose and develop the idea of state estimation for the monitoring of power systems.

Wood and Wollenberg dedicate a chapter of their book to state estimation [12]. Heydt [14] offers an introduction in state estimation and its applications in power engineering.

2. Modeling of synchronous machines

In order to formulate the state estimation equation for a synchronous generator, it is necessary to employ a mathematical model which represents the synchronous generator in the conditions under study. This model will comprise three stator windings, one field winding and one damper winding. It is assumed that measurements of the currents and voltages in all the windings are available, and these will be used as the states of the model under consideration. A clear contradiction of this assumption is the fact that damper current cannot be instrumented. One way to obviate this difficulty is to employ an observer that uses measurable quantities to estimate damper currents. The five windings mentioned above are magnetically coupled. This coupling is a function of the rotor position and therefore, the flux linking each winding is also a function of the rotor position [15]. Hence, the instantaneous terminal voltage of any winding takes the form,

$$v = -ri - \dot{\lambda} \tag{1}$$

where r is the winding resistance, i is the current and λ is the flux linkage. It should be noted that in this notation it is assumed that the direction of positive stator currents is out of the terminals, since the synchronous machine under consideration is a generator.

In the late 1920s Park [16, 17] formulated a change of variables which replaced the phase variables associated with the stator windings of synchronous machines with variables associated with variables associated with fictitious windings that are rotating with the rotor. The configuration of these windings can be seen in Fig. 1. The d axis of the rotor is defined to be at an angle θ radians with respect to a fixed reference position at some instant of time. If the stator phase currents i_a, i_b, and i_c are projected along the d and q axes of the rotor, the following relationships are obtained,

$$i_q = (2/3) \times [i_a \sin \vartheta + i_b \sin(\vartheta - 2\pi/3) + i_c \sin(\vartheta + 2\pi/3)]$$
$$i_d = (2/3) \times [i_a \cos \vartheta + i_b \cos(\vartheta - 2\pi/3) + i_c \cos(\vartheta + 2\pi/3)]. \tag{2}$$
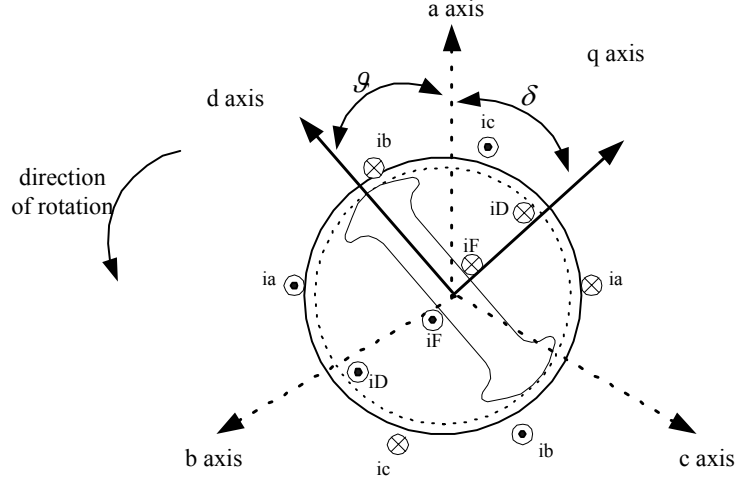
Fig. 1. Representation of a synchronous machine

It should be noted that in this formulation, the reference axis was chosen to be axis *a* to avoid an extra angle of displacement in all the terms. The effect of the above transformation is to convert the stator quantities from phases *a, b* and *c* to new variables the frame of which moves with the rotor. A matrix *P* called Park's transformation is defined, such that,

$$\mathbf{i}_{0dq} = \mathbf{P}\mathbf{i}_{abc}$$

where the current vectors are defined as,

$$\mathbf{i}_{0dq} = \begin{bmatrix} i0 \\ id \\ iq \end{bmatrix}, \qquad \mathbf{i}_{abc} = \begin{bmatrix} ia \\ ib \\ ic \end{bmatrix} \tag{3}$$

The Park's transformation is thus defined as,

$$\mathbf{P} = \sqrt{\tfrac{2}{3}} \begin{bmatrix} \tfrac{1}{\sqrt{2}} & \tfrac{1}{\sqrt{2}} & \tfrac{1}{\sqrt{2}} \\ \cos\vartheta & \cos(\vartheta - \tfrac{2\pi}{3}) & \cos(\vartheta + \tfrac{2\pi}{3}) \\ \sin\vartheta & \sin(\vartheta - \tfrac{2\pi}{3}) & \sin(\vartheta + \tfrac{2\pi}{3}) \end{bmatrix}. \tag{4}$$

The angle θ is given by

$$\vartheta = \omega_R t + \delta + \pi/2 \tag{5}$$

where ω_R is the rated (synchronous) angular frequency in rad/s and δ is the synchronous torque angle in electrical radians [20]. To transform the voltages and flux linkages,

$$\mathbf{v}_{0dq} = \mathbf{P}\mathbf{v}_{abc} \text{ and } \lambda_{0dq} = \mathbf{P}\lambda_{abc}. \tag{6}$$

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The mathematical model to be developed is of the form depicted in (1). As shown in Fig. 1, there are five mutually coupled coils: the three phase windings, the field winding and one damper winding. Therefore, the flux linkage equations for these windings are

$$
\begin{bmatrix} \lambda_a \\ \lambda_b \\ \lambda_c \\ \lambda_F \\ \lambda_D \end{bmatrix} = \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} & L_{aF} & L_{aD} \\ L_{ba} & L_{bb} & L_{bc} & L_{bF} & L_{bD} \\ L_{ca} & L_{cb} & L_{cc} & L_{cF} & L_{cD} \\ L_{Fa} & L_{Fb} & L_{Fc} & L_{FF} & L_{FD} \\ L_{Da} & L_{Db} & L_{Dc} & L_{DF} & L_{DD} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \\ i_F \\ i_D \end{bmatrix}
\tag{7}
$$

where L_{jk} is a self-inductance when $j = k$ and a mutual inductance when $j \neq k$. The inductances in the above matrix are given by well known expressions [15]. It is observed that (7) has time-varying terms which will cause complication when their derivatives are taken. Thus, it is convenient to refer all quantities to a rotor frame of reference through a Park's transformation. The Park's transformation is only applied to the stator portion of the equation. Performing the required mathematical manipulations the flux linkages are obtained in terms of the currents by the matrix equation:

$$
\begin{bmatrix} \lambda_0 \\ \lambda_d \\ \lambda_q \\ \lambda_F \\ \lambda_D \end{bmatrix} = \begin{bmatrix} L_0 & 0 & 0 & 0 & 0 \\ 0 & L_d & 0 & kM_F & kM_D \\ 0 & 0 & L_q & 0 & 0 \\ 0 & kM_F & 0 & L_F & M_R \\ 0 & kM_D & 0 & M_R & L_D \end{bmatrix} \begin{bmatrix} i_0 \\ i_d \\ i_q \\ i_F \\ i_D \end{bmatrix}
\tag{8}
$$

where

$$
L_d = L_s + M_s + \frac{3}{2} L_m \qquad L_q = L_s + M_s - \frac{3}{2} L_m \qquad L_0 = L_s - 2M_s
$$

$$
k = \sqrt{3/2}.
$$

Fig. 2 shows the schematic diagram of a synchronous machine. From this diagram, the generator voltage equations become

$$
\mathbf{v} = -\mathbf{r}\mathbf{i} - \dot{\lambda} - \mathbf{v}_n,
\tag{9}
$$

where the neutral voltage contribution $\mathbf{v}_n$ is given by

$$
\mathbf{v}_n = -r_n \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} - L_n \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \dot{i}_a \\ \dot{i}_b \\ \dot{i}_c \end{bmatrix}.
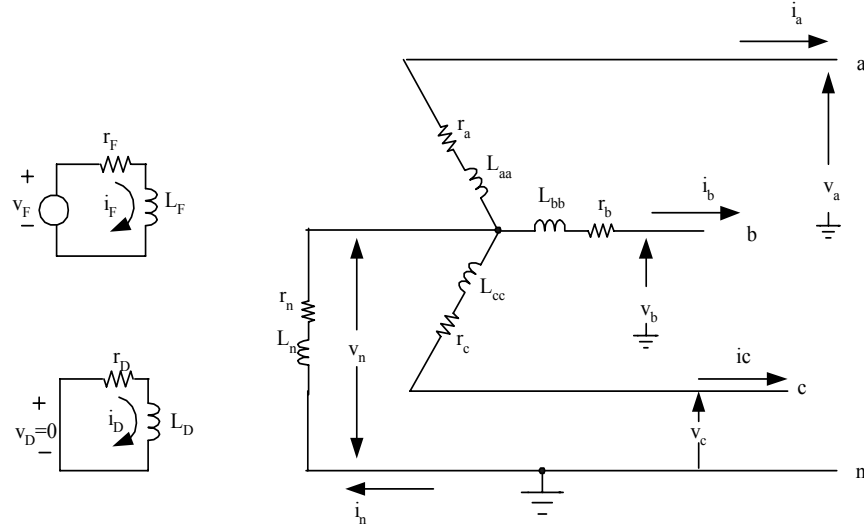\tag{10}
$$

Fig. 2. Schematic diagram of a synchronous machine

Equation (9) in its expanded form becomes,

$$
\begin{bmatrix} v_a \\ v_b \\ v_c \\ -v_F \\ v_D \end{bmatrix} = -\begin{bmatrix} r_a & 0 & 0 & 0 & 0 \\ 0 & r_b & 0 & 0 & 0 \\ 0 & 0 & r_c & 0 & 0 \\ 0 & 0 & 0 & r_F & 0 \\ 0 & 0 & 0 & 0 & r_D \end{bmatrix}\begin{bmatrix} i_a \\ i_b \\ i_c \\ i_F \\ i_D \end{bmatrix} - \begin{bmatrix} \dot{\lambda}_a \\ \dot{\lambda}_b \\ \dot{\lambda}_c \\ \dot{\lambda}_F \\ \dot{\lambda}_D \end{bmatrix} + \begin{bmatrix} \mathbf{v}_n \\ \mathbf{0} \end{bmatrix}.
$$

(11)

In (11) the voltage is expressed in terms of both currents and flux linkages. This is not desirable and therefore one of the two variables has to be replaced. Equation (8) is employed to replace the flux linkage by the current variables. The choice of replacing the flux linkages rather than the currents is based on two reasons. The main reason is that the available data from on-line measurements are voltage and current states. There will be no need to convert the currents into flux linkages in the above equation. The second reason is that the relationship between the voltages v_d and v_q and the state variables is much simpler than one involving flux linkages. Substituting all known parameters into (11), the mathematical model can be derived as,

$$
\begin{bmatrix} v_0 \\ v_d \\ v_q \\ -v_F \\ v_D \end{bmatrix} = -\begin{bmatrix} r+3r_n & 0 & 0 & 0 & 0 \\ 0 & r & \omega L_q & 0 & 0 \\ 0 & -\omega L_d & r & -\omega kM_F & -\omega kM_D \\ 0 & 0 & 0 & r_F & 0 \\ 0 & 0 & 0 & 0 & r_D \end{bmatrix}\begin{bmatrix} i_0 \\ i_d \\ i_q \\ i_F \\ i_D \end{bmatrix} - \begin{bmatrix} L_0+3L_n & 0 & 0 & 0 & 0 \\ 0 & L_d & 0 & kM_F & kM_D \\ 0 & 0 & L_q & 0 & 0 \\ 0 & kM_F & 0 & L_F & M_R \\ 0 & kM_D & 0 & M_R & L_D \end{bmatrix}\begin{bmatrix} \dot{i}_0 \\ \dot{i}_d \\ \dot{i}_q \\ \dot{i}_F \\ \dot{i}_D \end{bmatrix}.
$$

(12)

Equation (12) effectively is a formulation of the state variable equations in a form suitable for state estimation. Equation (12) can be easily rearranged in the form $\dot{x} = Ax + Bu$ provided that the above equations are linear. The only non-linearity in the above equations derives from

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the presence of the synchronous speed ω. The synchronous speed is almost constant and therefore (12) can be considered as linear.

3. State estimation and the Moore-Penrose pseudoinverse

State estimation is a process during which a number of unknown system state variables or parameters are assigned a value based on measurements from that system [12]. Typically, the number of measurements (or number of equations) is greater than the parameters to be estimated. In this case the system is overdetermined and the solution is found in a least squares sense. That is, it is desired that the sum of the squares of the differences between the estimated and the measured parameters to be minimized.

The system is usually arranged in the form

$$H \cdot x = z,$$

where H is a matrix of dimensions $m \times n$, x is a vector of dimension n and z is a vector of dimension m. In this notation m is the number of measurements and n is the number of parameters to be estimated. If $m = n$, then the system is completely determined. In other words, the number of equations is equal to the number of unknowns and there is a unique solution which can be found by inverting the matrix H. Therefore,

$$x = H^{-1} z.$$

In the overdetermined case it is not possible to invert H since $m \neq n$. The solution is not unique since in general it is not possible to satisfy all the equations exactly for any choice of the unknowns. A solution should be selected such that the error in satisfying each equation is minimum. It is desired to minimize the function,

$$f(\hat{x}) = (z - H\hat{x})^T \cdot (z - H\hat{x}) \tag{13}$$

where $(z - H\hat{x})$ is the error vector and $\hat{x}$ is the vector of the estimated parameters. The result of this function is a scalar and is a measure of the error.

It is desired to find a vector $\hat{x}$ such that $\hat{x} = A \cdot z$. Utilizing (13) and knowing that the minimum of a function occurs at the point where its derivative is equal to zero,

$$\frac{\partial f}{\partial \hat{x}} = \begin{bmatrix} \dfrac{\partial f}{\partial \hat{x}_1} \\ \dfrac{\partial f}{\partial \hat{x}_2} \\ \vdots \end{bmatrix} = \frac{\partial}{\partial \hat{x}}[z^T z - \hat{x}^T H^T z - z^T H\hat{x} + \hat{x}^T H^T H\hat{x}] = 0$$

$$\Rightarrow 0 - 2H^T z + 2H^T H\hat{x} = 0$$

$$\Rightarrow H^T H\hat{x} = H^T z.$$

(14)

Hence, if $[H^T H]^{-1}$ exists, the vector of the estimated parameters can be found by,

$$\hat{x} = [H^T H]^{-1} H^T z$$

(15)

where the quantity $[H^T H]^{-1} H^T$ is termed as the Moore-Penrose pseudoinverse or the generalized inverse and is symbolized by H^+.

4. Configuration of the state estimator

As shown earlier it is desired to arrange (12) in the form $H \cdot x = z$. The developed model of the synchronous machine is of the form

$$V = -R \cdot I - L \cdot \dot{I}.$$

Available data are some of the elements of matrices R and L, and measurements of the current and voltage states. In the general case, the current derivative is approximated by the forward difference formula,

$$\dot{i}(t) \approx \frac{i(t + \Delta t) - i(t)}{\Delta t} = \nabla i(t).$$

(16)

The next step is to attempt to separate the unknowns to the left hand side of each equation of the matrix equation and the knowns to the right hand side. The right hand side will then be the matrix Z, while the left hand side will be the matrix product Hx.

5. Testing

The machine parameter estimator algorithm was tested using a 800 MVA synchronous generator with parameters listed in Table 2. The set of differential equations which result from the mathematical model of the machine (Equation (12)) and the machine parameters of Table 2, was solved in MATLAB using a fourth order Runge-Kutta algorithm. This enabled creation of synthetic data and storage of voltage and current measurements in a data file. These data are similar to measurements produced by a digital fault recorder (DFR).

Table 2. Calculated parameters for use in synthetic data creation

Parameter	Value (p.u.)	Parameter name
r	0.0046	Stator phase resistance
r_n	100	Equivalent neutral resistance
L_q	1.72	Equivalent quadrature axis reactance
L_d	1.80	Equivalent direct axis reactance
M_F	1.339	Stator to field mutual inductance
M_D	1.339	Stator to damper winding mutual inductance
r_F	9.722×10^{-4}	Equivalent field resistance
r_D	8.823×10^{-3}	Equivalent resistance of damper winding
L_0	0.15	Equivalent zero sequence inductance
L_n	100	Equivalent neutral inductance
L_F	1.75791	Field winding self inductance
M_R	1.64	Rotor mutual inductance
L_D	1.68125	Self inductance of damper winding D

6. Estimation of machine parameters

It is desired to estimate each one of the parameters in (12) and to verify the validity of the program, as well as to ascertain which parameters are possible to be estimated. In case that a parameter is not estimated within an acceptable error using noise free data, then its estimation using noise corrupted data will not be feasible. There are nine parameters that are to be estimated in matrix R and eleven parameters in matrix L. The actual and estimated parameters in matrices R and L and the percent error between actual and estimated values can be seen in Tables 3 and 4.

From Tables 3 and 4 it can be readily observed that parameters $r+3r_n$ and L_0+3L_n cannot be estimated at all. However, this is expected since these quantities are located in the first equation of (12), which is decoupled from the others. All the voltage and current states in this equation are zero in the steady state and it is not possible to calculate these parameters. These two quantities are possible to be estimated in the transient case, as the zero axis quantities will not be zero. Observation of the other parameters in Tables 3 and 4 shows that it is possible to estimate all parameters with a percent error of effectively 0%. The maximum error observed was 0.07% and it occurred for the damper axis resistance r_D.

It is also useful to study the effect of estimating more than one parameter at a time. This will indicate whether multiple parameter estimation is feasible and it will enable the user to avoid multiple program executions. For this purpose it was decided to estimate five parameters simultaneously, three from matrix R and two from matrix L. The selection of the five parameters was rather arbitrary. However, in the case of parameters occurring in multiple positions, the parameter position selected was the one producing the smallest error in the previous case study. The results of a representative estimation of this form can be seen in Table 5.

Table 3. Estimated parameters in matrix R using synthetic data

Parameter	Actual value (p.u.)	Estimated value (p.u)	% Error
$r+3r_n$	300.0046	0	-100
R	0.0046	0.00460001	$2.1x10^{-4}$
ΩL_q	1.72	1.71999997	$-1.7x10^{-6}$
$-\omega L_d$	-1.80	-1.800000009	$-5x10^{-7}$
R	0.0046	0.00460002	$-4.3x10^{-4}$
$-\omega k M_F$	-1.64	-1.639999989	$-6.7x10^{-7}$
$-\omega k M_D$	-1.64	-1.639808075	-0.01
R_F	$9.722x10^{-4}$	$9.72200016 \ x10^{-4}$	$1.6x10^{-6}$
r_D	$8.82283x10^{-3}$	$8.82897987 \ x10^{-3}$	0.07

Table 4. Estimated parameters in matrix L using synthetic data

Parameter	Actual value (p.u.)	Estimated value (p.u)	% Error
L_0+3L_n	300.15	0	-100
L_d	1.80	1.800112	$6.22x10^{-3}$
kM_F	1.64	1.639572	-0.026
kM_D	1.64	1.639844	$-9.5x10^{-3}$
L_q	1.72	1.719415	-0.03
kM_F	1.64	1.6399998	$-1.2x10^{-5}$
L_F	1.75791	1.7579085	$-8.5x10^{-5}$
M_R	1.64	1.6400001	$-6.1x10^{-6}$
kM_D	1.64	1.6399969	$-1.9x10^{-4}$
M_R	1.64	1.6400117	$7.1x10^{-4}$
L_D	1.68125	1.6812544	$2.6x10^{-4}$

Table 5. Multiple simultaneous parameter estimation

Parameter	Actual value (p.u.)	Estimated value (p.u.)	% Error
r	0.0046	0.004600012	$2.6x10^{-4}$
$-\omega L_d$	-1.80	-1.800000009	$-5x10^{-7}$
r_F	$9.722x10^{-4}$	$9.7220000x10^{-4}$	0
L_F	1.75791	1.75790848	$8.6x10^{-5}$
M_R	1.64	1.64000000	0

In the case of r, L_d and L_F, it is observed that the error of estimation is unaltered for the case of simultaneous parameter estimation. For r_F and M_R it is surprising to note that the error

decreases to 0%. Not only there is no negative effect on the estimation of multiple parameters, but the effect is rather positive as the error of some of the parameters decreases.

7. Effect of noise in parameter estimation

It is expected that the measurements obtained from the DFR will be contaminated with noise. This noise may be due to equipment imperfections or inaccuracies or poor interface between DFR and the computer that is used to store the measurements. The DFR will collect data with a certain number of significant figures. The rest of the figures which may also be significant, will be lost. These reasons dictate the study of noise in parameter estimation. It is desired to study the effect of noise in the synthetic data case. To compare the sensitivity of the estimation between voltage noise and current noise, two case studies were performed. In the first case study, noise was added only to the voltage measurements while the current measurements were kept noise free (in the case study denominated S-EN-12-05). The results for this case study can be seen in Tables 6 and 7. Table 6 shows the lowest SNR in the voltage measurements achieved to produce an estimation with acceptable accuracy. As can be observed, even with an SNR of 4.7 in the field voltage and an SNR of 9 in the phase voltages, the estimated parameters of Table 7 are within acceptable accuracy, comparable to the noise free case in Tables 2 and 3. The only parameter deviating from the noise free case is the stator resistance r, which is estimated with an error of -10.5%.

**Table 6. Signal to noise ratios in the voltage measurements
(case study S-EN-12-05)**

SNR	Voltage
9	V_a
9	V_b
9	V_c
4.7	V_F

Note: The SNR is not recorded for V_D, since these voltages are zero. However, noise was added to these measurements as well.

In case study S-EN-12-06, noise was added to the current measurements in the form shown in Fig. 3. However, in this case, it can be seen that noise in the current measurements has an adverse effect on the estimation. The minimum allowed SNR in the phase measurements was 24,790 while that of the field current was 50,000. The only current that was able to withstand relatively high amount of noise was the damper winding current with an SNR of 36. The results are shown in Tables 8 and 9.

Table 7. Parameter estimation and percentage error using the noise contaminated voltages for case study S-EN-12-05

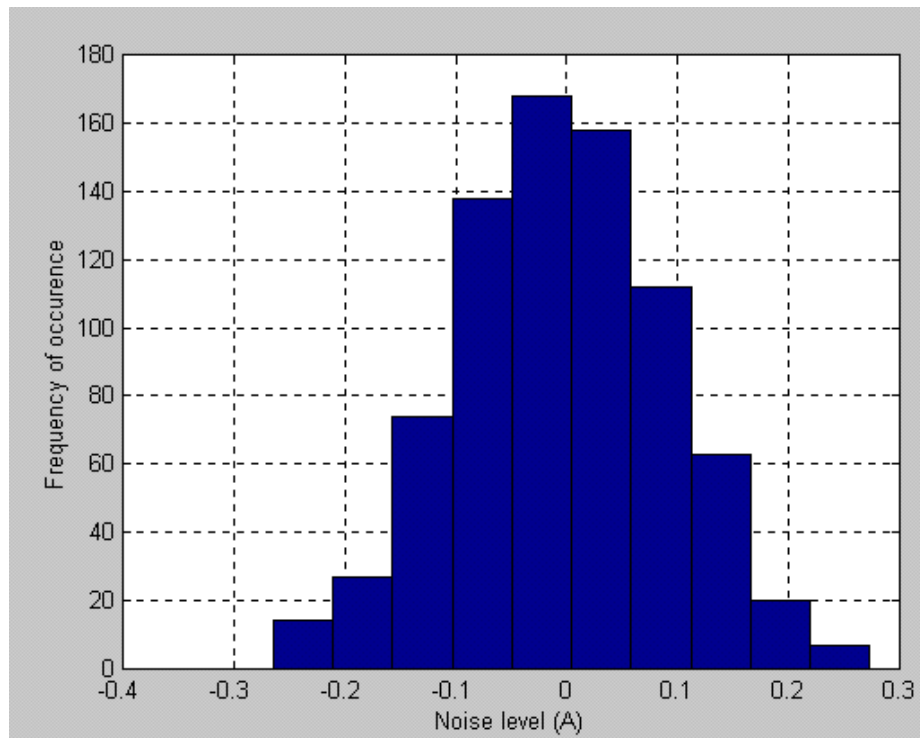| Parameter	Actual value (p.u.)	Estimated value (p.u)	% Error
$r+3r_n$	300.0046	-1.577854×10^9	-5×10^8
R	0.0046	0.00411830	-10.5
L_q	1.72	1.72146623	0.0852
L_d	1.80	1.79870678	0.072
kM_F	1.64	1.64192518	0.12
kM_D	1.64	1.63924315	-0.046
r_F	$9.722x10^{-4}$	$9.72199937 \times 10^{-4}$	-6.5×10^{-6}
r_D	8.82283×10^{-3}	$8.69623929 \times 10^{-3}$	-1.43
L_0+3L_n	300.15	4.07266887×10^7	1×10^7
L_F	1.75791	1.75802419	6.6×10^{-3}
M_R	1.64	1.64291578	0.18
L_D	1.68125	1.68183083	0.035

Fig. 3. Noise distribution for noise added in phase *a* current measurements for case study S-EN-12-06

**Table 8. Signal to noise ratios in the current measurements
(case study S-EN-12-06)**

SNR	Current
24,790	i_a
24,790	i_b
24,790	i_c
50,000	i_F
36	i_D

**Table 8. Parameter estimation and percentage error
using the noise contaminated currents for case study S-EN-12-06**

Parameter	Actual value (p.u.)	Estimated value (p.u)	% Error
$r+3r_n$	300.0046	0	100
R	0.0046	0.00460443	0.096
L_q	1.72	1.71997212	-1.62×10^{-3}
L_d	1.80	1.79998508252	-8.3×10^{-4}
kM_F	1.64	1.63997119	-1.7×10^{-3}
kM_D	1.64	1.66342311	1.4
r_F	$9.722x10^{-4}$	$9.82287981 \times 10^{-4}$	1.04
r_D	8.82283×10^{-3}	$1.29390938 \times 10^{-1}$	-1366
L_0+3L_n	300.15	0	100
L_F	1.75791	1.69726033	-3.4
M_R	1.64	1.67835420	2.3
L_D	1.68125	1.52456341	-9.3

11. Suppression of noise in measurements using a digital filter

The case studies performed show that it is imperative to filter the measurements obtained from the DFR before these measurements are applied to the *Estimator*. This noise attenuation will allow accurate estimation and higher confidence in the application. Possible meter noise will be attenuated and therefore the reliability of the *Estimator* will not be impeded by meter in-accuracies. For the purposes of this application two general classes of filters are under considera-tion. The first class is the low pass filter, which will attenuate the high frequency noise compo-nent and allow the low frequency 60 Hz signal to pass through. The second class of filter con-sidered is the band pass filter. This class of filter will attenuate all signals except the 60 Hz sig-nal, which is the signal of interest. The two types of filters and their characteristics are discussed in this section.

Representative types of low pass filters are the moving average, the Butterworth filter, the Chebyshev filter and the elliptic filter [18-20]. The filters that are considered in this research

work are the moving average filter and the Butterworth filter. The moving average filter in the discrete time domain is given by [18],

$$ y_n = \frac{1}{N} \sum_{i=0}^{N-1} x_{n-i} \tag{17} $$

where x_k are the input data and N is the degree of the moving average. After transforming (17) into the z-domain, the transfer function of an N-point moving average is given by,

$$ H(e^{j\omega \Delta T}) = \frac{1}{N} \sum_{i=0}^{N-1} e^{-ji\omega \Delta T} . \tag{18} $$

The advantage of this type of filter is that it is easy to program. However, it has a slow roll off, which may allow some frequencies to pass through. A moving average model is shown in Fig. 4.
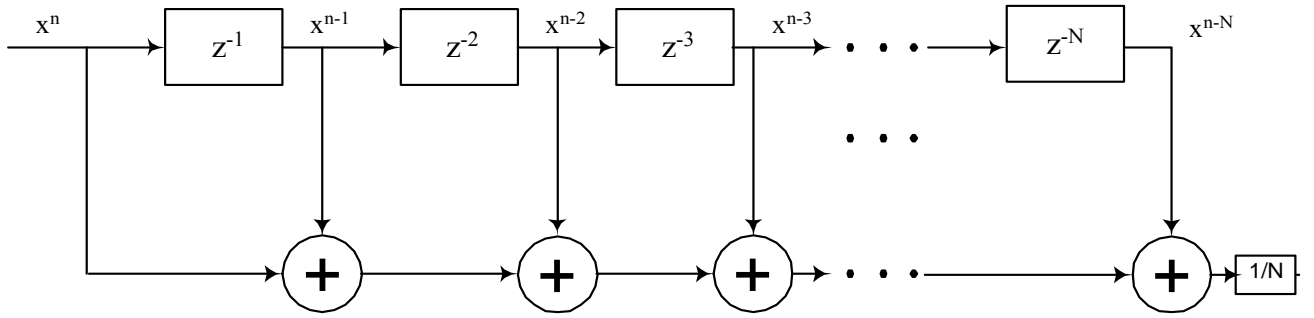

Fig. 4. Moving average model implementation

The second type of low pass filter considered for this research work is the Butterworth filter. This filter has a good transient response and a fast roll off. The general N^{th} order Butterworth filter has a magnitude squared function in the discrete case [19],

$$ |H(j\Omega)|^2 = \frac{1}{1+(j\Omega/j\Omega_c)^{2N}}, \tag{19} $$

where Ω_c is the cutoff frequency. As N increases, the frequency response becomes sharper. However, at the cutoff frequency the magnitude of the transfer function is $1/\sqrt{2}$ for every value of N. The Butterworth filter is an all pole filter and has a transfer function of the form [20],

$$ H(s) = \frac{Kb_0}{s^n + b_{n-1}s^{n-1} + \cdots + b_1 s + b_0}, \tag{20} $$

where K is a constant. An example of an implementation of this filter is shown in Fig. 5. This implementation has a first order section followed by a second order section.

The second class of filters to be studied are the band pass filters. These filters have a pass band between two cutoff frequencies ω_L and $\omega_U > \omega_L$, and two stop bands, $0 < \omega < \omega_L$ and $\omega > \omega_U$. The bandwidth of the band pass filters is defined as [21]

$$BW = \omega_U - \omega_L .$$

By selecting the two cutoff frequencies it will be possible to attenuate all frequencies that are of no interest to this application. This is the advantage of the bandpass filter over the low pass filter. In the low pass filter case, components at frequencies below 60 Hz are allowed to pass through along with the signal. All classes and types of filters will be examined and case studies will be performed with all of them to select the most appropriate for this application.
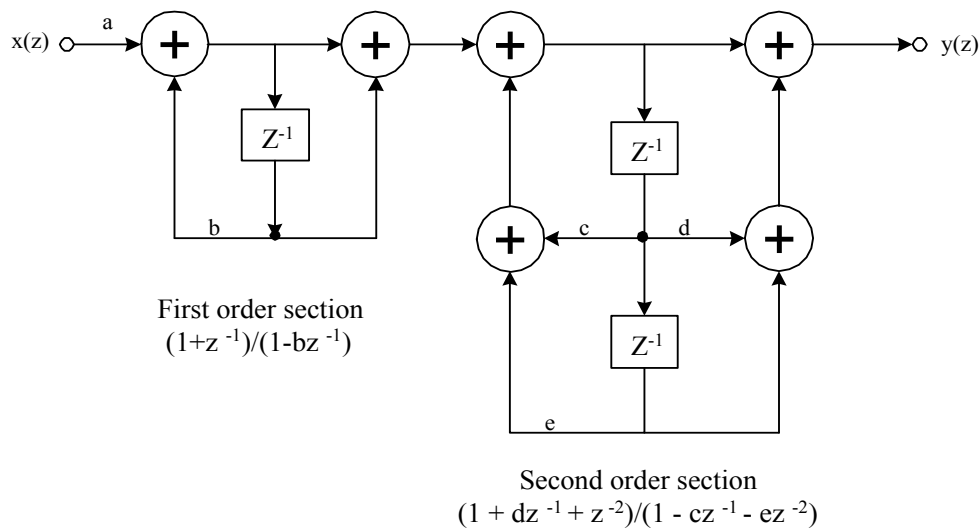
First order section
$(1+z^{-1})/(1-bz^{-1})$

Second order section
$(1 + dz^{-1} + z^{-2})/(1 - cz^{-1} - ez^{-2})$

Fig. 5. Cascade implementation of a low pass Butterworth digital filter [22]

9. Graphical user interface implementation using visual C++

One of the major objectives of this research work is to develop a visual graphical user interface (GUI) in the form of a Windows application for a synchronous machine state estimator. This application will enable the practicing engineer and interested utilities to estimate the parameters of a synchronous machine without having to decommit the unit or get involved in time consuming methods of estimation. The application developed during this research work is unique due to three main characteristics: on-line operation, portability and user friendly interaction. On-line operation is the distinguishing characteristic of this application. It enables on-line and expeditious estimation of any given synchronous machine based on measurements of the field and stator voltages and currents. Such measurements are readily available and in large quantities in every utility. Moreover, the application developed is portable, since it can be installed in any personal computer operating under Windows. The application does not require a Visual C++ environment, since it is a stand-alone application, able to operate without the support of external C++ libraries.

User friendly interaction is achieved by means of the dialogs and context-sensitive help provided on request. The input and output dialogs are self explanatory and will be described in Sections X and XI respectively. Moreover, these dialogs and each of their components are analyzed within the program itself in the Help section. General guidelines for correct operation of the program and interpretation of the results are also provided.

10. Input dialog and estimator configuration

On double clicking the executable file of the application, the main window of the program appears. It offers a variety of options on its toolbar, like any other Windows program. To begin the process of estimating machine parameters, the user must open the input screen as shown in Fig. 6. This is achieved by selecting the option *Estimator* on the toolbar of the main window, and then selecting the *Set up Estimator* option.

Fig. 6. Input window of the *Estimator*

The user can set up the *Estimator* and calculate the parameters of the synchronous machine that is to be studied, in three steps. The first step is to enter the name of the data file in the edit box as shown in Fig. 6. This can be done by clicking on the *Browse* button and navigating through the hard disk of the computer until the desired file is located. The file should be of type .txt to be eligible for usage by the application. Text files can be created either by using the Windows Notepad, or any other software with similar capabilities. Another option is to create text files using Microsoft Excel and save the file as a text -tab delimited format. The formatting of the data is of major importance. The data should be entered column-wise in eleven columns. If the specific data arrangement required by the application is not strictly adhered to, the program will not estimate the parameters correctly.

The second step on behalf of the user is to input the known parameters of the synchronous machine. These parameters may be known either from previous off-line tests or from manufacturer data. Sample values are shown in Fig. 6 and these are the default values for the generator that is being studied for this application. The existence of default values does not require the user to enter the values anew every time it is desired to execute the application. The fact that all values are set to default values should not be confusing to the user. If the user desires the estimation of a certain parameter, then the default value of that specific parameter does not interfere in any way in the estimation. The third and final step of this process is to select the parameters that are desired to be estimated. The user has the opportunity to select up to five parameters for estimation. This selection can be done by simply clicking on the check box corresponding to the parameter to be estimated as shown in Fig. 6.

12. Output dialog and estimated parameters

Upon execution of the main program of the application, which contains the state estimator, the values of the estimated parameters and the rms error for this estimation are returned to the graphical user interface for output. The resulting output window can be seen in Fig. 7.
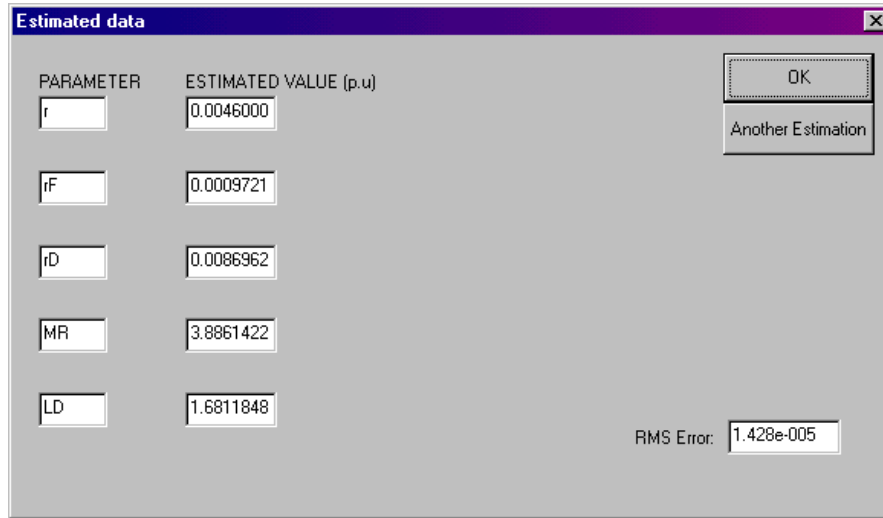

Fig. 7. Output window of the *Estimator*

On the left side of the output window, the user can see the parameters selected previously and their estimated value in per unit. The rms error on the lower right side of the estimator is a measure of confidence on the estimated parameters and is given by,

$$rms\ error = \sqrt{residual \Big/ \#\ of\ measurements}$$

where

$$(residual)^2 = \{[H]\cdot[x]-[Z]\}^T \cdot \{[H]\cdot[x]-[Z]\}$$

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and $\hat{x}$ is the vector of the estimated parameters.

12. Interpretation of the rms error and the chi-squared test

Small values of rms error as calculated by the *Estimator* in Fig. 7, indicate reliability of results. Larger values of rms error indicate results that cannot be trusted for correct interpretation. It is suggested that in such cases the user selects a smaller number of parameters to be estimated, supplies the *Estimator* with an increased number of measurements, or even use a digital fault recorder with a greater amount of reliability so as to produce higher quality measurements with less noise. The residual, which is the basis for the calculation of the rms error, is ideally equal to zero for error free estimations. Its value represents a measure of how closely the estimated values follow the measured or expected values. Instead of relying on intuition as to how large or how small the residual or the rms error should be, a standardized method could be followed to ascertain reliability of the results. A widely used method for such purposes is the χ^2 test. This method will be analyzed in this section and it will be applied in future steps to the GUI application so as to issue warnings in cases that the estimation might not be reliable.

The residual *J(x)* is a random number since the measurement errors are random numbers as well. Therefore, it can be shown that *J(x)* has a probability density function known as a chi-squared distribution, also written as $\chi^2(K)$. *K* is called the degrees of freedom of the chi-squared distribution and is defined as,

$$K = N_m - N_s,$$

where N_m is the number of measurements, and N_s is the number of states. The mean value of the chi-squared distributed residual is *K*, and its standard deviation is $\sqrt{2K}$ [12]. To ascertain how large a residual needs to be so as to be considered as a bad estimation, the χ^2 test has to be set up. A threshold value of *J(x)* has to be decided and this value is denoted t_J. Such threshold values can be in the order of three times the standard deviation as noted above. Therefore, if *J(x)* > t_J, then bad measurements or unreliable estimation is detected. The next step is to calculate the probability that *J(x)* is greater than t_J. This probability is called the significance level α and it is desired to be as small as possible.

13. Conclusions and future steps

In this report, a method to identify synchronous machine parameters from on-line measurements is shown. The method is based on least squares estimation and a simple formula for the derivative operator. The method is developed to be used with a Visual C++ engine and graphical user interface (GUI), so that the practicing power engineer may link machine measurements taken in an on-line environment with the *Estimator*. Nine out of eleven parameters of the synchronous machine model were estimated accurately. The field resistance was estimated with approximately zero error ($1.6x10^{-6}$%). Eight other machine parameters were estimated with errors varying from 0 to 0.07%. This error is negligible for the purposes of this estimation. Two other parameters, $r+3r_n$ and L_0+3L_n were not possible to be estimated. Multiple parameters at a time were also estimated accurately. This enables estimation of more than one machine parame-

ter in the real data case, when more than one parameter is be unknown. The accuracy of estimation was shown not to degrade with multiple parameter estimation.

Noise suppression is of major concern in this research work. The *Estimator* itself is able to withstand signal to noise ratios equal to 9 for phase voltages and SNRs equal to 4.7 for field winding voltages. Because of the presence of current derivative, noise in current measurements cannot be tolerated to a high level. It was shown that even large SNRs for current caused a significant increase in the error of estimated parameters.

The GUI was developed in Visual C++ and its correct operation was verified. The GUI is user friendly and self-guiding. Calculation time is in the order of a few milliseconds, while the results are presented on the computer screen automatically. Extension of the GUI for the real data case is thus possible and it will be the next step of this research work.

Unreliable estimation can be ascertained utilizing the χ^2 test. The GUI can have default or user-defined confidence levels, which will enable calculation of the threshold value of the residual for reliable estimation. This threshold value can then be compared to the value of the residual for the specific estimation and if it is smaller, then an audible or visual warning will be given to the user.

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