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KALMAN FILTER ANALYSIS IN DYNAMIC STATE OF POWER SYSTEM

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Abstract - ***State estimation (SE) is a technique used to find unknown values of the state variables based on some imperfect measurement. This method uses statistical criteria to estimate the actual value of those unknown variables, state estimation is an essential method used for monitoring power system, dynamic state estimation of a dynamic state is the indispensable control and stability prediction under transients conditions, a non-linear Kalman filter was developed and used to estimate the state of the system based on measurement. The algorithms are numerically demonstrated using the IEEE 9 bus test system.***

Key Words: *Power systems, dynamic state estimation (DSE), Kalman filter,*

1. INTRODUCTION

State estimation was introduced by Schweppes and Wildes in the early 1970s [1].Since then, many researchers have worked in this area to produce many techniques of calculating the state of a power system. The concept of state estimation is to use the SCADA data, to calculate voltage magnitude and angle at all the buses in a power system. This SCADA data includes, power injection measurements at various buses, power flow measurements over transmission lines and voltage Magnitude measurements at some of the buses [6]. The state estimator computes the voltage magnitudes and voltage angles at the buses of the power system. Power system is not a static system, but it changes very slowly with time and continuously. That means, when the load on the buses changes, the generations also have to change to overcome these changes in load. This in turn causes the change in power flows and injections at the buses, also leads to change in voltage angular at the buses and perhaps changes in voltage magnitude at some buses depending on the size of this change; therefore, change the nature of the power system from static state to dynamic state nature. These dynamic behaviors of the power system are difficult to overcome by the conventional Static State Estimation (SSE). This led to the development of a new algorithm called Dynamic State Estimation (DSE) [7] [8]. The development of a new and efficient dynamic estimator is to improve the measurement filtering practice for this a new state estimator based Kalman filtering techniques is proposed and tested. In this paper, not only describe the dynamic model for the time behavior of the system state, but will Show more details about the DSE, mainly the state predicting and state filtering. When the state variables are estimated at time k by state estimation technique, using these state variables to forecast the state vectors at time k + 1 using linear exponential smoothing. The state vectors are filtered based on Extended Kalman Filter and unscented Kalman filter method. The proposal is tested using IEEE 9 bus test system. The test includes normal and abnormal operations.

2. TYPES OF STATE ESTIMATION

2.1 Static State Estimation

It is the data processing algorithm for converting redundant meter readings and other available information in to an estimate of the vector while measured data are taken to be time invariant and state model of the power system is concerned[1][4].

2.2 Tracking State Estimation

The algorithms are based on a simple extension of the static state estimation techniques. They utilize the recent available value of the system states to update their estimated values non iteratively during the subsequent sampling period. This class of estimators has been arisen from the natural need of making static state estimators as efficient as possible in regard to the computational speed making them more suitable for real-time implementation [2].

2.3 Dynamic State Estimation

Accommodate in addition to the present states, the previous estimates of the states. The capability of forecasting the state vector one step ahead is an important advantage of the advantage of the dynamic estimators. State prediction gives a longer decision time to the system operator, because economic dispatching, security assessment and other functions can be performed in advance. In dynamic state estimation, dynamic model for the time behavior of system states is utilized, whereas tracking and static state estimators do not require any dynamic model of the system states. In the present thesis only static state estimation has been studied [11].

3. DYNAMIC STATE ESTIMATION

Dynamic model that monitors system operating conditions more completely than static models can be represented by a process equation (7) and a measurement equation (8) as follows:

$$x_{k+1} = f(k, x_k) + q_k \quad (7)$$

$$y_k = h(k, x_k) + r_k \quad (8)$$

Where k is the time sample; x_k is the state vector; q_k Represents modeling uncertainties corresponding to a white Gaussian noise with zero man and covariance matrix Q_k; y_k is the measurement vector; **h** is a set of nonlinear load flow. Functions for the current network configuration; and r_k is a Gaussian error vector with zero mean and diagonal covariance matrix, R_k.

In this dynamic state-space model, equation (7) can be interpreted as the memory of the system state time evolution, and equation (8) is considered its refreshment. Such memory will be responsible for the forecasting capability of the model. Depending on the availability of measurements, the model can be adequate or parsimonious. The basic idea of a state estimation function is to determine the most likely system state vector x for either the static steady-state or dynamic state of the system.

$$x = [\theta_i, V_i, P_{inject}, \delta_i, \varpi]T$$

Based on the quantities measured and acquired by remote terminal units (RTUs), presented as:

$$y = [V, P_{flow}, Q_{flow}, P_{inject}, Q_{inject}]^T$$

In general, DSE is achieved by implementing three steps, i.e., parameter identification, state prediction (forecasting), and state correction (filtering) [2].

3.1 Parameter Identification

The parameters F_K , g_k and Q_k [2]. Are identified using Holt's two-parameter linear exponential smoothing method [2][12].This method is very simple, used when the data shows a trend. In this method, the values of $\mathbf{F_K}$, $\mathbf{g_k}$ can be obtained as follows.

$$F_k = \alpha_k(1+, \beta_k) \quad (9)$$

$$g_k = (1+, \beta_k)\,(1-\alpha_k)\tilde{x}_k - \beta_k a_{k-1} + (1-\beta_k) b_{k-1} \quad (10)$$

Where I is the identity matrix, and all associated parameters can be calculated based on a priori knowledge. **α** and **β** represent the smoothing parameters. [14].

3.2 State Predicting or State Forecasting

At this stage, state vector $\tilde{\mathbf{x}}_{k+1}$ is predicted with its covariance matrix $\mathbf{P}_{\tilde{x}_{k+1}}$ using the following equations.

$$\tilde{\mathbf{x}}_{k+1} = F_K \hat{x}_k + g_k \quad (11)$$

$$\mathbf{P}_{\tilde{x}_{k+1}} = F_K P_{\hat{x}_k} F_k^T + Q_k \quad (12)$$

While $P_{\hat{x}_k}$ is the covariance matrix to estimate $\hat{x}_k$ at time k.

3.3 State Correction or State Filtering

The forecasted state new set of measurements, $\mathbf{z}_{k+1}$, the predicted state vector $\hat{\mathbf{x}}_{k+1}$ can be corrected (filtered), yielding a new state vector with its error covariance. $\mathbf{P}_{\tilde{x}_{k+1}}$

$$J(x) = [y-h(x)]^T R^{-1} [y-h(x)] + [x-\tilde{x}]^T P_x^{-1} [x-\tilde{x}] \quad (13)$$

Note that, the time index (k + 1) has been omitted.
Extended Kalman Filter (EKF) used for minimizing the objective function and getting the final filtering state.

$$\hat{x}_{k+1} = \tilde{x}_{k+1} + K_{k+1}\,[z_{k+1} - h(\tilde{x}_{k+1})] \quad (14)$$

$$K_{k+1} = P_{\tilde{x}_{k+1}} H_{k+1}^T R_{k+1}^{-1} \quad (15)$$

$$\mathbf{P}_{\tilde{x}_{k+1}} = [H_{k+1}^T R_{k+1}^{-1} + \mathbf{P}_{\tilde{x}_{k+1}}]^{-1} \quad (16)$$

Where K is called the gain matrix (m × n) dimensioned.

4. SYSTEM MODELING

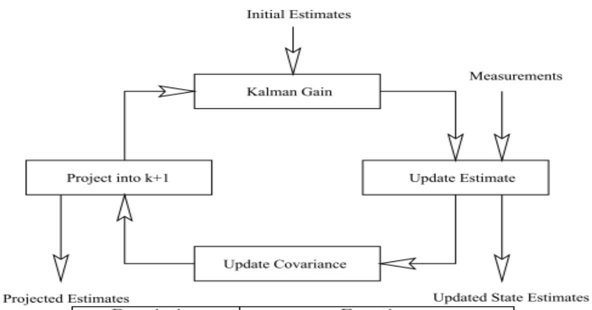
4.1 Model

The model, Kalman Filter's performance and computation, so we have assumed state transition matrix and measurement state matrix to be unity. The process noise added is White Gaussian noise with signal to noise ratio equal to -0.50. Similarly, the measurement noise is also White Gaussian noise with signal to noise ratio equal to -0.50 now system equation equations can be given as.

$$x_{k+1} = x_k + w_k \quad (17)$$

$$z_k = x_k + v_k \quad (18)$$

4.2 Algorithm for Kalman Filter Implementation in this paper.



Description	Equation
Kalman Gain	$K_k = P'_k H^T \left(H P'_k H^T + R\right)^{-1}$
Update Estimate	$\hat{x}_k = \hat{x}'_k + K_k (z_k - H \hat{x}'_k)$
Update Covariance	$P_k = (I - K_k H) P'_k$
Project into $k+1$	$\hat{x}'_{k+1} = \Phi \hat{x}_k$ $P_{k+1} = \Phi P_k \Phi^T + Q$

Fig.1. Flow chart

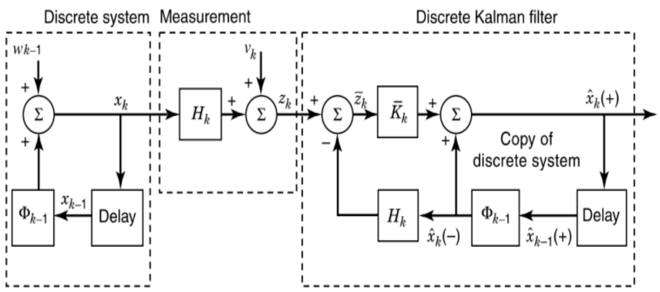


Fig 2. Block diagram for Kalman filtration process

5. TEST SYSTEM AND RESULT

The performance of the Kalman filter was investigated via a real time simulation on an IEEE 9 bus network as shown in figure. It consists of 3 lumped loads .the generators are connected to grid through a step down transformer rated132kv/11kv this test system is modeled using MATLAB simulink. Also the DSE is based on three measurements at substation to measure active and reactive power flow .in this test system the outputs are carried out as follows.

5.1 Steady Condition

In this condition it can be observed that the estimated values of DSE is close to the actual value with small variation due to lumped load for voltage magnitude and phase angle

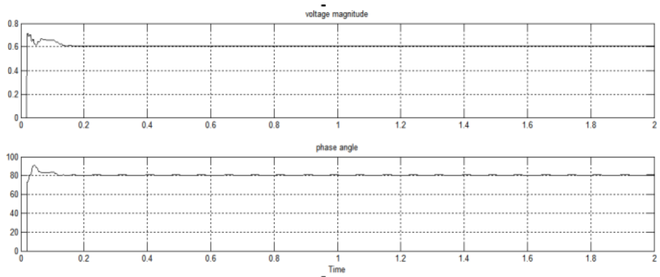


Fig.3.voltage magnitude and phase angle

5.2 Dynamic Condition

In this test system sudden changes occur due to dynamic load on bus and occurrence of an external fault at time in seconds. At bus no.8 that causes a voltage dips in the voltage. Active power and Reactive power loads at aforementioned buses are changes at time t=0.1 to t=0.3 seconds.

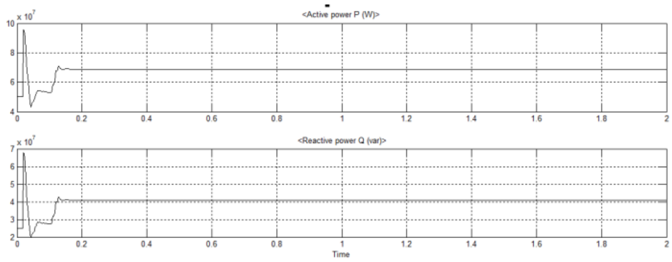


Fig. 3.dynamic load power waveforms

5.3 Kalman Filter observation

For given system modeling. The Observability Gaussian process, which are state space matrices, A, B, C, and D, initial state, x0, and covariance matrices, Q and R; and similar parameters for the Kalman Filter

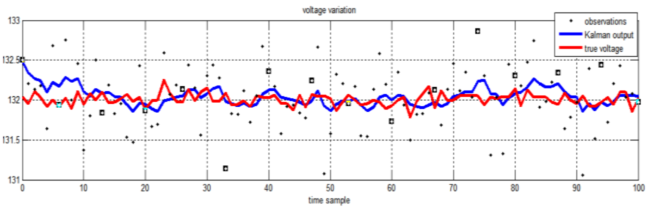


Fig.5.Kalman filter output

6. CONCLUSIONS

Based on this paper addressed the important role of DSE in estimating accurate state variables and prediction ahead of real time monitoring operation. The performance of the Kalman filter based dynamic state estimation verified by IEEE 9bus test network system carried out different unconditional observations due to changing load. This application of state estimation technique made the proposed scheme economical for practical implementations in any power system network. Furthermore complex dynamics models of generators or load with severe non linearities could be implemented in power system dynamic estimators.

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BIOGRAPHIES

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Kinhal Vadirajacharya was born in 1959. He graduated in Electrical Engineering from Gulbarga University, Gulbarga in 1984. He obtained M.E. (Power Electronics) from Devi Ahalya Vishwavidyalaya, Indore in 1998, and obtained Ph.D. on Performance Investigation of Unified Power Quality Conditioner from Indian Institute of Technology Roorkee in 2009. He has wide teaching experience, and currently working as Associate professor in electrical engineering department at Dr. Babasaheb Ambedkar Technological University, Lonere. He has guided projects at U.G., P.G. and Ph.D. research level. He has more than fifty technical publications in journals and conferences of international repute. His fields of interest include power quality conditioning, FACTS, smart grid interface issues and energy audit and conservation.