2011 8th International Multi-Conference on Systems, Signals & Devices

FAULT DIAGNOSIS FOR DYNAMIC POWER SYSTEM

A. THABET[a], M. BOUTAYEB[b], G. DIDIER[c], S. CHNIBA[d], M.N ABDELKRIM[a]

[a]Research unit Modeling, Analysis and Control of Systems,University of Gabes -TUNISIA
(e-mail: assem.thabet@ yahoo.fr / naceur.abdelkrim@enig.rnu.tn)
[b]Research center of automatic of Nancy (CRAN),FRANCE
(e-mail:Mohamed.Boutayeb@iut-longwy.uhp-nancy.fr)
[c]Group of Research in Electrical engineering and Electronics of Nancy (GREEN), FRANCE.
(e-mail: Gaetan.Didier@green.uhp-nancy.fr)
[d]Energy and environment research unit (ENENV), University of Gabes -TUNISIA
(e-mail: saichni@enig.rnu.tn)

ABSTRACT

The fault diagnosis problem for dynamic power systems is treated, the nonlinear dynamic model based on a differential algebraic equations is transformed with reduced index to a simple dynamic model. Two nonlinear observers are used for generating the fault signals for comparison purposes, one of them being an extended Kalman estimator and the other a new extended kalman filter with moving horizon with a study of convergence based on the choice of matrix of covariance of the noises of system and measurements. The paper illustrates a simulation study applied on IEEE 3 buses test system.

Index Terms— Fault diagnosis, Observers, Kalman filtering, Power system state estimation

1. INTRODUCTION

The fault diagnosis of dynamic power system based on observers (state estimation or prediction)is an effective online tool for providing consistent data base in Energy Management Systems for advanced control center applications such as security analysis, economic dispatch. The problem of state estimation in power system to generate a residue signal has mainly focused on static estimation from redundant measurement [1], [2] then to get an effective supervision, it is extremely important to develop a dynamic model with the different variables and to consider a robust estimator who reflects a reliable image in the terms of capacity as estimation, robustness, computing time and stability where the most important objective is to detect and avoid the defects in the minimum of time [3] and a possible application in real-time [4]. The existing dynamic model treated in Differentials-Algebraic Equations (DAE) systems, is simplified by linearization and used in linear form [5] or considered as a swing model which is obtained by assuming that the bus voltage magnitude is tightly regulated at the specified operating point then the size of model is reduced since reactive power in the network is neglected [6]. New models given by [7] in which are included all the variables in a power systems with different nature of generators and loads. In the state estimation for this class of system, the dynamic model is considered as a mathematical model rather than a physical one, in consequence to applying simplification techniques of index [8], or to synthesizing an observer for this type of model DAE [9] which is based on a definition of spaces of linear combinations and its algebraic complement for the calculation of the observer gain.

Nomenclature
DAE: Differential-Algebraic Equations
ODE: Ordinary Differential Equations
LMI: Linear Matrix Inequality
M: Inertia constant of the generator
D: Damping constant of the generator
δ: mechanical rotor angle of the rotating machine
ω: mechanical angular velocity
ω_s: electrical angular velocity
P_M: mechanical power input
P_j, Q_j: nodal active and reactive power
$P_{c,d}$: transit power
Y_{bus}: nodal admittance matrix
$G_{ij} + jB_{ij}$: real and imaginary terms of bus admittance matrix corresponding to i^{th} row and j^{th} column
N: total number of system buses
n_g: number of generator buses
n_l: number of load buses
P_{G_i}: electrical power supplied by the generator
θ_i, U_i: phase and voltage at bus i

In what follows we present a dynamic power system model and a simple diagram of simulation and we introduce a classical state estimator ,Extended Kalman Estimator E.K.E, and the new Extended Kalman Filter with Moving Horizon (EKF-MH) to generate a residue signal with a study of convergence based on the choice of matrices of covariance of the noises of system and measurements, while inserting some numerical approximations and showing the interest of applying this type of estimator to diagnose our proposed model.

2. DYNAMIC POWER SYSTEM MODEL

The dynamics of a power system can be modeled with a combination of nonlinear differential equations, and nonlinear algebraic equations. The nonlinear differential equations correspond to the nonlinear dynamics of the system, and the nonlinear algebraic equations correspond to the algebraic constraints of the system. In a sense, the algebraic equations provide the region upon which the trajectories defined by the solutions of the differential equations. Often these sets of equations are solved separately in different analysis techniques. Assuming that the system is at an equilibrium point and neglecting the nonlinear differential equations is the basis for traditional power flow studies, focusing on the iterative solution of the nonlinear algebraic equations. On the other hand, for traditional transient stability studies, the focus is only on the nonlinear differential equations, and the algebraic equations are assumed to be satisfied. The DAE model of a power system includes both sets of equations. The solution is accomplished in an iterative fashion, with the important feature that all the desired system characteristics are included. The general form of the DAE model is given as:

$$\begin{array}{rc} \dot{x}_d(t) = & F_d(x_d(t), x_a(t), u(t)) \\ 0 = & g(x_d(t), x_a(t)) \\ y(t) = & h(x_d(t), x_a(t)) \end{array} \tag{1}$$

With: $x_d(t) \in \mathbb{R}^{n_d}$ and $x_a(t) \in \mathbb{R}^{n_a}$ are respectively dynamic and algebraic states, $F(.) \in \mathbb{R}^{n_d}$ a function representing the nonlinear differential equations, $g(.) \in \mathbb{R}^{n_a}$ represents the nonlinear algebraic constraints (equations), $u(t) \in \mathbb{R}^p$ the control and $y(t) \in \mathbb{R}^m$ the output system. The problem with the system (1) is that $\dot{x}_a(t)$ does not appear explicitly.

2.1. Problem formulation

To formalize the problem of setting in equation, we will treat the case of the 3 buses test system (Fig. 1).

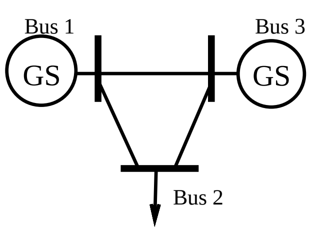

Figure 1. 3 buses test system

the set of equation of this network is following form (Model with rotor dynamics and static loads [7]):

$$\left\{ \begin{array}{c} f_i^I : \dot{\delta} - \omega_i + \omega_s = 0 \\ f_i^{II} : \dot{\omega}_i = \frac{\omega_s}{2M}(P_{M_i} - P_{G_i}(\delta, \theta, V) - D\omega_i) \\ g_i^I : P_j - P_j(\delta, \theta, V) = 0 \\ g_i^{II} : Q_j - Q_j(\delta, \theta, V) = 0 \\ y_q : P_{c,d} = P_{c,d}(\delta, \theta, V) \end{array} \right. \tag{2}$$

with : $i : 1...n_g - 1; j : n_g + 1...n_g + n_l; q : 1...m; c, d : 1...N$ and

$$P_{G_i} = \sum_{j=1}^{N} |V_i||V_j|[G_{ij}\cos(\delta_i - \theta_j) + B_{ij}\sin(\delta_i - \theta_j)]$$

Therefore the model (2) can be rewritten under this form:

$$\begin{array}{c} F(\dot{x}, x, \beta) = u \\ y = h(x, \beta) \end{array}$$

with : $x = [\delta_i, \omega_i, \theta_i, V_i]^T$,$u = \frac{P_{M_i}}{M}$,$\beta = \{Y_{bus}\}$,$F(.) = [f_i, g_j]^T$ and $y = P_{c,d}$ where u and y will be the control and the output of system.
Thus for this network the system of equations is:
the state vector is :

$$x = [x_1\ x_2\ x_3\ x_4]^T = [\delta_3\ \omega_3\ \theta_2\ U_2]^T$$

and the system equation is :

$$\left\{ \begin{array}{lc} f^I : & \dot{x_1} = x_2 - \omega_s \\ f^{II} : & \dot{x_2} = \frac{\omega_s}{2M}(P_{M_3} - P_{G_3}(x_1, x_3, x_4) - Dx_2) \\ g^I : & P_2 - P_2(x_1, x_3, x_4) = 0 \\ g^{II} : & Q_2 - Q_2(x_1, x_3, x_4) = 0 \\ y_1 : & P_{3,2}(x_1, x_3, x_4) \end{array} \right.$$

with : x_1 and x_2 are the dynamic variables , x_3 and x_4 are the algebraic variables; and :

$$\left\{ \begin{array}{l} P_2(x_1, x_3, x_4) = x_4[U_1^{imp}(G_{2,1}\cos(x_3) + B_{2,1}\sin(x_3)) + (x_4 G_{2,2}) \\ \quad + U_3^{imp}(G_{2,3}\cos(x_3 - x_1) + B_{2,3}\sin(x_3 - x_1))] \\ Q_2(x_1, x_3, x_4) = -x_4[U_1^{imp}(G_{2,1}\sin(x_3) - B_{2,1}\cos(x_3)) \\ -(x_4 B_{2,2}) + U_3^{imp}(G_{2,3}\sin(x_3 - x_1) - B_{2,3}\cos(x_3 - x_1))] \\ P_{3,2}(x_1, x_3, x_4) = U_3^{imp^2} G_{3,2} \\ \quad - U_3^{imp} x_4(G_{3,2}\cos(x_1 - x_3) + B_{3,2}\sin(x_1 - x_3)) \end{array} \right.$$

While using (1) the system is rewritten with:

$$\left\{ \begin{array}{l} \dot{x}_d = \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = F_d(x_1, x_2, x_3, x_4, u) = [f^I, f^{II}]^T \\ g(x_1, x_2, x_3, x_4) = [g^I, g^{II}]^T = 0 \\ y(t) = P_{3,2}(x_1, x_3, x_4) \end{array} \right.$$

2.2. Semi-explicit DAE of index 1

If at an equilibrium point, system (1) are called semi-explicit [10]. Index-1 property requires that $g(x_d, x_a)$ is solvable for x_a and $\det(g(x_d, x_a) \neq 0$. (to simplify :$x_d(t) = x_d, x_a(t) = x_a$)

$$\begin{array}{rc} 0 = & g_{x_d}(x_d, x_a)\dot{x}_d + g_{x_a}(x_d, x_a)\dot{x}_a \\ 0 = & g_{x_d}(x_d, x_a)F_d(x_d, x_a, u) + g_{x_a}(x_d, x_a)\dot{x}_a \end{array} \tag{3}$$

where : $g_{x_a}(x_d, x_a) = \frac{\partial g(x_d, x_a)}{\partial(x_a)}$ and $g_{x_d}(x_d, x_a) = \frac{\partial g(x_d, x_a)}{\partial(x_d)}$
In other words, the differentiation index is 1 if by differentiation of the algebraic equations for time an implicit ODE system results :

$$\begin{array}{rl} \dot{x}_d = & F_d(x_d, x_a, u) \\ \dot{x}_a = & -g_{x_a}^{-1}(x_d, x_a) g_{x_d}(x_d, x_a) F_d(x_d, x_a, u) \end{array} \quad (4)$$

where $g_{x_a}^{-1}(x_d, x_a) \in \mathbb{R}^{n_a \times n_a}$ and $g_{x_d}(x_d, x_a) \in \mathbb{R}^{n_a \times n_d}$. A study of nature and stability of DAE system is given by [11].
Finally the complete model in form ODE is according to :

$$\left\{ \begin{array}{c} \dot{x} = \begin{pmatrix} \dot{x}_d \\ \dot{x}_a \end{pmatrix} = \bar{f}(x_d, x_a, u) \\ = \begin{pmatrix} F_d(x_d, x_a, u) \\ -g_{x_a}^{-1}(x_d, x_a) g_{x_d}(x_d, x_a) F(x_d, x_a, u) \end{pmatrix} \\ \\ \bar{y} = \begin{pmatrix} 0 \\ y \end{pmatrix} = \bar{h}(x_d, x_a) = \begin{pmatrix} g(x_d, x_a) \\ h(x_d, x_a) \end{pmatrix} \end{array} \right. \quad (5)$$

It should be noted that the assumptions and the propositions given can be generalized for the other forms of dynamic power system models (models including characteristics of the loads [12] and generators [7]).
Another suggestion for the dynamic simulation of power systems is this proposed diagram (Fig. 2) , which is based on the model (1) : for the dynamic variables we use ordinary simulation (block of integration + nonlinear function) and for those algebraic we will integrate an algebraic constraint resolver under the environment $SIMULINK$ of $MATLAB^{®}$. The simulation diagram is as follows:

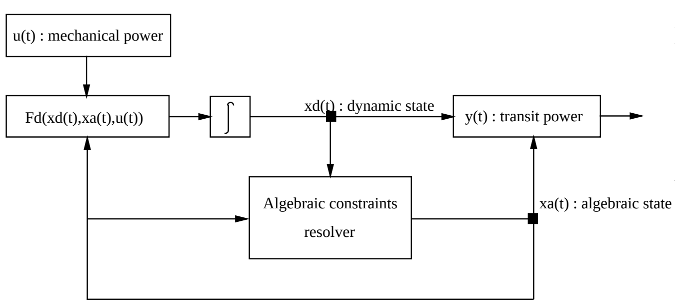

Figure 2. Diagram of dynamic simulation of power system

3. EXTENDED KALMAN ESTIMATOR

3.1. Extended Kalman Estimator

The Kalman filter is a recursive estimator. That means that to consider the state running, only the preceding state and current measurements are necessary. The history of the observations and the estimates is thus not necessary. In the extended Kalman filter (EKF), the state transition and observation models need not be linear functions of the state but may instead be (differentiable) functions [13], the considered discrete system is following form:

$$\left\{ \begin{array}{l} x_{k+1} = f(x_k, u_k) + v_k \\ y_k = h(x_k, u_k) + w_k \end{array} \right. \quad (6)$$

with : v_k and w_k are respectively noise to the system and the measurements. The function f can be used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state. However, f and h cannot be applied to the covariance directly. Instead a matrix of partial derivatives (the Jacobean) is computed. At each time step the Jacobean is evaluated with current predicted states. These matrices can be used in the Kalman filter equations. This process essentially linearizes the non-linear function around the current estimate. In this paper, we used the form of the most simplified estimator EKE (we used Euler discretization of step size T_e, $x_{k+1} = x_k + T_e \bar{f}(x_k, u_k)$ to discretize the continuous model (5)):

$$\begin{array}{c} \hat{x}_{k+1} = f(\hat{x}_k, u_k) + K_k e_k \\ K_k = F_k P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \\ P_{k+1} = (F_k - K_k H_k) P_k F_k^T + Q_k \\ e_k = y_k - h(\hat{x}_k, u_k) \end{array} \quad (7)$$

where:
$F_k = F(\hat{x}_k, u_k) = \frac{\partial(x_k + T_e \bar{f}(x_k, u_k))}{\partial x_k}|_{x_k = \hat{x}_k}$ and
$H_k = H(\hat{x}_k, u_k) = \frac{\partial \bar{h}(x_k, u_k)}{\partial x_k} = \begin{pmatrix} \frac{\partial g(x_k)}{\partial x_k} \\ \frac{\partial h(x_k)}{\partial x_k} \end{pmatrix} |_{x_k = \hat{x}_k}$.
with: $P_0 = \mu I_n > 0$.
There are some attempts to apply EKF on DEA system [14], but our proposition is to apply it in the classic general form with some numerical approximations that we propose for the Jacobean calculation.
Initially, it should be noted that due to the difficulty (seen impossible) to find F_k (following the transformation of the algebraic variables in ODE model), we will make the following numerical approximation:
We have:

$$F_k = F(\hat{x}_k, u_k) = \frac{\partial(x_k + T_e \bar{f}(x_k, u_k))}{\partial x_k}|_{x_k = \hat{x}_k}$$
$$= \left\{ \begin{array}{c} \frac{\partial(x_{d_k} + T_e F_d(x_{d_k}, x_{a_k}, u_k))}{\partial(x_{d_k}, x_{a_k})} \\ \frac{\partial(x_{a_k} + T_e(-g_{x_a}^{-1}(x_{d_k}, x_{a_k}) g_{x_d}(x_{d_k}, x_{a_k}) F_d(x_{d_k}, x_{a_k}, u_k)))}{\partial(x_{d_k}, x_{a_k})} \end{array} \right\} \quad (8)$$

The numerical approximation is used on the second term of F_k since it is very difficult to determine, is calculated as follows:

$$\frac{\partial(x_{a_k} + T_e(-g_{x_a}^{-1}(x_{d_k}, x_{a_k}) g_{x_d}(x_{d_k}, x_{a_k}) F_d(x_{d_k}, x_{a_k}, u_k)))}{\partial(x_{d_k}, x_{a_k})}$$
$$\approx (x_{a_k} + T_e(-g_{x_a}^{-1}(x_{d_k}, x_{a_k}) g_{x_d}(x_{d_k}, x_{a_k}) \frac{\partial F_d(x_{d_k}, x_{a_k}, u_k)}{\partial(x_{d_k}, x_{a_k})})) \quad (9)$$

for : $x_{d_k} = \hat{x}_{d_k}$ and $x_{a_k} = \hat{x}_{a_k}$ and $g_{x_a}^{-1}$ and g_{x_d} are calculated numerically.
A simple scalar residual may then be generated by :

$$r_k^{E.K.E} = y_k - y_k^e$$

where : y_k is a real output and y_k^e is an estimated one.

3.2. Extended Kalman Filter with Moving Horizon

We propose here to use a EKF which takes into account a moving horizon of measurements to improve the precision as well as the robustness of estimation. Our recent research shows that we always obtain better results by using our approach on linear and nonlinear systems. We present in this section the synthesis of the estimator.
We consider the system 6, the proposed observer is given by:

$$\hat{x}_{k+1} = f(\hat{x}_k) + K_k \begin{pmatrix} y_k - h(\hat{x}_k) \\ y_{k-1} - h(\hat{x}_{k-1}) \\ \vdots \\ y_{k-M+1} - h(\hat{x}_{k-M+1}) \end{pmatrix} \quad (10)$$

with : M is a size of moving horizon.
In what follows we calculate the various parameters of the filter.
We have :

$$P_k^k = E(\tilde{x}_k \tilde{x}_k^T)$$
$$\tilde{x}_{k+1} = x_{k+1} - \hat{x}_{k+1}$$

We consider the following approximations :

$$f(x_k) - f(\hat{x}_k) = F_k \tilde{x}_k$$
$$h(x_k) - h(\hat{x}_k) = H_k \tilde{x}_k$$

and : $E(w_k) = E(v_k) = 0$. (with F_k and H_k are calculated in the same way as in E.K.E)
We develop P_{k+1}^{k+1} to obtain :

$$\begin{aligned} P_{k+1}^{k+1} &= F_k P_k^k F_k^T + K_k C_k \bar{P}_k C_k^T K_k^T \\ &- F_k [P_k^k \;\; P_k^{k-1} \;\; \ldots \;\; P_k^{k-M+1}] C_k^T K_k^T \\ &- K_k C_k \begin{pmatrix} P_k^k \\ P_{k-1}^k \\ \vdots \\ P_{k-M+1}^k \end{pmatrix} F_k^T + K_k R_k K_k^T + Q_k \end{aligned} \quad (11)$$

where : $C_k = diag[H_k(\hat{x}_k) \;\; \ldots \;\; H_k(\hat{x}_{k-M+1})]$.
In the expression 11, intervenes total estimation error covariance matrix $\bar{P}_k$. This matrix is calculated as follows:

$$\bar{P}_{k+1} = \begin{pmatrix} P_{k+1}^{k+1} & P_{k+1}^k & \ldots & P_{k+1}^{k-M+2} \\ P_k^{k+1} & & & \\ \vdots & & \ddots & \\ P_{k-M+2}^{k+1} & & \ldots & P_{k-M+2}^{k-M+2} \end{pmatrix} \quad (12)$$

with each iteration we must calculate the first component of $\bar{P}_{k+1}$ with the relation 11 and for the other elements, they are calculated by the following expression:

$$P_{k+1}^{k-i} = E(\tilde{x}_{k+1} \tilde{x}_{k-i}^T) \quad (13)$$

$$P_{k+1}^{k-i} = F_k P_k^{k-i} - K_k C_k \begin{pmatrix} P_k^{k-i} \\ P_{k-1}^{k-i} \\ \vdots \\ P_{k-M+1}^{k-i} \end{pmatrix} \quad (14)$$

We calculate then K_k in order to minimize the trace of error covariance matrix (P_{k+1}^{k+1}):

$$\frac{\partial trace(P_{k+1}^{k+1})}{\partial K_k} = 0 \quad (15)$$

thus, we obtain K_k which satisfy 15 :

$$K_k = F_k [P_k^k \;\; P_k^{k-1} \;\; \ldots \;\; P_k^{k-M+1}] C_k^T (C_k \bar{P}_k C_k^T + R_k)^{-1} \quad (16)$$

The fact of using a moving horizon to the measures introduces a matrix $\bar{P}_{k+1}$, the calculation of K_k then takes into account preceding measures which differ from classical E.K.F.
The initialization of the E.K.F-MH is given by the E.K.E in its classical formulation:

$$\bar{P}_0 = diag[P_M^{E.K.E} \;\; P_{M-1}^{E.K.E} \;\; \ldots \;\; P_0^{E.K.E}] \quad (17)$$

where $P_k^{E.K.E}$ is a estimation error covariance matrix of E.K.E.
In the same way that in the EKE the scalar residual is generate, with the possibility of choosing :

$$r_k^{E.K.F-MH} = y_{k-M+1} - y_{k-M+1}^e$$

3.3. Convergence Analysis

In this section, we present an extension of the principal theorem for convergence analysis of E.K.E and E.K.F-MH based on the method of [15], [16] and [17] which includes an unknown diagonal matrix to model linearization errors and a Lyapunov function which leads us to the resolution of a LMI which depends on the choice on R_k and Q_k (respectively matrix of covariance of the noises of the system and measurements).
We present some guiding steps for the case of EKE. (For briefness, many steps and demonstrations are omitted)

Initially,the error vector is defined : $\tilde{x}_k = x_k - \hat{x}_k$ and a candidate Lyapunov function :

$$V_{k+1} = \tilde{x}_{k+1}^T P_{k+1}^{-1} \tilde{x}_{k+1}$$

where :

$$\begin{cases} \tilde{x}_{k+1} = \alpha_k (F_k - K_k H_k) \tilde{x}_k = \alpha_k \tilde{F}_k \\ P_{k+1}^{-1} = (\tilde{F}_k P_k F_k^T + Q_k)^{-1} \\ \alpha_k = diag(\alpha_{1k}, ..., \alpha_{(n_d+n_a)k}) \end{cases}$$

with a decreasing sequence $\{V_k\}_{k=1,...}$ means that there exists a positive scalar $0 < \xi < 1$ so that :

$$V_{k+1} - (1 - \xi) V_k \leq 0$$

therefore, which gives us this LMI:

$$\tilde{F}_k^T \alpha_k (\tilde{F}_k P_k F_k^T + Q_k)^{-1} \alpha_k \tilde{F}_k - (1 - \xi) P_k^{-1} \leq 0 \quad (18)$$

and similar to the technology used by [16],[15], We make the extension of the following theorem:

1. the system (6) is A-locally uniformly rank observable, there exists $k \geq A-1$ where the observability matrix :

$$rank(O(k-A+1,k)) = \begin{bmatrix} H_{k-A+1} \\ H_{k-A+2}F_{k-A+1} \\ .... \\ H_k F_{k-1}...F_{k-A+1} \end{bmatrix} = (n_d + n_a) \quad (19)$$

in practice, we use a numerical rank test on $O(k-A+1,k)$.

2. F_k, H_k are uniformly bounded matrices and F_k^{-1} exist.

3. the matrices Q_k and R_k are chosen such as :

   (a) For E.K.E :

$$Q_k = \gamma e_k^T e_k I_{n_d+n_a} + \lambda I_{n_d+n_a}$$
$$R_k = \varsigma H_k P_k H_k^T + \tau I_m$$

   where $e_k = r_k^{E.K.E}$ and : γ have to be chosen sufficiently large and positive, λ positive scalar which is small enough and ς and τ a positive scalar fixed by the user.

   (b) For E.K.F-MH :

$$Q_k = \alpha e f_k^T e f_k I_{n_d+n_a} + \varepsilon I_{n_d+n_a}$$
$$R_k = \mu C_k \bar{P}_k C_k^T + \rho I_M$$

$$\text{where } ef_k = \begin{pmatrix} y_k - h(\hat{x}_k) \\ y_{k-1} - h(\hat{x}_{k-1}) \\ \vdots \\ y_{k-M+1} - h(\hat{x}_{k-M+1}) \end{pmatrix}$$

   and : α have to be chosen small and positive, ε positive scalar which is little large enough and μ and ρ a positive scalar.

4. SIMULATION RESULTS

Studies are carried out on IEEE 3 buses test systems to evaluate the performance of the dynamic proposed model and the new observer (E.K.F-MH) . For the discretization of the dynamic model (5) we used Euler discretization of step size $T_e = 10^{-4}s$. The measurement values are generated by adding low variance noise ($\pm 1\%$ of real value) to the calculated measurements (transit power $P_{3,2}$) based on the diagram (Fig 2).
We start initially by the figure (Fig 3) which shows the evolution of the rank of the observability matrix (numerical calculation with $A = 4$).

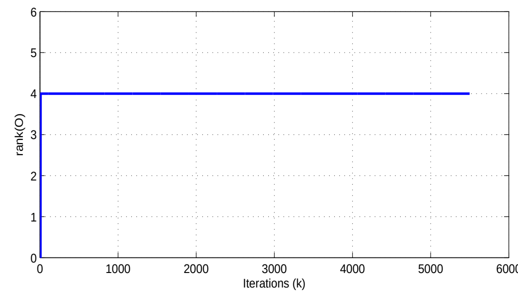

Figure 3. Evolution of the $rank$ of observability matrix: $rank(O_{3buses}^{(k-4,k)})$

After verifying the observability of the system, we are interested in faults detection.
First time we are interested in stability and convergence of two versions of the Kalman filter (E.K.F-MH and E.K.E), why we take (classical choice):

$$Q_k^{E.K.E} = Q_k^{E.K.F-MH} = 10^{-5} I_4$$
$$R_k^{E.K.E} = 10^{-3}$$
$$R_k^{E.K.F-MH} = 10^{-3} I_4$$

and we present the evolution of $\hat{U}_2(k)$ (Fig 4) after the injection of a defect on the generator node 3 ,$P_{G_3} = 0$ (electrical power supplied by the generator) between the iterations 1550 and 1600 with the classical value of R_k and Q_k :

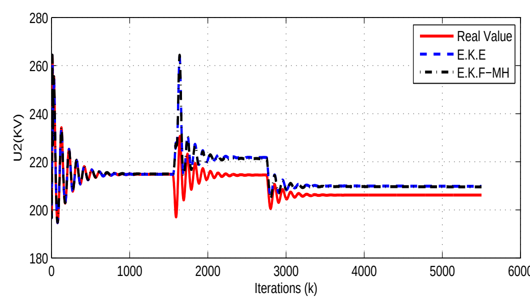

Figure 4. Evolution of estimated bus voltage in node 2 : $\hat{U}_2(k) = \hat{x}_4(k)$ with R_k and Q_k constant

Figure (Fig 4) shows well that with the classical choice of the matrix R_k and Q_k the two estimators do not converge to the good values, then the generated residue is false. We choose in all what follows the following values of a matrix of covariance of the noises of the system and measurements (with correction and based on the theorem presented in section Convergence analysis:

$$\begin{cases} Q_k^{E.K.E} = 10 e_k^T e_k I_4 + 5 I_4 \\ R_k^{E.K.E} = 10 H_k P_k H_k^T + 1 \\ Q_k^{E.K.F-MH} = 0.001 e f_k^T e f_k I_4 + 0.005 I_4 \\ R_k^{E.K.F-MH} = 0.001 H_k \bar{P}_k H_k^T + 0.005 I_4 \end{cases}$$

and we show again the variation of $\hat{U}_2(k)$ again ,(Fig 5):

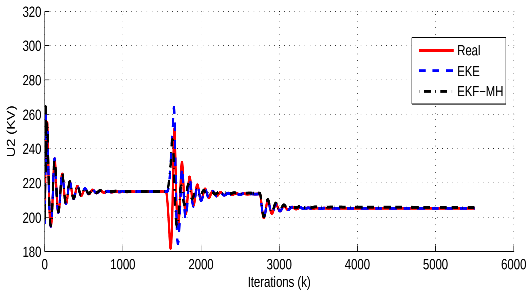

Figure 5. Evolution of estimated bus voltage in node 2 : $\hat{U}_2(k) = \hat{x}_4(k)$

Figure (Fig 5) shows in a clear way the interest of the good choice of the expressions of R_k and Q_k.
In what follows we are interested in the generation and the evolution of the residue signal.
We start initially with the injection of a defect on the generator node 3 ,$P_{G_3} = 0$ from iteration 2500, and we show the variation of the residue (Fig 6) :

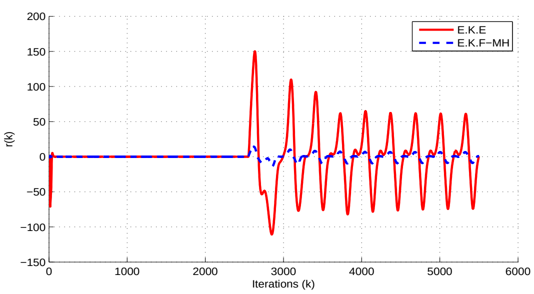

Figure 6. Evolution of residue r_k

Figure (Fig 6) shows well that the residue given by the application of E.K.F-MH gives a variation better than that given by E.K.E in its variation at the time of the first iterations that can be a false alarm or indication of defect (like given by E.K.E).
Now we show the variation of the residue during the application of the two defects (Fig 7) between the iterations respectively :1550 to 1700 (a short-circuit between nodes 2 and 3) and 2750 to 2900 (break-line between nodes 2 and 3) :

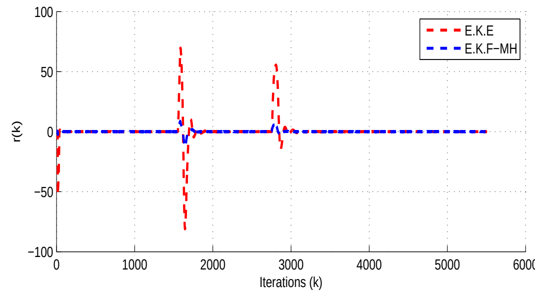

Figure 7. Evolution of residue r_k

Figure (Fig 7) show well that the variation of the residue calculated by E.K.F-MH remains limited that in the interval of the injection of defect from where a clear idea on the quality of the estimate and consequently a perfect fault signal but with E.K.E indicate that the fault is out of interval of variation.
We present in (Fig 8) the evolution of the residual signal when we inject two defects in the same interval, the first is break-line between nodes 2 and 3 on iterations 2500 to 3100 and the second defect is a short-circuit at iterations 3000 to 3050 :

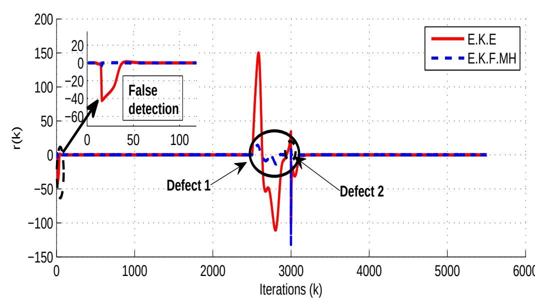

Figure 8. Evolution of residue r_k

Figure (Fig 8) gives a clear idea on the variation of the residual signal generated by E.K.F-MH only in the intervals of injection of the defects that does not allow to distort the indication of the defects and consequently a perfect residue and a reliable estimator.

5. CONCLUSION

A new and efficient observer (E.K.F-MH) has been described and investigated while based on moving horizon to generate a perfect residual signal to fault detection for dynamic power system. We also used the classical method of E.K.E to dynamic state estimation of power system while including some numerical approximation for the calculation of Jacobean and which was preceded by a convergence analysis. The results show well the good choice of R_k and Q_k proposed in term of robustness, convergence and ,in a very clear way, the good quality of fault detection with a combination of successive and simultaneous injection of the major real type of defect.

6. REFERENCES

[1] R. Neela and P. Aravindhababu, "A new decoupling strategy for power system state estimation," *International Journal of Energy Conversion and Management*, vol. 50, pp. 2047–2051, 2009.

[2] A. Thabet, S. Chniba, D. Gaetan, M. Boutayeb, and M.N Abdelkrim, "Power systems load flow and state estimation: Modified methods and evaluation of stability and speeds computing.," *International Review of Electrical Engineering*, vol. 5, pp. 1110–1118, 2010.

[3] Alexey Shumsky, "Robust analytical redundancy relations for fault diagnosis in nonlinear systems," *Asian Journal of Control*, vol. 4, pp. 159–170, 2002.

[4] R.M Guerraand J.J R.Pasaye and A.S Lopez, "Fault diagnosis innonlinear systems: An application to a three-tank system," in *Proc. American Control Conference Anchorage*, Seattle, Washington, USA, 2008, pp. 2136–2141.

[5] M. A. Pai, P. W. Sauer, B. C. Lesieutre, and R. Adapa, "Structural stability in power systems-effect of load models," *IEEE Transactions on Power Systems*, vol. 10, pp. 609–615, 1995.

[6] Ernst Scholtz, *Observer based monitors and distributed wave controllers for electromechanical disturbances in power systems*, Ph.D. thesis, Massachusetts Institute Technology, USA, 2004.

[7] C. J. Dafis, *An observbility formulation for nonlinear power systems modeled as differential algebraic systems*, Ph.D. thesis, Drexel university, PA, USA, 2005.

[8] T. Wichmann, "Simplification of nonlinear dae systems with inex tacking," in *European Conference on Circuit Theory and Design*, Espoo, Finland, 2001, pp. 173–176.

[9] J. Aslund and Erik Frisk, "An observer for non linear differential-algebraic systems," *Autmatica*, vol. 42, pp. 959–965, 2006.

[10] B. W. Gordon, "Dynamic sliding manifolds for realization of high index differential-algebraic systems," *Asian Journal of Control*, vol. 5, pp. 454–466, 2003.

[11] D. C. Tarraf and H. H. Asada, "On the nature and stability of differential-algebraic systems," in *Proc. American Control Conference Anchorage*, Anchorage, Al USA, 2002, pp. 3546–3551.

[12] D. Karlsson and D. J. Hill, "Modelling and identification of nonlinear dynamic loads in power systems," *IEEE Transactions on Power Systems*, vol. 9, pp. 157–166, 1994.

[13] Ali Zemouch, *Sur l'observation de l'etat des systemes dynamiques non lineaires*, Ph.D. thesis, Université Louis Pasteur, Strasbourg I, France, 2007.

[14] V. M. Becerra, P. D. Roberts, and G. W. Griffiths, "Applying the extended kalman filter to systems described by nonlinear differential-algebraic equations," *Control Engineering Practice*, vol. 9, pp. 267–281, 2001.

[15] M. Boutayeb and C. Aubry, "A strong tracking extended kalman observer for nonlinear discrete-time systems," *IEEE Transactions on Automatic Control*, vol. 44, pp. 1550–1556, 1999.

[16] M. Boutayeb, "Identification of nonlinear systems in the presence of unknown but bounded disturbances," *IEEE Transactions on Automatic Control*, vol. 45, pp. 1503–1507, 2000.

[17] Y.Song and J.W. Grizzle, "The extended kalman filter as a local asymptotic observer for nonlinear discrete-time systems," *Journal of Mathematical Systems, Estimation and Control*, vol. 5, pp. 59–78, 1995.