Power System States Estimations Using Kalman Filter

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Abstract

Power system state estimation plays an important role in the analysis of control and system stability and many other key functions such as economic analysis of load, optimal power flow (OPF), events analysis and gaining static and dynamic parameters of systems are based on state estimation. Conventional state estimation due to low rates of update of SCADA system, cannot demonstrate the dynamic situations (several seconds). In order to deal with the obstacles due to linearization and calculation of Jacobian matrix, a non-linear dynamic state estimation without calculation of the Jacobian matrix is provided in this paper. Kalman filter is a mathematical method that aims to provide values closer to actual values from measurements that include noise and inaccuracy. The method matches the non-linear characteristics of system as well as probability of measured values. After, Kalman filter state estimation method is presented in both linear and nonlinear modes and simulation results are presented in MATLAB.

1. Introduction

The structure of the transmission system in the developed world is faced with two major challenges: reliability and extensibility. New technologies to produce electric power by wind and solar energy replace fossil fuels in power plants with synchronized machine [1-2]. With these changes due to concentrated synchronized production the current power model in transmission system cannot be fixed. In recent decades for many reasons there have been no effective investments in the transmission system [3-4]. Technologies related to control and computational layers play an important role in avoiding the blackouts of the transmission system. But the majority of monitoring and control instruments of energy management systems (EMSs) are based on steady-state model of the system. Therefore, it cannot be properly show dynamic performance of the system [5-6]. This limit is due to dependency of EMS to very slow update rate of SCADA systems. With the advent of phasor measurement unit (PMU) based on wide area measurement systems (WAMSs) new techniques for dynamic security assessment (DSA) are developed to assess the security of system that is an effective method for studying the dynamics of the system compared to conventional EMSs [7-10]. Exact knowledge of dynamic state of system is through dynamic state estimation (DSE) and it can be said that state estimation is the core of these techniques [11-13]. Most studies related to dynamic state estimation are in the field of linear systems [11-12]. These papers include linearizing the algebraic and differential equations can be done by calculating the Jacobian matrix. Linear approximation leads to errors, which could be effective in the whole of the time, especially for higher-power and complex systems [14]. The Jacobian matrix is performed for algorithms with complex calculations. Using linear designs, recent papers have done research aimed at eliminating linearization and using unscented conversion and preventing the calculation of Jacobian matrix at any repetition [3, 13-14].

Power system state estimation plays an important role in the analysis of control and system stability and many other key functions such as economic analysis of load, OPF, events analysis and gaining static and dynamic parameters of systems are based on state estimation [15-16]. Conventional state estimation due to low rates of update of SCADA system, cannot demonstrate the dynamic situations (several seconds). In order to deal with the obstacles due to linearization and calculation of Jacobian matrix, a non-linear dynamic state estimation without calculation of the Jacobian matrix is provided in this paper. At the beginning, it is tried to simply explain state estimation using [17] and then its application and its relationship with other sectors in the power system are elaborated.

In the following, to better understand the paper a linear system, which in fact are the equations of motion is used and simulation results are presented in MATLAB. Kalman filter has errors when the input data is not obtained from dynamics simulation, so using DigSilent software dynamic state of system is modeled simulation results in is provided at this software but it should be noted that this data is not used in MATLAB software.

2. State Estamition

First, we need to be discussing state estimation to some extent and provide an example using reference [17] to properly understand the concept. In this reference, the concept has been simply stated for static state. In the eighteenth century for the first time, scientists observed wonderful arrangement in measuring errors. They found that observed samples or distributions are approximated by continuous distribution as it was called normal curve of errors, and attributed them to the laws of chance. An operator must have access to the right information from the system, to detect errors in the system based on that information and based on this information, he can decide on overvoltage, overload etc. The task of state estimation is to provide right information for operator at different conditions, what made the state estimation successful is the advantage of probability rules; as mentioned above, the measurement errors are normally distributed and when a non-measurement error exist in calculations it can be detected with this method and its effect can be reduced or eliminated. Measuring converters in the power system, like any other device are prone to error, if these errors are small they may not be detected and measured value can incorrectly enter the calculation and even the output may be useless; for example, the device may be installed in reverse order and may provide a negative value. In some cases, parts of telecommunication system may be disconnected and the operator may not be available; these were the reasons for development of state estimation at the past.

Networks used in [17] are provided in Figure 1. With state estimation, using the algorithm in Figure 2 values of Table I is achieved. Random error is added to the measured values to obtain the measurement with the random error. According to Table I, it is possible to achieve efficiency of state estimation in the power system. For example, measurement of M_{23} shows the active power to be 8.6^{MW}, but the actual value, 2.9^{MW}, the value proposed by estimator is equal to 3^{MW}. Despite the measurement error, the estimation algorithm calculated some values, which is much closer to the actual values. There are other advantages for state estimation algorithm including, a) The ability of state estimation for detection bad measurements, b) The ability for estimation of the values of which are not measured or communicated. The following a brief explanation of reference [17] is given.

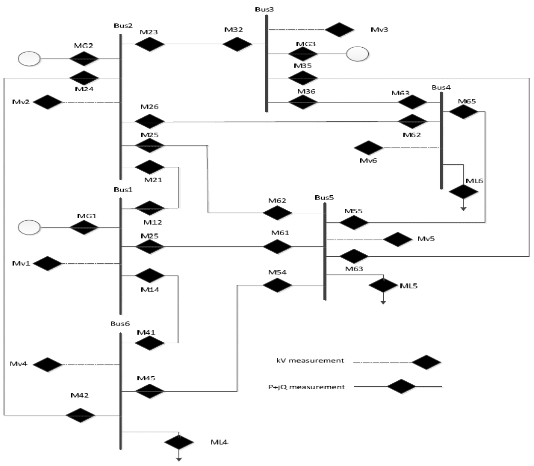


Fig. 1. The circuits used in reference [17] to better understand the state estimation in power system

2.1. State Estimation for Detection of Bad Measurements

The ability for detection of bad measurement in the power system is valuable for operators. The converters may be wired incorrectly or may have a wrong function. Identifying these errors using statistical theory is very simple but lengthy. By checking the value of J(x) you can understand the existence of a bad measurement in the system, so that a threshold is defined based on the probability, so if the Jacobian is less than this value (t_j), it is supposed that there is no bad measurement in the system, but if it is larger than this threshold, there is a bad measurement in this system.

But the question that arises here is that what the reason for bad measurement is in the system to be corrected. If the difference between predicted and measured is shown with y_i, it has a normal distribution with mean of zero and standard deviation of σ_{yi}, then it will be normalized so it has a standard deviation of 1. If the normalized value is larger than 3 cases these measurements has the risk of bad measurement; we will begin with the largest value and put it aside. Again state estimation is performed for the rest of the data and J(x) will be specified; on the basis of the new threshold, if it was less than threshold, a bad measurement is achieved; otherwise, the operation must be repeated for other candidates. It is necessary to mention here that some of the measurements are with very small errors. Therefore, it is not possible to detect them, but what is important is that the operator knows that there is no big error in the data.

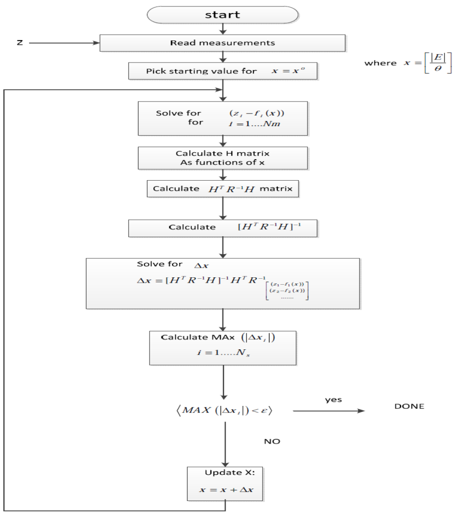


Fig. 2. Algorithm used to state estimation of Figure 1

2.2. Estimation of the Values of Which are not Measured or Communicated

Another important feature of state estimation is estimation of the values of which cannot be transmitted. It may be due to problems in telecommunications, as well as non-installation of measuring instruments and transfer of it to the control center. If in Figure 1, data from all buses of 3, 4, 5 and 6 is not transmitted to the control center, still we can use the state estimation algorithm, the values of voltage and phase of other buses can be estimated and then generation, currents and loads can be achieved; the results are shown in Table II. As can be seen in Table II, estimated values are not very close in comparison with when the full data is transmitted.

2.3. Application of State Estimation in Power System

Measuring the analog output of the generators should go directly to the AGC program and other data before it is used by other programs must be processed in state estimation program. To run the state estimation, first network topology (connection of line 5 to bus and load, on/off state of switches) must be specified, then the electric model of power transmission system will be sent state estimation program. The output of state estimation include voltage and phase all buses, current MW and MVAr in lines, bus loads and product of generators. These values and electrical model are a basic for economic distribution of load, investigation of events and correction of production. Since, we have the complete electric model of transmission lines so the penalty factor can be calculated as well.

3. Linear Kalman Filter

Kalman filter is a mathematical method that aims to provide values closer to actual values from measurements that include noise and inaccuracy. From the standpoint of theory, Kalman filter is an algorithm to infer an accurate result in a linear dynamic system and all variables have Gaussian distribution. The first implementation of the Kalman filter returns to his visit from NASA research center that he found that he can use this method to estimate the Apollo route. Kalman filter of system dynamics model that control inputs and measurement systems comprise it provide better value for the estimation of the system variables compared to the individual measurements. First, to be better understand the Kalman filter in non-linear mode, an understandable example is expressed to specify the concepts used in non-linear mode. For example, the aim is to determine the exact position of a vehicle, which there is a GPS in the vehicle that can locate the device with an error of up to several meters; the estimation of GPS is in the form of noise that sometimes sudden jumps can be observed, but there is always maximum error. The position of vehicle can through be obtained taking integration of speed and direction over time. It means that by gaining changes of momentum and changes of wheel the data can be obtained. In this example, the Kalman filter operates in two distinct phases; a) Predict phase, b) Update phase

3.1. Predict Phase

The last position of the vehicle changes in accordance with the laws of motion in physics and accelerator pedal as well as steering wheel position, and not only a new location estimation is calculated but also a new covariance is achieved.

3.2. Update Phase

A measurement of the position of the vehicle is obtained by GPS that is along with uncertainty. Covariance obtained from the previous step will determine how much it affects the location obtained from the update phase. In simple terms, if the estimate is so that it goes away from the actual location, GPS returns it to the actual position. The interesting point here is that if the dynamics of the system is not modeled carefully, the efficiency of this model considerably reduces. In other words, because this method uses probabilistic models and since these laws have come into existence form the phenomena in nature the data obtained from simulation of dynamic system should be used.

As can be seen in the earlier parts no simulation has been done, but at the end results are presented using data obtained from simulation of system dynamics. The filter is a recursive estimator. It means that it uses only previous step and the measurement for estimating the current position. Location and vehicle speed in linear state space is defined by following equation:

$$X_k = \begin{bmatrix} x \\ \dot{x} \end{bmatrix} \quad (1)$$

It is assumed that the vehicles between k and k-1 under constant acceleration α_k with normal distribution and the mean value is 0 and standard deviation is σ_a. Equation (2) is obtained from the law of motion as follows:

$$X_k = Fx_{k-1} + Ga_k \quad (2)$$

where F and G can be achieved of equations 3 and 4:

$$F = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad (3)$$

$$G = \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \quad (4)$$

Table 1. The values obtained from the state estimation of figure 1

State estimation solution with Measurement at buses 1 and 2 only									
	Base-Case Value			Measured Value			Estimated Value		
Measurement	KV	MW	MVAR	KV	MW	MVAR	KV	MW	MVAR
M_{v1}	241.5			238.4			238.8		
M_{G2}		107.9	16.0		113.1	20.2		112.4	20.5
M_{12}		28.7	-15.4		31.5	-13.2		30.6	-13.4
M_{14}		43.6	20.1		38.9	21.2		44.7	19.4
M_{15}		35.6	11.3		35.7	9.4		37.1	14.6
M_{v2}	241.5			237.8			237.6		
M_{G2}		50.0	74.4		48.4	71.9		48.2	71.7
M_{21}		-17.8	12.8		-34.9	9.7		-29.6	11.1
M_{24}		33.1	46.1		32.8	38.3		30.5	40.2
M_{25}		15.5	15.4		17.4	22.0		16.1	16.8
M_{26}		26.2	12.4		22.3	15.0		22.4	15.2
M_{23}		2.9	-12.3		8.6	-11.9		8.8	-11.7
M_{v3}	246.1			250.7			241.4		
M_{G3}		60.0	89.6		55.1	90.6		272.2	94.9
M_{32}		-2.9	5.7		-2.1	10.2		-8.7	5.5
M_{35}		19.1	23.2		17.7	23.9		15.1	25.3
M_{36}		43.8	60.7		43.3	58.3		20.9	64.0
M_{v4}	227.6			225.7			225.0		
M_{L4}		70.0	70.0		71.8	71.9		67.6	61.2
M_{41}		-42.5	-19.9		-40.1	-14.3		-43.6	-18.9
M_{42}		-31.6	-45.1		-29.8	-44.3		-29.3	-39.7
M_{45}		4.1	-4.9		0.7	-17.4		5.3	-2.6
M_{v5}	226.7			225.2			221.4		
M_{L5}		70.0	70.0		72	67.7		71.9	76.7
M_{54}		-4.0	-2.8		-2.1	-1.5		-5.2	-4.8
M_{51}		-34.5	-13.5		-36.6	-17.5		-35.9	-15.9
M_{52}		-15.0	-18.0		-11.7	-22.2		-15.5	-19.0
M_{53}		-18.0	-26.1		-25.1	-29.9		-14.0	-28.0
M_{56}		1.6	-9.7		-2.1	-0.8		-1.4	-9.0
M_{v6}	231.0			228.9			226.2		
M_{L6}		70.0	70.0		72.3	60.9		40.5	77.2
M_{65}		-1.6	3.9		1	2.9		1.4	3.4
M_{62}		-25.7	-16.0		-19.6	-22.3		-21.9	-18.8
M_{63}		-42.8	-57.9		-46.8	-51.1		-20.0	061-8

Table 2. Use of the state estimation for Figure 1 in the case where there is only information from 2 buses

State estimation solution									
	Base-Case Value			Measured Value			Estimated Value		
Measurement	KV	MW	MVAR	KV	MW	MVAR	KV	MW	MVAR
M_{v1}	241.5			238.4			240.6		
M_{G2}		107.9	16.0		113.1	20.2		111.9	18.7
M_{12}		28.7	-15.4		31.5	-13.2		30.4	-14-4
M_{14}		43.6	20.1		38.9	21.2		44.8	21.2
M_{15}		35.6	11.3		35.7	9.4		36.8	11.8
M_{v2}	241.5			237.8			239.9		
M_{G2}		50.0	74.4		48.4	71.9		47.5	70.3
M_{21}		-27.8	12.8		-34.9	9.7		-29.4	11.9
M_{24}		33.1	46.1		32.8	38.3		32.4	45.3
M_{25}		15.5	15.4		17.4	22.0		15.6	14.8
M_{26}		26.2	12.4		22.3	15.0		25.9	10.8
M_{23}		2.9	-12.3		8.6	-11.9		3.0	-12.6
M_{v3}	246.1			250.7			244.7		
M_{G3}		60.0	89.6		55.1	90.6		59.5	87.4
M_{32}		-2.9	5.7		-2.1	10.2		-3.0	6.2
M_{35}		19.1	23.2		17.7	23.9		19.2	22.9
M_{36}		43.8	60.7		43.3	58.3		43.3	58.3
M_{v4}	227.6			225.7			226.1		
M_{L4}		70.0	70.0		71.8	71.9		70.2	70.2
M_{41}		-42.5	-19.9		-40.1	-14.3		-43.6	-20.7
M_{42}		-31.6	-45.1		-29.8	-44.3		-30.9	-44.4
M_{45}		4.1	-4.9		0.7	-17.4		4.3	-5.1
M_{v5}	226.7			225.2			225.3		
M_{L5}		70.0	70.0		72.0	67.7		71.8	69.4
M_{54}		-4.0	-2.8		-2.1	-1.5		-4.2	-2.5
M_{51}		-34.5	-13.5		-36.6	-17.5		-35.6	-13.6
M_{52}		-15.0	-18.0		-11.7	-22.2		-15.1	-17.4
M_{53}		-18.0	-26.1		-25.1	-29.9		-18.1	-25.8
M_{56}		1.6	-9.7		-2.1	-0.8		1.3	-10.1
M_{v6}	231.0			228.9			230.1		
M_{L6}		70.0	70.0		72.3	72.3		68.9	65.8
M_{65}		-1.6	3.9		1.0	1.0		-1.2	4.4
M_{62}		-25.7	-16.0		-19.6	-19.6		-25.4	-14.5
M_{63}		-42.8	-57.9		-46.8	-46.8		042.3	-55.7

In equation (5) Wk~N (0, Q) is easily obtainable by variance definition as follows:

$$X_k = Fx_{k-1} + W_k \quad (5)$$

The Q value is obtained through equation (6) as follows:

$$Q = GG^T \sigma_a^2 = \begin{bmatrix} \frac{\Delta t^4}{2} & \frac{\Delta t^3}{2} \\ \frac{\Delta t^3}{2} & \Delta t^2 \end{bmatrix} \sigma_a^2 \quad (6)$$

At each time step, measured values (equation (7)) are along with noise, and it is assumed that v_k has normal distribution with a mean of 0 and standard deviation of σ_x.

$$z_k = Hx_k + v_k \quad (7)$$

where in equation (7), H=[1 0]. Then by knowing each state we go to the next state. This information can be assuming as $\hat{x}_{0|0} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ and $P_{0|0} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$. It should be noted that for simulation the equation of constant acceleration for linear motion is used as $x = \frac{1}{2}at^2$.

4. Nonlinear Kalman Filter

Kalman filter is provided primarily for linear modes but it is used in non-linear modes as follows: At each time step, the Jacobian matrix is calculated according to the predict phase. Now, this matrix can be used in the Kalman filter; by this method linearization can be performed around the estimation point. But it should be noted that the calculation of Jacobian matrix is very time consuming for complex functions and also when in the equation (8), presented as below, two functions of f and h are highly nonlinear, linearization leads to very poor performance of filter:

$$x_k = f\left(x_{k-1}, u_k\right) + w_k;\; z_k = h\left(x_k\right) + v_k \tag{8}$$

Unscented Kalman filter (UKF) uses specific sampling technique to make a matrix, where σ points are chosen; now with the use of the information, estimation and covariance of estimation can be obtained. The interesting point here is that there is no need to calculate the Jacobian matrix. For this filter UKF is used.

4.1. Predict Phase

Two equations are converted to equation (9) to estimate position and covariance as follows:

$$x^a_{k-1|k-1} = \left[\hat{x}^T_{k-1|k-1} \quad E\left[w^T_k\right]\right]^T;\; P^a_{k-1|k-1} = \begin{bmatrix} P_{k-1|k-1} & 0 \\ 0 & Q_k \end{bmatrix} \tag{9}$$

σ=2L+1 points is calculated by equation (10) and L is added to the matrix, as follows:

$$\begin{aligned} x^0_{k-1|k-1} &= x^a_{k-1|k-1} \\ x^i_{k-1|k-1} &= x^a_{k-1|k-1} + \left(\sqrt{(L+\lambda)P^a_{k-1|k-1}}\right)_i \quad i = 1,\dots L \\ x^i_{k-1|k-1} &= x^a_{k-1|k-1} - \left(\sqrt{(L+\lambda)P^a_{k-1|k-1}}\right)_{i-L} \quad i = L+1,\dots 2L \end{aligned} \tag{10}$$

In equation (10), $\left(\sqrt{(L+\lambda)P^a_{k-1|k-1}}\right)_i$ the aim is to select i^{th} column of matrix. Using σ points obtained and using it non-linear equation f, equation 11 can be obtained as follows:

$$x^i_{k|k-1} = f\left(x^i_{k-1|k-1}\right) \quad i = 0\dots 2L \tag{11}$$

The weighted σ points are combined for prediction phase and equation (12) is obtained as below:

$$\begin{aligned} \hat{x}_{k|k-1} &= \sum_{i=0}^{2L} W^i_s x^i_{k|k-1} \\ P_{k|k-1} &= \sum_{i=0}^{2L} W^i_c \left[x^i_{k|k-1} - \hat{x}_{k|k-1}\right]\left[x^i_{k|k-1} - \hat{x}_{k|k-1}\right]^T \end{aligned} \tag{12}$$

Typical values for the parameters of (13) are as follows:

$$\begin{aligned} W^i_s &= \frac{\lambda}{L+\lambda};\; W^i_c = \frac{\lambda}{L+\lambda} + (1-\alpha^2+\beta) \\ W^i_s &= W^i_c = \frac{1}{2(L+\lambda)};\; \lambda = \alpha^2(L+\kappa) - L \end{aligned} \tag{13}$$

4.2. Update Phase

The difference of this section with the previous section is that here the mean and covariance of the measurement noise is used, which is shown in equations (14) and (15):

$$x^a_{k|k-1} = \left[\hat{x}^T_{k|k-1} \quad E\left[v^T_k\right]\right]^T;\; P^a_{k|k-1} = \begin{bmatrix} P_{k|k-1} & 0 \\ 0 & R_k \end{bmatrix} \tag{14}$$

$$\begin{aligned} x^0_{k|k-1} &= x^a_{k|k-1} \\ x^i_{k|k-1} &= x^a_{k|k-1} + \left(\sqrt{(L+\lambda)P^a_{k|k-1}}\right)_i \quad i = 1,\dots L \\ x^i_{k|k-1} &= x^a_{k|k-1} - \left(\sqrt{(L+\lambda)P^a_{k|k-1}}\right)_{i-L} \quad i = L+1,\dots 2L \end{aligned} \tag{15}$$

Here an σ point obtained from (15) is given to equation (16) as follows:

$$\gamma^i_k = h\left(x^i_{k|k-1}\right) \quad i = 1,\dots 2L \tag{16}$$

Now, by applying weighted values in equation (16), equation (17) can be obtained that is used for covariance and estimated measured value as follows:

$$\hat{z}_k = \sum_{i=0}^{2L} W^i_s \gamma^i_k;\; P_{x_k z_k} = \sum_{i=0}^{2L} W^i_c \left[x^i_{k|k-1} - \hat{x}_{k|k-1}\right]\left[\gamma^i_k - \hat{z}_k\right]^T \tag{17}$$

$$\begin{aligned} k_k &= P_{x_k z_k} P^{-1}_{x_k z_k};\; \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - \hat{z}_k\right) \\ P_{k|k} &= P_{k|k-1} - K_k P_{x_k z_k} K^T_k \end{aligned} \tag{18}$$

It can be seen that the initial values for next state are obtained according to outputs of equation (18).

5. Simulation Results

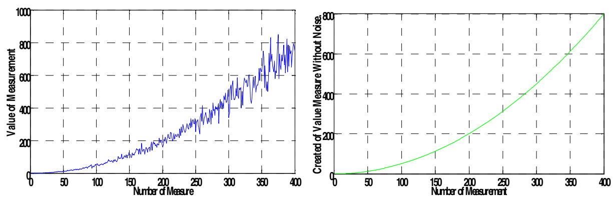
In this section the simulation results of this study are presented using linear Kalman filter and non-linear Kalman filter at sample power system.

5.1. Linear Kalman Filter

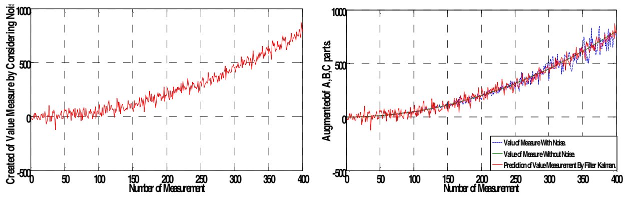
Figure 3 shows the performance of linear Kalman filter; (a), estimated values of measurer using linear Kalman filter, (b) measured value produced without taking into account the noise on the measured value(c)measured value produced by taking into account the noise on the measured value and (d) shows a, b and c at the same time. Filter acts excellent for small values but for larger ones it does not operate properly; it seems as mentioned earlier, this model does not provide correct answers in cases where the system is not dynamically modeled.

5.2. Non-linear Kalman Filter

Figure 4 shows non-linear Kalman filter which respectively include, (a) estimated values of measurer using non-linear Kalman filter, (b) value produced by measurer without taking into account the noise on the measurer, (c) value produced by measurer with taking into account the noise on the measurer, (d) shows a, b and c at the same time. As seen in Figure 4, it seems that this method was able to eliminate the noise at an acceptable level. IEEE 9-bus 3 generators system implemented in DigSilent. The effect of non-linear Kalman filter is examined fairly. Synchronous 2nd generator curves obtained is shown in Fig. 5.

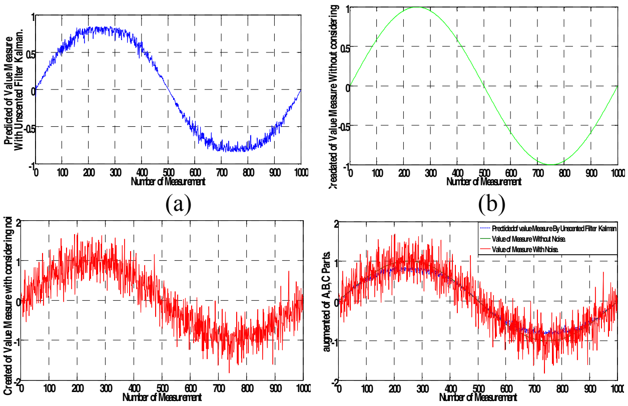


(a) (b)



(c) (d)

Fig. 3. Using a linear Kalman filter, (a) estimated values of measurer using linear Kalman filter, (b) measured value produced without taking into account the noise on the measured value,(c) measured value produced by taking into account the noise on the measured value, and (d) shows (a), (b) and (c) at the same time



(a) (b)

(c) (d)

Fig. 4. Application of non-linear Kalman filter, (a) estimated values of measurer using non-linear Kalman filter, (b) value produced by measurer without taking into account the noise on the measurer, (c) value produced by measurer with taking into account the noise on the measurer, (d) shows (a), (b) and (c) at the same time

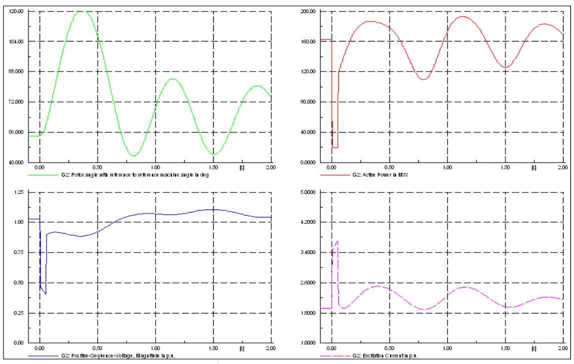


Fig. 5. Synchronous 2nd generator curves obtained of IEEE 9-bus and 3 gen.

6. Conclusion

Given the importance of estimation in the power systems to obtain important information such as pharos voltage and current of branches in static state or dynamic state estimation of power systems, such as angle of rotor of synchronous machine and so on, the need for a proper estimation method is felt. The method should be adapted to the conditions of system and characteristics of the estimators. The feature of the system is its non-linearity and feature of measurements is the probability of its values. Kalman Filter can adapt to these features and has accurate answers resistant to noise at the right time. The simulation results are shown for both linear and nonlinear systems. The estimation method used for linear and non-linear systems are respectively linear and nonlinear Kalman filters.

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