

Dynamic State Estimator Based on Wide Area Measurement System During Power System Electromechanical Transient Process

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1. Introduction

The wide area measurement system (WAMS) developed rapidly in recent years [1-3]. It has been applied to the studies on many topics in monitoring and control of power systems. But as a kind of measurement system, WAMS has the measurement error and bad data unavoidably. The steady measurement errors of WAMS have been prescribed in corresponding IEEE standard [4], but the dynamic measurement errors now become the focus of discussion [5-6] and attract the attention of PSRC workgroup H11. If the dynamic raw data is applied directly, the unpredictable consequence will be resulted in, which will do a lot of damage to power systems. Therefore, the dynamic estimation for the state variables during electromechanical transient process is the backbone for WAMS based dynamic applications and real-time control.

There was no effective means to measure the power system dynamic process before WAMS come forth; therefore, the dynamic estimation for power system state variables during electromechanical transient process was not feasible. In reference [7], a dynamic estimator for generator flux state variables during transient process is proposed, but the dimension of the flux state variables is relative high, and the accurate values of parameters can not be achieved easily. In reference [8], a non-linear dynamic state observer for generator rotor angle during electromechanical transient process is proposed, but the method is only applicable to one machine infinite bus system (OMIB), and the fault scenarios is required to satisfy the preset mode.

After WAMS come forth, many references focused on the steady state estimation with PMU measurements and had many achievements [9-11]. Comparing with the steady state estimation, the traditional dynamic state estimation [12-15] aims at the relative slow load fluctuation, which is different with the proposed dynamic state estimation during electromechanical transient process. The traditional dynamic state estimation employs the measurement equations based on the network constraints, and predicts the state variables using exponential smoothing techniques. But during the power system fault stage and consequent dynamic process, the network topology is changed and can not be acquired in time; the bus voltage phase angles has jump discontinuities and are not easy to be predicted. Thereby, the centralized dynamic estimation which adopts the measurement equations

based on network constraints and regards the bus complex voltages as the state variables is not feasible for the electromechanical dynamic process.

In this paper, a novel WAMS based dynamic state estimator during power system electromechanical transient process is proposed. The estimator chooses the generator rotor angle and electrical angular velocity as the state variables to estimate. The generator output power measured by PMU is used to decouple the generator rotor movement equation and the outer network equation. And the linear Kalman filter based dynamic state estimator mathematical model is presented. The WAMS measurement noise and dynamic model noise are analyzed in detail. The total flow chart and the bad data detection and elimination approach are given as well. The numerical simulation is carried out on the IEEE 9-bus test system and a real generator in North China power grid. The simulation results indicate that the proposed real time dynamic estimator can estimate the generator rotor angles accurately; therefore, which can serve the power system dynamic monitoring and control system better.

2. Kalman filter

The time-invariant linear system model can be written as [16]

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{Ax} + \mathbf{Bu} \\ \mathbf{y} = \mathbf{Cx} \end{cases} \quad (1)$$

The discrete form of equation (1) is

$$\begin{cases} \mathbf{x}(t+T) = \mathbf{\Phi}(T)\mathbf{x}(t) + \mathbf{\Gamma}(T)\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{Cx}(t) \end{cases} \quad (2)$$

where

T is the sampling period, $t=kT, k=0, 1, 2, \dots$,

$\mathbf{\Phi}(T)$ is the state transition matrix, and

$\mathbf{\Phi}(T) = \exp(\mathbf{AT}) = \sum_{i=0}^{\infty} \mathbf{A}^i T^i / (i!) , \mathbf{A}^0 = \mathbf{I}; \mathbf{\Gamma}(T) = \left[\int_0^T \mathbf{\Phi}(\alpha) d(\alpha) \right] \mathbf{B}$, and \mathbf{I} is the identity matrix.

When subject to a random plant and measurement noise, the sampled-data system can be expressed as

$$\begin{cases} \mathbf{x}(k+1) = \mathbf{\Phi}\mathbf{x}(k) + \mathbf{\Gamma}\mathbf{u}(k) + \mathbf{\Gamma}\mathbf{w}(k) \\ \mathbf{y}(k) = \mathbf{Cx}(k) + \mathbf{v}(k) \end{cases} \quad (3)$$

The plant noise sequence $\mathbf{w}(k)$ and the measurement noise sequence $\mathbf{v}(k)$ are assumed to be Gaussian stationary white-noise sequence with zero means and covariance:

$$\begin{aligned} E[\mathbf{v}(k)] &= E[\mathbf{w}(k)] = \mathbf{0} \\ E[\mathbf{w}(k)\mathbf{w}^T(j)] &= \mathbf{Q}\delta_{kj} \quad \delta_{kj} = \begin{cases} 1 & k = j \\ 0 & k \neq j \end{cases} \\ E[\mathbf{v}(k)\mathbf{v}^T(j)] &= \mathbf{R}\delta_{kj} \end{aligned}$$

where, Q is the plant noise covariance matrix, R is the measurement noise covariance matrix.

The initial state $x(0)$ is assumed to be uncorrelated with the plant and measurement noise sequences and is Gaussian with mean covariance:

$$E[x(0)] = \hat{x}(0); E[(x(0) - \hat{x}(0))(x(0) - \hat{x}(0))^T] = P_0$$

The Kalman filter formulas for time-invariant linear model can be largely divided into two steps: prediction step and filtering step.

The prediction step is:

$$\begin{cases} \bar{x}(k+1) = \Phi x(k) + \Gamma u(k) \\ P'_{k+1} = \Phi P_k \Phi^T + \Gamma Q \Gamma^T \end{cases} \quad (4)$$

where, $\bar{x}(k+1)$ is the predictive value of state variables x at time step $k+1$, P'_{k+1} is the predictive error covariance matrix (pre-measurement covariance matrix) at time step $k+1$, and P_k is the estimated error matrix at time step k .

The filtering step is:

$$\begin{cases} K_{k+1} = P'_{k+1} C^T (C P'_{k+1} C^T + R)^{-1} \\ \hat{x}(k+1) = \bar{x}(k+1) + K_{k+1} (y(k+1) - C \bar{x}(k+1)) \\ P_{k+1} = (I - K_{k+1} C) P'_{k+1} \end{cases} \quad (5)$$

where, K_{k+1} is the Kalman gain matrix at time step k , $\hat{x}(k+1)$ is the estimated value of state variables x at time step $k+1$, and P_{k+1} is the estimated error matrix at time step $k+1$ (post-measurement covariance matrix).

3. The proposed dynamic estimator model

3.1 The proposed dynamic estimator model for generator variables

During the power system fault stage and consequent dynamic process, the network topology is changed and can not be acquired in time; the bus voltage phase angles has discontinuities and are not easy to be predicted. Therefore, the generator rotor angle and electrical angular velocity are regarded as the estimated state variables which can not mutate suddenly and obey the rotor motion equation. Moreover, the generator angle trajectories implicate abundant dynamic information; thereby, acquiring accurate generator rotor trajectories is of great importance to power system real time control.

The rotor motion equation is written as follows:

$$\begin{cases} \frac{d\delta}{dt} = (\omega - 1)\omega_0 \\ \frac{d\omega}{dt} = \frac{1}{T_J} (T_m - T_e - D\omega) = \frac{1}{T_J} \left(\frac{P_m}{\omega} - \frac{P_e}{\omega} - D\omega \right) \end{cases} \quad (6)$$

where, δ is the generator rotor angle (rad), ω is the generator electrical angular velocity; T_m and T_e are the mechanical torque and electrical torque on generator shaft respectively; P_m and P_e are the mechanical input power and electrical output power respectively; T_J is the moment of inertia of the machine rotor and D is the damping coefficient.

It can be seen from equation (6) that if the electrical torque (power) and mechanical torque (power) at any time step are known, the generator motion equation will be decoupled from outer network [17]. Therefore, the generator rotor motion becomes single rigid body motion in two-dimension state space (displacement and velocity). If the generator mechanical torque is assumed constant, when only the electrical torque curve in time domain is known, the rotor motion equation is decoupled from outer network.

Equation (6) is written as follow form:

$$\begin{bmatrix} \dot{\delta} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & \omega_0 \\ 0 & -\frac{D}{T_J} \end{bmatrix} \begin{bmatrix} \delta \\ \omega \end{bmatrix} + \begin{bmatrix} -\omega_0 \\ \frac{T_m - T_e}{T_J} \end{bmatrix} \quad (7)$$

It is noted that equation (7) is a standard time-invariant linear system which is qualified to linear Kalman filter well.

The torque can not be measured easily, hence the second term (controlling variable vector) of the right side of equation (7) is written as the form of P_m and P_e , then the equation (7) is written as follow:

$$\begin{bmatrix} \dot{\delta} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & \frac{180}{\pi} \omega_0 \\ 0 & -\frac{D}{T_J} \end{bmatrix} \begin{bmatrix} \delta \\ \omega \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{T_J} \end{bmatrix} \begin{bmatrix} -\frac{180}{\pi} \omega_0 \\ (P_m - P_e) / \omega \end{bmatrix} \quad (8)$$

where, the unit of δ is degree.

Comparing equation (8) with equation (1), we have

$$\mathbf{x} = \begin{bmatrix} \delta \\ \omega \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} 0 & \frac{180}{\pi} \omega_0 \\ 0 & -\frac{D}{T_J} \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{T_J} \end{bmatrix} \quad \mathbf{u} = \begin{bmatrix} -\frac{180}{\pi} \omega_0 \\ \frac{P_m - P_e}{\omega} \end{bmatrix} \quad (9)$$

It should be pointed out that even the state variable ω appears in controlling variable vector \mathbf{u} of formula (8), thereby, formula (8) is not a strict state equation, but it does not affect the application of Kalman filter. The reasons are:

1. The state differential equation only adopted in predictive step to calculate the state variable at next time step. Even though $u(k)$ is the function of $\omega(k)$, $\omega(k)$ has been estimated by Kalman filter at last time step, so it can be regarded as a known variable to substitute in equation (8)

- During electromechanical transient process, the value of ω is about 1 (p.u.) and the off nominal range of ω is about from parts per thousand to 2 percent. It can be seen from equation (8) that the impact of ω fluctuation upon the controlling variable is so small that can be covered by the dynamic plant noise.

δ can be measured by PMU synchronistically (direct measurement or inferred by generator terminal electrical variables). If the pulse sequences of the rotor angular velocity meter are synchronized by GPS, the electrical angular velocity ω also can be measured by PMU. Therefore,

$$\mathbf{y} = \begin{bmatrix} \delta \\ \omega \end{bmatrix} \quad \mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{10}$$

If only δ can be measured by PMU, then:

$$\mathbf{y} = [\delta] \quad \mathbf{C} = [1 \ 0] \tag{11}$$

Calculating the state transition matrix (equation (2)) in engineering, only the three former terms are taken into account, which can achieve sufficient accuracy.

$$\Phi(T) \approx \mathbf{I} + \mathbf{A}T + \mathbf{A}^2T^2 / 2 = \begin{bmatrix} 1 & \frac{180}{\pi} \omega_0 T (1 - \frac{DT}{2T_j}) \\ 0 & 1 - \frac{DT}{T_j} (1 - \frac{DT}{2T_j}) \end{bmatrix}$$

$$\Gamma(T) = \left[\int_0^T \Phi(\alpha) d(\alpha) \right] \mathbf{B} = \begin{bmatrix} T & \frac{180}{\pi} \omega_0 \frac{T^2}{2T_j} (1 - \frac{DT}{3T_j}) \\ 0 & \frac{T}{T_j} - \frac{DT^2}{2T_j^2} (1 - \frac{DT}{3T_j}) \end{bmatrix}$$

Now, the generator dynamic equation qualified to Kalman filter (equation (2)) is built up, but to realize the predictive step (equation (4)) and filtering step (equation (5)) of Kalman filter algorithm, the exact value of plant noise covariance \mathbf{Q} and measurement noise \mathbf{R} . the following error analysis analyzes the problem in detail.

3.2 Error and noise analysis

The measurement noise (error) covariance matrix \mathbf{R} and plant noise covariance matrix \mathbf{Q} are analyzed respectively in terms of the rotor angle measurement mode (direct measurement mode or indirect measurement mode).

3.2.1 The direct measurement mode of rotor angle and electrical angular velocity

The direct measurement method of generator rotor angle using rotor position sensor has relative higher accuracy. The method assumes that the electrical angular velocity is constant

during one cycle, but in fact, the electrical angular velocity varies about parts per thousand during one cycle. According to analysis, the measurement error due to this is about $1\sim 2^\circ$. Moreover, the detection precision of rotor position pulse also affects the measurement error. Considering all above factors, the standard deviation of the rotor angle direct measurement error can be set as 2° , and the corresponding variance is 4° .

The measurement of electrical angular velocity is equivalent to the measurement of rotor angular velocity (electrical angular velocity = number of pole pairs \times rotor angular velocity). In modern power systems, the rotor angular velocity can be measured by velocity meter for turbine generator and hydro generator. The principle of velocity meter is described below. There is a 60-tooth gear installed in the rotor shaft and the detection circuit of velocity meter detects the pulse generated by each tooth of the gear. Therefore, 6° divided by the time interval between two pluses is the value of instantaneous angular velocity. If the pulse sequences generated by rotor angular velocity meter are synchronized by GPS, the electrical angular velocity ω can also be measured by PMU. The synchronized accuracy and the pulse detection accuracy both affect the measurement error, thereby, the standard deviation of the direct measurement error of rotor electrical angular velocity can be set as 0.001 (p.u., i.e. $0.05\sim 0.06$ Hz), and the corresponding variance is $1e-6$.

It can be seen that when both the rotor angle and the electrical angular velocity can be measured by PMU directly, the corresponding measurement noise covariance matrix is as follows:

$$\mathbf{R} = \begin{bmatrix} 4 & 0 \\ 0 & 10^{-6} \end{bmatrix} \quad (12)$$

3.2.2 The indirect measurement mode of rotor angle

The direct measurement method of generator rotor angle is required to install the rotor position sensor, but some old style generators do not satisfy the installation condition. The direct synchronized measurement of electrical angular velocity is also required to install the additional GPS receiver and carry out necessary alteration. Thereby, these generators can not adopt the direct measurement mode and have to infer the rotor angle using the generator terminal electrical variables measured by PMU. The inferred rotor angle is regarded as the indirect measurement value of rotor angle and used in Kalman filter to estimate the rotor angle and electrical angular velocity.

If the generator terminal voltage phasor \dot{U}_t and current phasor \dot{I}_t is measured, the virtual internal voltage \dot{E}_Q which is used to fix on the q axis position is written as,

$$\dot{E}_Q = \dot{U}_t + \dot{I}_t(R + X_q) \quad (13)$$

where, R is stator resistance, X_q is q axis synchronous reactance, the angle of \dot{E}_Q is rotor angle δ .

An alternative equation is:

$$\delta' = a \tan \frac{PX_q - QR}{U_t^2 + PR + QX_q} \quad (14)$$

where, δ' is the rotor angle with reference to terminal voltage phase. P, Q are the generator output active power and reactive power, respectively.

It is assumed that the voltage phase of the generator terminal bus is θ , therefore, the generator rotor angle δ is:

$$\delta = \theta + \delta' \tag{15}$$

where, δ' is the rotor angle with reference to terminal voltage phase. P, Q are the generator output active power and reactive power, respectively.

It should be kept in mind that equation (13) and (14) are both derived with the assumption that there is no damping current in rotor amortisseur, thereby, the equations have sufficient precision in steady state, but considerable errors may be resulted in during dynamic process. Especially in fault duration, the inferred rotor angle will produce an obvious discontinuity.

Strictly speaking, the error propagation theory should be used to calculate the indirect measurement error variance of the inferred rotor angle accurately, whereas, the formula is very complex and hard to calculate due to the factors such as measurement variation, damping current, time-variant parameters and iron saturation, etc. therefore, according to the errors variance of PMU direct measurements (terminal voltage, terminal current and output power) and considering all factors mentioned above synthetically and simply, the standard deviation of the indirect measurement error of rotor angle can be set as 3° , and the corresponding variance is 9° .

Therefore, when only the rotor angle can be inferred by the PMU generator terminal measurements indirectly, the corresponding measurement noise covariance matrix is as follows:

$$\mathbf{R} = [9] \tag{16}$$

Since the phasor calculation has time delay, the sampling value with synchronous time stamp is adopted to calculate the instantaneous output active and reactive power directly.

$$\begin{aligned} P &= u_a i_a + u_b i_b + u_c i_c \\ Q &= \frac{1}{\sqrt{3}}(u_a(i_c - i_b) + u_b(i_a - i_c) + u_c(i_b - i_a)) \end{aligned} \tag{17}$$

where, $u_a, i_a; u_b, i_b$ and u_c, i_c are the instantaneous sampling value of phase a , phase b and phase c generator terminal voltage and current, respectively.

3.2.3 The dynamic plant noise analysis

The dynamic plant noise represents the errors of model and parameters. It can be seen from equation (8) that the involved parameters are generator inertial constant T_J and damping coefficient D . T_J can be acquired exactly normally; D is very small and only reflects the mechanical friction and the windage since the electrical damping has been covered by the measured output active power. Therefore, the dynamic plant noise mainly roots in the measurement error of electrical output active power and the variation of mechanical input

power P_m . Since P_m is hard to measure accurately, it is assumed constant and its variation due to governor action is regarded as dynamic plant noise when only governor operates and generator reject and fast valving are not triggered.

In terms of relative standards [4], the standard deviation of electrical active power measurement error varies between 1%~2%, considering the variation of P_m , the plant noise covariance matrix Q is set as:

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & 0.0004P_{e0} + 0.0001 \end{bmatrix} \quad (18)$$

where, P_{e0} is the generator electrical output active power in pre-fault steady state.

It should be pointed out that Q varies with the measured active power P_e , but considering the impact of computational cost and bad data, equation (18) can satisfy the precision requirement generally.

To avoid the impact of the time delay of phasor calculation, the instantaneous sampling value should be employed to calculate the instantaneous electrical active power P_e .

$$P_e = P + I_t^2 R = u_a i_a + u_b i_b + u_c i_c + I_t^2 R \quad (19)$$

where, $I_t^2 R$ is the copper loss of generator stator armature.

4. Flow chart and implementation

The proposed WAMS based dynamic state estimator during electromechanical process is described as in Fig. 1.

The problems which should be noted in the implementation of the proposed estimator are described as follows:

4.1 Startup criterion

The steady state estimation aims at the power system steady state, whereas the proposed dynamic state estimator aims at the power system electromechanical transient process. Therefore, the startup criterion is needed for the proposed dynamic state estimator. The general startup criterion of the micro-computer based protection can be adopted as the startup criterion in the proposed dynamic estimator. The criterion triggers startup if three sequential instantaneous sampling values of generator terminal voltage and current all exceed the preset threshold.

After startup, a appropriate length of historical data of rotor angle, electrical angular velocity and electrical output power are backdated to ensure the convergence of Kalman filter before the startup time (power system fault occurring time).

4.2 Bad data identification and elimination

The rotor angle and electrical angular velocity have no discontinuous variation; therefore, the absolute residuals related with the bad measurement data will be increased anomaly. This feature can be used to identify and eliminate the bad data.

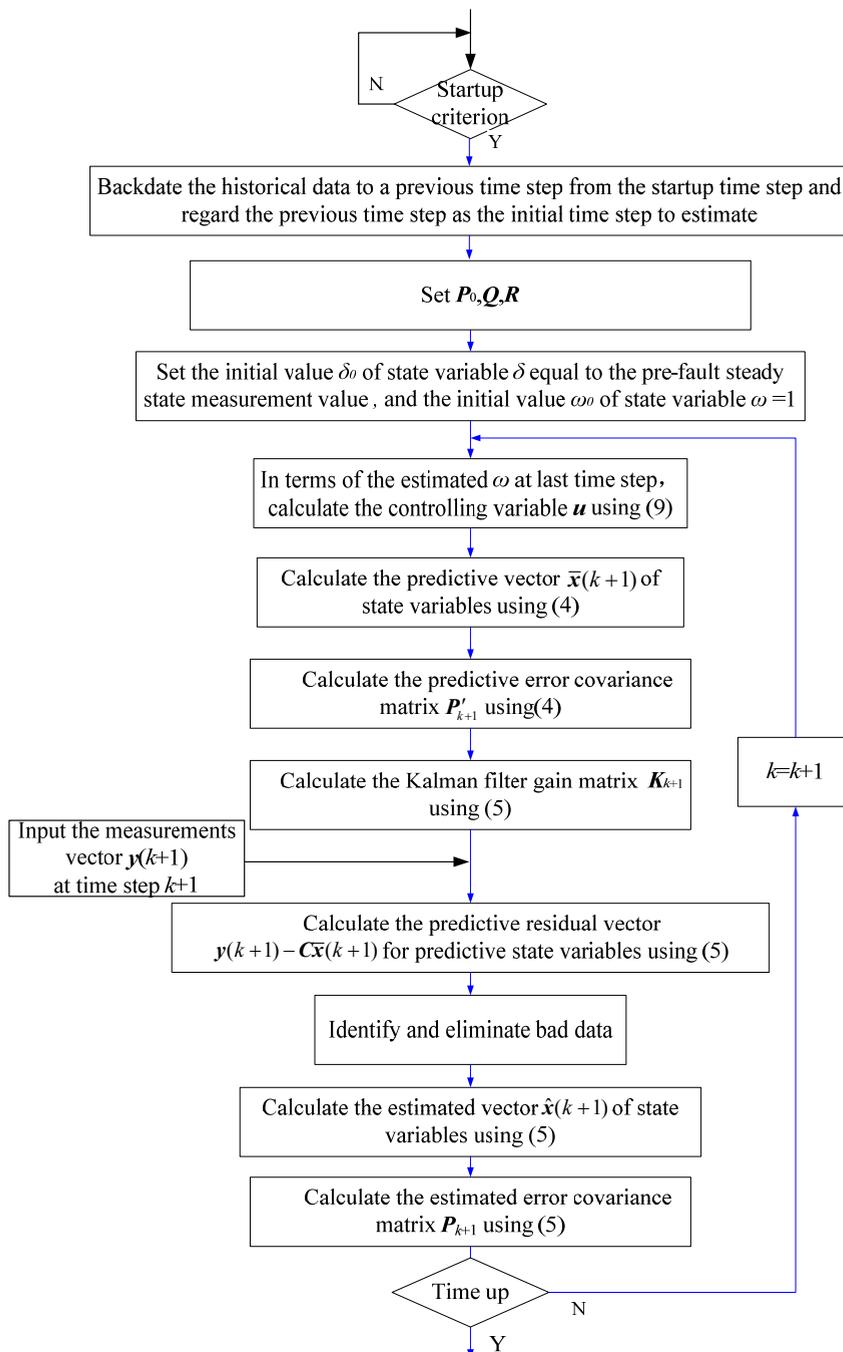


Fig. 1. Flow chart of the proposed dynamic state estimator.

For the example of rotor angle direct measurement, $\Delta\delta(k+1)$ denotes the predictive residual at time step $k+1$, and it can be calculated as follows:

$$\Delta\delta(k+1) = \delta_m(k+1) - \bar{\delta}(k+1) \quad (20)$$

where, $\delta_m(k+1)$ denotes the measurement value at time step $k+1$, $\bar{\delta}(k+1)$ denotes the predictive value at time step $k+1$.

The average of three previous sequential predictive absolute residual $\Delta\delta_{absmean} = (|\Delta\delta(k)| + |\Delta\delta(k-1)| + |\Delta\delta(k-2)|) / 3$, so, the bad data identification criterion at time step $k+1$ is described below:

$$|\Delta\delta(k+1)| > 5 \times \Delta\delta_{absmean} \quad (21)$$

If equation (21) holds, the corresponding measurement is identified as bad data. To eliminate its adverse impact, the absolute predictive residual $|\Delta\delta(k+1)|$ at time step $k+1$ is replaced by $\Delta\delta_{absmean}$, but its sign is reserved. After that, the filtering step of Kalman filter and the estimation at next time step are continued.

Equation (21) aims at the single bad data point, but does not work for the serial bad data points. For instance, there are serial bad data points with negative residuals in measurement from time step $k+1 \sim k+n$, if the criterion is applied, the absolute predictive residuals at time step $k+1 \sim k+n$ will be all replaced by $\Delta\delta_{absmean}$, and the negative sign will be reserved, thus, the predictive residuals at time step $k+1 \sim k+n$ tend to reach a negative constant, which breaks the randomness of predictive residuals. In this situation, the divergence of Kalman filter may be resulted in and the sequent normal measurement points may be identified the bad data wrongly.

To avoid this, the function $\sin(k)$ is used to recovery the randomness of predictive residuals at bad data points. In general, The value of function $\sin(k)$, $k=1, \dots, n$ (rad) obey the random distribution rule in the range of $[-1, +1]$, thereby, if there is bad data at time step $k+1$, the substitute of the predictive residuals at the time step is

$$\Delta\delta(k+1) = \sin(k+1) \cdot \Delta\delta_{absmean} \quad (22)$$

As mentioned before, the inferred rotor angle using equation (13) and (14) will produce an obvious discontinuity in fault duration. But in fact, the real rotor angle has no discontinuous variation; therefore, the discontinuity during fault stage can be regarded as a series of bad data. Applying the above bad data identification and elimination method, the more accurate rotor angle will be estimated.

5. Numerical study

IEEE 9-bus test system shown in Fig.2 and a real generator in North China power grid are chosen to carry out the numerical simulation.

In IEEE 9-bus test system, Gen1 and Gen2 are chosen as the generator to estimate. Gen1 and Gen2 are both equipped with governors and voltage regulators, and Gen2 is equipped with PSS. All the generators adopt the sixth-order detail model. A three-phase metal short-circuit fault is set on the beginning end of line BusB-Bus1 at the 50th cycles, and the circuit breakers

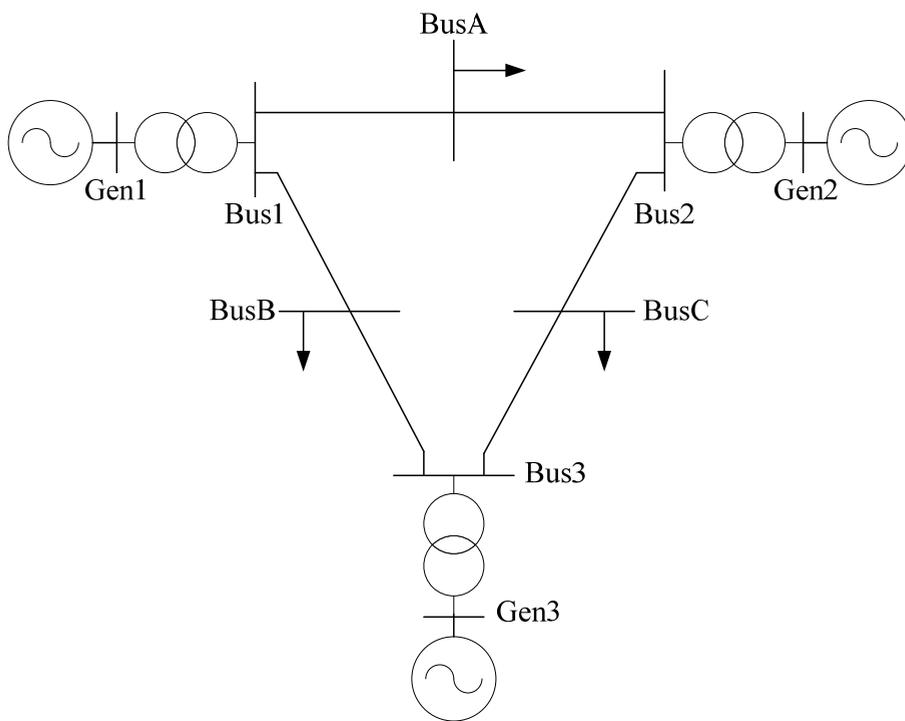


Fig. 2. IEEE 9-bus test system.

of both ends trip to clear fault at the 56th cycles. The true values of rotor angles, electrical angular velocities and electrical output power are acquired by commercial power system simulation software BPA, and the time step length is 2 cycles. The measurement values consist of true values, additional measurement errors and bad data. The errors of all types of measurements are assumed to follow the normal distribution with zero mean and the standard deviations which are given in Section III.B.

Since the measurement precision of rotor angle in steady state is relative high, the steady measurement value can be set as the initial value of state variable δ , and the initial value of state variable ω is set to 1 (p.u.). the reliability of initial value is relative high, the initial covariance matrix P_0 is set to zero matrix for convenience. The startup time step is the 50th cycle, the initial time step to estimate is the 26th cycle and the end time step is the 600th cycle. Fig. 3 gives the dynamic estimation effect of Gen 2 with δ and ω direct measurement. Fig. 4 shows the dynamic estimation effect of Gen 2 when only δ can be measured indirectly.

It can be seen form Fig.3 that the proposed dynamic estimator has favorable filter effect and eliminates the measurement noise and bad data effectively for δ and ω direct measurement. The subgraph (c) which zooms in the interested part of estimation effect for δ shows clearly that the proposed estimator eliminates the adverse impact of serial bad data points successfully.

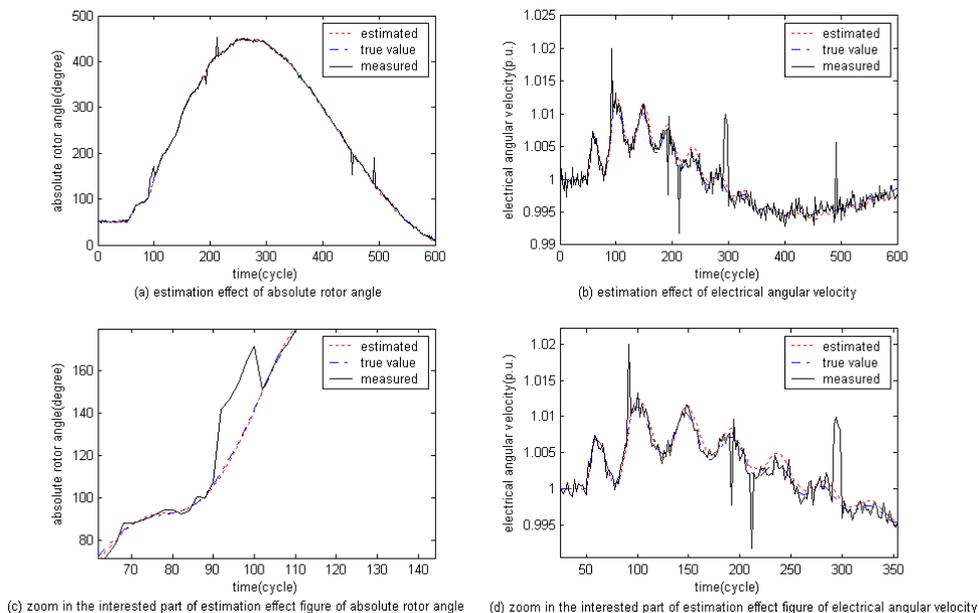


Fig. 3. The estimation effect of Gen2 with δ and ω direct measurement.

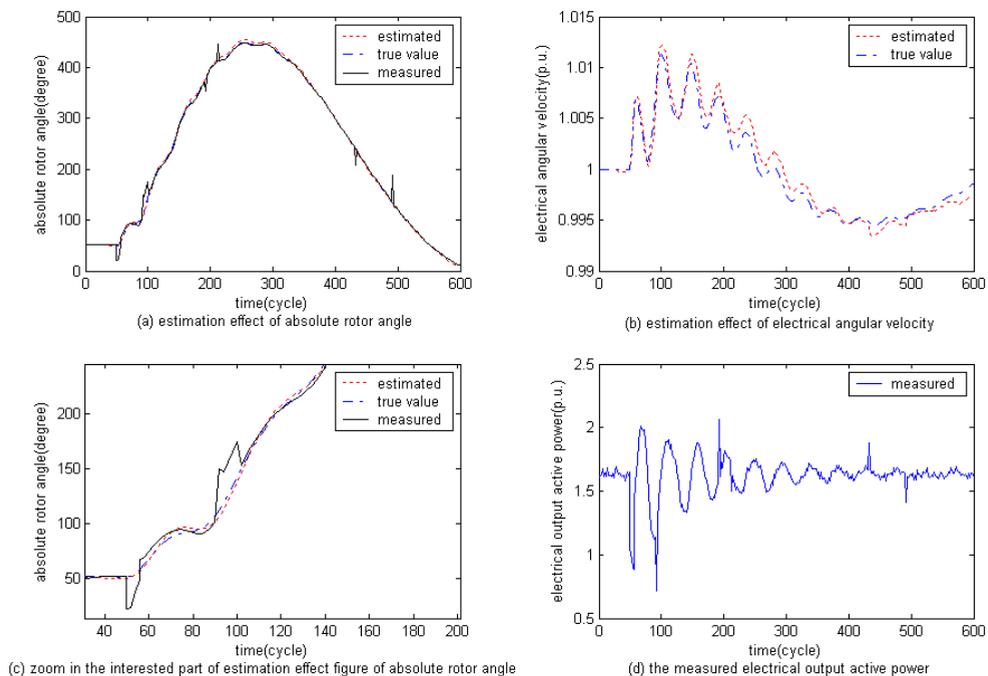


Fig. 4. The estimation effect of Gen2 when only δ can be measured indirectly.

The similar conclusion can be drawn from Fig. 4. Moreover, the subgraph (a) and (c) show that the indirect measurement of rotor angle δ has an obvious sag in fault duration. Applying the proposed bad data elimination method for serial bad data, the sag is made up well, which smoothes the estimated curve for δ and achieves excellent filter effect. Since there is no measurements of electrical angular velocity, the estimation effect for ω is not as good as that in Fig.3, but is still acceptable.

Whether the state variables δ and ω are measured directly or indirectly, the considerable measurement noises and bad data are added on the electrical output active power introduced as the controlling variable (Fig. 4(d)), but the estimation effect is almost not affected. The reason is that the proposed dynamic estimator is an integral process of the electrical output active power substantially, and the integral itself has better antinoise performance.

To acquire the quantified estimation index, the filter effect ρ and index ε ^[13] are defined as:

$$\rho = \frac{\sum_{i=1}^n (\hat{x}_i - x_i^+)^2}{\sum_{i=1}^n (x_i^M - x_i^+)^2} \tag{23}$$

$$\varepsilon = \frac{\sum_{i=1}^n \left| \frac{\hat{x}_i - x_i^+}{x_i^+} \right| \times 100\%}{n} \tag{24}$$

where, i indicates the sequence number of time step, n indicate the total number of time steps. \hat{x}_i, x_i^M and x_i^+ indicate the estimated value, measured value and true value of state variable x (δ or ω) at time step i respectively. The filter effect ρ and index ε of δ and ω are calculated respectively for the difference between their quantities is very large.

Table 1 gives the estimation indices of Gen1 and Gen2 with different measurement modes, and all results in Table I are the average values over 100 runs of Monte Carlo. It can be seen from Table I that the proposed dynamic estimator achieves good estimation effects with different measurement modes, and the estimation time is about 0.1 ms, which can satisfy the requirements of real-time applications. The estimation results of Gen 1 and Gen 2 with direct measurement of δ and ω is higher than those with only indirect measurement of δ . Moreover, the estimation precisions of Gen1 are higher than those of Gen2, because that the inertia constant of Gen1 is bigger than of Gen2, which makes the estimation of Gen1 is more immune to the dynamic plant noise.

A real generator in North China power grid is also chosen as the estimated generator, a three-phase metal short-circuit fault is put on a 500 kV line in the grid to excite the electromechanical transient, and the corresponding circuit breakers are tripped to clear fault after 5 cycles. All the simulation conditions are same as those of IEEE-9 test system except that the time step length is 1 cycle. The simulation results is given in Table 2.

The similar conclusion can be drawn from Table II; moreover, the estimation precisions are higher than those in IEEE 9 test-system. Since the generator is decoupled with outer network in the proposed dynamic estimator, the parallel dynamic estimation of different generators in large power system can be executed simultaneously. Therefore, the fast speed of the proposed dynamic estimator is not affected by the increasing numbers of generators in large power systems.

Generator	Measurement mode	State variable	Estimation indices		Estimation time(ms)	
			ρ	ε		
Gen1	1	direct	δ	0.0539	1.20	0.1247
		direct	ω	0.0132	0.0157	
	2	indirect	δ	0.1663	1.65	0.1047
		No	ω	No	0.0178	
Gen2	1	direct	δ	0.1226	1.47	0.1273
		direct	ω	0.1554	0.0619	
	2	indirect	δ	0.2620	2.20	0.1067
		No	ω	No	0.0803	

Table 1. Estimation results of G1 and G2 in IEEE 9-bus system.

Generator	Measurement mode	State variable	Estimation indices		Estimation time(ms)	
			ρ	ε		
Generator	1	direct	δ	0.0282	0.84	0.1240
		direct	ω	0.0078	0.0091	
	2	indirect	δ	0.0594	1.12	0.1160
		No	ω	No	0.0119	

Table 2. Estimation results of one generator in practical grid.

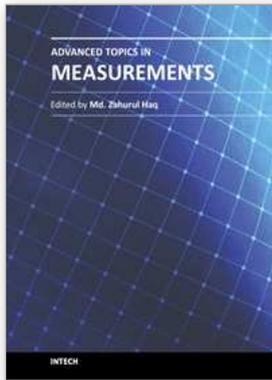
6. Conclusion

A WAMS based distributed dynamic state estimator for generator rotor angle and electrical angular velocity during power system electromechanical transient process is proposed in this paper. The WAMS measurement noise and dynamic model noise are analyzed concretely, and the bad data detection and elimination approach are given as well. The simulation results indicate that the proposed dynamic estimator has high estimation precision and fast computational speed; which satisfies the real-time requirements. The estimated generator rotor angle and electrical angular velocity eliminate the adverse impact of measurement noises and bad data; therefore, the proposed dynamic estimator can serve the power system dynamic monitoring and control system better.

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