Dynamic Power System State Estimation Using Combined Load Forecasting and Kalman Filtering

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Abstract

The state estimators on today's electric power transmission system operate on measurements taken from a single snapshot and perform estimation statically. We propose that improvements in robustness and accuracy can be realized through use of time history data via discrete-time dynamic state estimation using a dynamic model based on the power-flow balance equations. Further use of this model incorporating load forecast information to enable state prediction is explored.

Problems and Goals

State Estimation Error comes from

- Measurement errors
- Model topology errors
- Model parameter errors

Existing State Estimators

- Use only present measurements (no time history)
- Use the previous state estimate as a starting point for the present solution (assuming the previous state is closer to the present state than flat start)

We are developing dynamic state estimation methods that will

- Improve state estimator accuracy by using load forecast data and previous estimate
- Improve estimator robustness by decreasing effect of sporadic bad data on the estimate
- Provide an estimate of the future state allowing advance warning of operating limit violations

References and Acknowledgments

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Methodology

State Estimation

Process the vector of measurements,

$$\mathbf{z} = [z_1 \ \cdots \ z_M] = [h_1(\mathbf{x}) \ \cdots \ h_M(\mathbf{x})] + \text{noise}$$

consisting of

- Voltage magnitudes
- Real and reactive power injections ($P_i + jQ_i$)
- Real and reactive power flows ($P_{ik} + jQ_{ik}$)
- Current flow magnitudes (I_{ik})

to find the best estimate of the state, x

$$\mathbf{x} = [\delta_1 \ \cdots \ \delta_N \ \ V_1 \ \cdots \ V_1]^T$$

New Dynamic Model

Several algorithms exist to generate load forecasts. We can use this information to give us an idea of what X will be when the next set of measurements is available. Forming a vector of the loads

$$\mathbf{u} = [P_1 \ \cdots \ P_N \ \ Q_1 \ \cdots \ Q_1]^T$$

we can analyze the interplay between u and x via the Load(Power)-Flow balance equations.

$$f_i(\mathbf{x},\mathbf{u}) = V_i e^{j\delta_i} \sum_{k=1}^{N} (Y_{ik} V_k e^{j\delta_k}) - (P_i + jQ_i) = 0$$

Incremental change in load (Δu) leads to incremental change in state (Δx)

The increment is approximated by linearizing of the Power-Flow Equations

$$J d\mathbf{x} = d\mathbf{u} \qquad J = \frac{\partial \mathbf{f}(\mathbf{x},\mathbf{u})}{\partial \mathbf{x}}$$

$$\mathbf{x}_{t+Ts} = \mathbf{x}_t + J^{-1}(\mathbf{u}_{t+Ts} - \mathbf{u}_t)$$

Iterated Kalman Filter (IKF)

The Kalman filter combines information from the state forecast and measurements in four steps:

1) Predict X using dynamic model

$$x_{t+Ts/t} = x_{t/t} + J^{-1}(u_{t+Ts} - u_t)$$

2) Update state prediction covariance

3) Update state estimate using measurements

$$x_{t+Ts/t+Ts} = x_{t+Ts/t} + K(z_{t+Ts} - h(x_{t+Ts/t+Ts}))$$

4) Update state estimate covariance

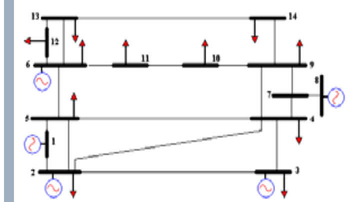
The IKF improves over Extended Kalman filter by making repeated corrections to account for nonlinearities in measurements.

$$H = \frac{\partial h(x)}{\partial x}$$

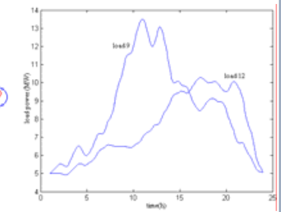
$$x^{k+1}_{t+Ts/t+Ts} = x_{t+Ts/t} + K(z_{t+Ts} - h(x^k_{t+Ts/t+Ts}) - H(x_{t+Ts/t} - x^k_{t+Ts/t+Ts}))$$

Example

IEEE 14-Bus test system

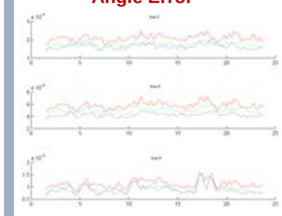


Simulated load profile

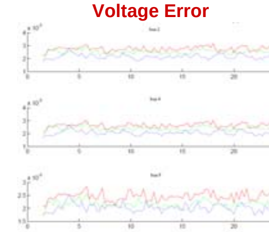


State estimation using the IKF with our dynamic model showed **greater than 10% improvement over static estimation** alone.

Angle Error



Voltage Error



Angle in radians and voltage in p.u..
Key: (Static State Estimator) (Static Augmented Estimator) (Dynamic State Estimator)

Future Work

Bad data detection

Bad data detection based on residuals: h(X)-z.

Many residuals are "smeared" due to the bad data, making identification difficult.

Dynamic model gives a baseline for comparison in identifying bad data (i.e., an independent check of data integrity).

Network parameter estimation

Dynamic model allows correlation of parameter data between estimates.

Provides additional redundancy to enable parameter estimation that is unavailable in static estimation.

Network topology error identification

Dynamic model aids in distinguishing whether large measurement residuals are due to bad data or changes in topology.

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