State Estimation Advancements Enabled by Synchrophasor Technology

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Outline

- EMS/SCADA
- State Estimation
  - State Definition / Measurement Model
  - Solution Algorithms
  - State Estimation Quality / Bad Data Analysis
- Traditional State Estimation Biases
- State Estimation & SynchroPhasor Technology
- Hybrid State Estimation
- Linear State Estimation
- Distributed State Estimation Architecture
- Three-Phase State Estimation
- Dynamic State Estimation
Energy Management System (EMS): a system of computer-aided tools and the associated hardware and communications infrastructure, used by operators to monitor, control, and optimize the performance of the generation and/or transmission system.

EMS Applications:
- State Estimation
- Automatic Generation Control (AGC)
- Load Forecasting
- Economic Dispatch, Optimal Power Flow
- Volt/VAr Control
- Security Assessment (Real-Time Contingency Analysis, Voltage Stability, Transient Stability)
- Congestion Management, Available Transfer Capability
- Unit Commitment, Ancillary Services

Source: A. P. Sakis Meliopoulos
Supervisory Control And Data Acquisition (SCADA)

SCADA Functionality

• Data Acquisition (Substation level): Collects and transmits status (breaker status etc.) and analog data (voltage magnitude etc.)

• Supervisory Control (Control Center level): Sends control signals (breaker trip etc.) to substation devices

• Real-Time Database

• Mapboard and User Interface

• Interfaces with Physical Devices
  – Remote terminal unit (RTU)
  – Intelligent electronic device (IED)
  – Programmable logic controller (PLC)
  – Digital Fault Recorder (DFR), Relays

• Communications
  – Power line carrier
  – Microwave
  – Radio
  – Fiber optics

Source: A. P. Sakis Meliopoulos

Source: INEEL
## State Estimation

- Computes a statistical estimate of the system operating condition/state:
  - Voltage magnitude and phase of system buses
  - Derived quantities: P & Q flows and injections
- Used for System Monitoring
- Provides model for EMS functions (network security and market management applications):
  - Dynamic Security Assessment (DSA)
  - RTCA
  - OPF
  - etc.

*Source: ERCOT*
State Estimation Flowchart

Analog Measurements
V, I, Pi, Qi, Pf, Qf
+ Pseudo-Measurements

Status Data

Topology Processor

Observability Analysis

State Estimator

Bad Data Analysis
Topography Processor

- Input: Status data (circuit breaker status, interrupt switch status, transformer tap setting, etc.)
- Provides network model configuration for the state estimator

Source: Siemens PTI
State Definition

- **State definition –** \([x]\): Positive sequence voltage phasors (bus voltage magnitudes and angles) of system’s buses
  
  \[
  [x] = \begin{bmatrix} \tilde{V}_1 & \cdots & \tilde{V}_n \end{bmatrix}
  \]

- **Angle reference (SCADA-based SE):** Arbitrarily selected bus for which the angle is set equal to zero

- **State vector defined in polar or Cartesian coordinates**
  
  \[
  \tilde{V}_1 = V_{1,RE} + j \cdot V_{1,IM} = V_1 \angle \theta_1
  \]

  \[
  x = \begin{bmatrix} V_{1,RE} & V_{1,IM} & \cdots & V_{n,RE} & V_{n,IM} \end{bmatrix}
  \]

  or

  \[
  x = \begin{bmatrix} V_1 & \theta_1 & \cdots & V_n & \theta_n \end{bmatrix}
  \]
Measurements & Measurement Model

- **Measurement Set** $[z]$:
  - Real & reactive power injection
  - Real & reactive power flow
  - Voltage magnitude
  - Current magnitude

- **Measurement Model**:

  $$[z] = [h([x])] + [e]$$

  - $h$: vector function - maps measurements to states (non-linear or linear)
  - $e$: measurement error
**Measurement Model Assumptions**

- Gaussian distribution of measurement error
  - known standard deviation. \( E\{e_i^2\} = \mu_i^2 \) Reflects accuracy of metering device
  - expected mean value is zero \( E\{e_i\} = 0 \)
  - error of a measurement is uncorrelated to the error of any other measurement \( E\{e_i \cdot e_j\} = 0 \)
Solution Algorithm - WLS

- Weighted Least Squares (most commonly used)
- Formulation:

\[
\min_{x} J(x) = r^T W r
\]

- where: \( r = z - h(x) \): residual vector

\[
W = \text{diag} \left[ \frac{1}{\sigma_i^2} \right] : \text{weight matrix}
\]

- Linear Case: Direct Solution. Jacobian is constant.

\[
\hat{x} = (H^T WH)^{-1} H^T W z
\]

- Nonlinear Case: Newton’s iterative algorithm:

\[
\hat{x}^{j+1} = \hat{x}^j + (H^T WH)^{-1} H^T W (z - h(\hat{x}^j))
\]

- where H: Jacobian of \([h([x])]\)
Other Solution Algorithms

- Weighted Least Absolute Value

$$\min \ J(x) = \sum_{i=1}^{m} |w_i \cdot r_i| \quad s.t \ r_i = h_i(x) - z_i \quad i = 1,\ldots,m$$

- Linear programming solution

- Min-Max Solution

$$\min \ J(x) = r^* = \max(|r_1|, \ldots, |r_n|) \quad s.t \ w_i \cdot |h_i(x) - z_i| \leq r^* \quad i = 1,\ldots,m$$

- Linear programming solution

Disadvantages: 1) Computationally demanding and 2) Vulnerable to leverage measurements

Advantage: Built-in bad data analysis

- Non-Iterative Direct State Calculation

- R&D stage

Source: Dr. Bruce Fardanesh (NYPA)
Quality of State Estimation

- Estimation confidence level (chi-square test):
  \[ \Pr\left[ \chi^2 \geq \zeta \right] = 1.0 - \Pr(\zeta, \nu) \]
  
  - \( \chi^2 = \sum_{i=1}^{m} s_i^2(x) \) : Random variable chi-square distributed
  
  - \( \zeta = \sum_{i=1}^{m} \left( \frac{h_i(\hat{x}) - z_i}{\sigma_i} \right)^2 \) : Objective function evaluated at the state estimate
  
  - \( \nu = m - n \) : Degrees of freedom

- Covariance matrix of state estimates: \( C_x = \left( H^T W H \right)^{-1} \)

- Standard deviation of state estimates: \( \sigma_{x_i} = \sqrt{C_x(i,i)} \)

- Covariance matrix of measurement estimates:
  \[ Cov_{\hat{b}} = H \left( H^T W H \right)^{-1} H^T \]

- Standard deviation of measurement estimates:
  \[ \sigma_{\hat{b}} = \sqrt{Cov_{\hat{b}}(i,i)} \]
Bad Data Detection, Identification and Rejection

- Largest Normalized Residual Hypothesis Test:
  - If the measurement set contains a bad datum, the largest normalized residual corresponds to that bad datum
  - Iterative bad data rejection
  - Computationally demanding

- Alternative approach: Measurement re-weighting
  - Less computationally demanding but not always effective

- Bad data analysis relies on measurement redundancy

Source: A. P. Sakis Meliopoulos
Traditional SE: Reasons for Poor Performance

Present Implementation

- Single Phase, Positive Sequence Models
  - reasonable modeling assumptions made in the 70’s due to computational power constraints
- Voltage & Current Magnitudes, P & Q Measurements
- Non Simultaneous Measurements
- Centralized Architecture

Biased State Estimation

- Unbalanced Operation
- System Asymmetries
- Measurement Time Skewness
- Large Scale Problem with Long Execution Time (runs every 30 secs-3 mins)

Source: MISO
Synchrophasor Technology – Enabler of Enhanced State Estimation

- PMUs provide synchronized measurements with a common, globally valid time reference (UTC time)
- Time Precision 1 $\mu$s, 0.02 Degrees at 60 Hz, Magnitude: 0.1%
- State Estimation can be reformulated both algorithmic and architectural to take advantage of the characteristics of the new technology

Source: NASPI
Elimination of State Estimation Biases

Unbalanced Operation & System Asymmetries

- PMUs provide Three Phase Measurements
- Three-phase formulated State Estimation

Measurement Time Skewness

- PMUs provide GPS Synchronized and Time Tagged Phasor Measurements

Large Scale Problem with Long Execution Time

- Linear State Estimation – Direct Solution
- GPS-Synchronized measurements make it possible to “distribute” the state estimation process. The results of a local synchrophasor based state estimator are “globally” valid
- More effective data quality check and bad data processing

Computationally demanding state estimation quality check and bad data processing
Linear vs Non-Linear State Estimation

**IF:**

All measurements are GPS synchronized voltage and current phasors (Synchrophasor Data)

AND

All models are linear (transmission lines, transformers, etc.)

→ Linear State Estimator (Direct Solution)

Non-linear models (generators, etc.) or non-GPS synchronized data (conventional relays, SCADA data, etc.)

→ Nonlinear State Estimator
Hybrid State Estimation

- State definition – \([x]\): The same
  - Positive sequence voltage phasors (bus voltage magnitudes and angles) of system’s buses

\[
[x] = \begin{bmatrix}
\tilde{V}_1 \\
\vdots \\
\tilde{V}_n
\end{bmatrix}
\]

- Measurement Set & Model
  - Additional Measurements: Voltage and Current Phasors (magnitude and phase angles) → Increased measurement redundancy and robustness due to “state (phase angle) measurement”
  - Traditional Measurements:
    \[
    Z = h(X) + e \quad \text{Nonlinear}
    \]
  - Phasor Measurements:
    \[
    Z = H(X) + e \quad \text{Linear}
    \]

- Solution algorithm: Non-linear WLS (same as in traditional SE)
Hybrid State Estimation – Jacobian Matrix

\[ H = \begin{bmatrix}
V_{1,RE} & V_{1,IM} & \cdots & V_{n,RE} & V_{n,IM} \\

P_k \\
Q_k \\
\vdots \\
P_{km} \\
Q_{km} \\
\vdots \\
V_{k,SCADA} \\
I_{km,SCADA} \\
\bar{V}_{k,PMU} \\
\bar{I}_{km,PMU}
\end{bmatrix} \]

Constant Number Non-Constant Number
Hybrid State Estimation – Challenges

- Angle reference: Still required
  - a) Power flow slack bus used as reference bus. PMU necessary at slack bus. Other PMU measurements referenced to that.
  - c) Risky because of reference PMU accuracy

- Synchronization of PMU & SCADA measurements
  - PMU data: Time-tagged – UTC time reference
  - SCADA data: Time-tagged by EMS clock

- PMU data down-sampling

- State Estimation Accuracy and Robustness Improvement
  - Number of additional PMU measurements?
  - Critical PMU locations?
**Linear State Estimation**

- **State Definition** – \([x]\): The same
  - Positive sequence voltage phasors (bus voltage magnitudes and angles) of system’s buses

\[
[x] = \begin{bmatrix}
\tilde{V}_1 \\
\cdots \\
\tilde{V}_n
\end{bmatrix}
\]

- **Measurement Set & Model**
  - Phasor Measurements:

\[
Z = H(X) + e
\]  \hspace{1cm} \text{Linear}

- **Solution Algorithm**: **Linear WLS. Direct Solution.**
Linear State Estimation – Characteristics

- No need for reference angle (all angles are already referenced based on UTC time)

- Faster bad data analysis
  - WLS: Still “Largest Normalized Residual Hypothesis Test” used but the solution of each individual state estimation is faster
  - LAV: Linear programming solution. Bad data analysis is part of the solution. No iterations needed

- Synchrophasor-Only State Estimation & Observability
  - PMU location defines observable states
Algebraic Observability

- Number of measurements greater than number of states (m>n). Necessary but not sufficient condition.
- System is observable if $H$ has also full rank ($\text{Rank}(H)=n$).
- Critical measurement: If lost a state becomes unobservable.
- Redundant measurement: If removed observability is not affected.
- Challenges:
  - Bad data in critical measurements cannot be detected.
  - Redundancy needed.
  - Without redundancy LSE results can be questionable.
Synchrophasors & Observability

- **Traditional state estimation**
  - Observable islands are not synchronized. Each island has a reference bus. SCADA measurements at the islands’ boundary buses are needed to synchronize islands

- **Synchrophasor-only state estimation**
  - Observable islands are synchronized
  - Optimal PMU placement for full system observability

- **Optimal PMU placement**
  - Well established in the literature (integer programming optimization formulation)
  - Main objective: Minimize number of PMUs
  - Additional objectives: achieve specific redundancy level (bad data analysis)
  - PMU placement has many practical and techno-economic constraints
Observability Analysis

- Islands are synchronized

Source: Ali Abur
Distributed State Estimation

- State estimation performed based on a decentralized architecture
  - Area and/or substation level implementation

- Advantages
  - Reduced dimensionality. Faster computational performance
  - Facilitates use of more accurate models (three phase, dynamic)
  - Reduced communications burden and associated time latencies
  - Easier data validation
    - Easier bad data detection, identification, rejection

- GPS-Synchronized measurements make it possible to “distribute” the state estimation process without the need of additional state estimation for coordination

- The results of a local state estimator are “globally” valid if there is at least one valid GPS-synchronized datum
Area Level Implementation

Area State Definition

\[ x_i = \begin{bmatrix} x_{i,\text{internal}} \\ x_{i,\text{neighboring}} \end{bmatrix} \]

- PMUs are required at the boundary buses for the neighboring buses to be observable.
Area Level Implementation

- The computed state vector is only sent to the central location. No need for measurements to be communicated.
- The system state vector is synthesized from the individual areas’ state vector without need of additional state estimation.
- Accuracy cross-check of the boundary buses state estimates at the central location.
- Bad data analysis is easier at the area level.
- The architecture can be also implemented with only SCADA measurements but then an additional central state estimation for coordination is needed.
Substation Level Implementation

- **State Definition:** Voltage phasor at each bus of the substation + at the boundary bus of neighboring substations
- Facilitates three-phase and dynamic state estimation formulation
- Easier Data and Model Validation (small model size)
  - Redundancy
  - Bad data analysis
- Takes advantage of substation automation

Source: A. P. Sakis Meliopoulos
Three-Phase State Estimation

- Traditional State Estimation assumes balanced operation of the system and uses positive sequence network model and measurements.
- Actual power system operates near balanced conditions and is not perfectly symmetric.
- Availability of three-phase synchrophasor measurements and detailed three-phase asymmetrical network modeling can eliminate traditional state estimation biases.
- Advantage: Can capture system unbalanced operation and system asymmetries.

Source: A. P. Sakis Meliopoulos
Three-Phase State Estimation Formulation

- **State Definition –** \([x]\): Phase voltage phasors of system’s buses

\[
[x] = \begin{bmatrix}
\tilde{V}_{1,A} & \tilde{V}_{1,B} & \tilde{V}_{1,C} & \cdots & \tilde{V}_{n,A} & \tilde{V}_{n,B} & \tilde{V}_{n,C}
\end{bmatrix}
\]

- **Measurement Set & Model**
  - Three-phase Voltage and Current Synchrophasor Measurements:

\[
\begin{bmatrix}
\vdots & \tilde{V}_m^x, A & \tilde{V}_m^x, B & \tilde{V}_m^x, C & \cdots & \tilde{I}_m^{x-y}, A & \tilde{I}_m^{x-y}, B & \tilde{I}_m^{x-y}, C & \cdots
\end{bmatrix}^T = \tilde{H} \cdot [x] + [e]
\]

- Same rules on linear vs nonlinear (hybrid) implementation apply

- Disadvantage: State estimation problem size increases. Distributed implementation needed for acceptable computational performance.
Three-Phase vs Symmetrical Component Network Modeling

- Three-phase state estimation could be applied using modal decomposition theory and symmetrical component network modeling
  - Three-phase measurements transformed into their symmetrical components
    \[
    \tilde{V}_x^+, \tilde{V}_x^-, \tilde{V}_x^0, \tilde{I}_{xy}^+, \tilde{I}_{xy}^-, \tilde{I}_{xy}^0
    \]
  - Solve a state estimation individually for each symmetrical component
  - Transform the estimates back from symmetrical components to individual phases
- System asymmetry not modeled
Dynamic State Estimation (DSE)

- Running a static state estimation (algebraic equations) with a PMU measurement rate (e.g. 60 times/sec) is **NOT** a dynamic state estimation

- In dynamic state estimation dynamic system modeling (differential equations) is used:
  \[
  \frac{dx(t)}{dt} = f(x(t), y(t), t) \quad 0 = g(x(t), y(t), t)
  \]
  
  \(x(t)\): dynamic states \(y(t)\): algebraic states

- Application challenges:
  - Measurements resolution and time alignment
  - Model accuracy
  - Computational performance

- Synchrophasor measurements facilitate application of dynamic state estimation

- Technology Readiness Level: R&D – few actual demos
Dynamic State Estimation – Mathematical Model

- **Discrete nonlinear model:**
  \[
  x_k = f(x_{k-1}, w_{k-1}) \quad w_k \sim (0, Q_k)
  \]
  \[
  z_k = h(x_k) + v_k \quad v_k \sim (0, R_k)
  \]

- **Linear model:**
  \[
  x_k = A \cdot x_{k-1} + w_{k-1} \quad w_k \sim (0, Q_k)
  \]
  \[
  z_k = H \cdot x_k + v_k \quad v_k \sim (0, R_k)
  \]

\(x_k\) : State vector

\(z_k\) : Measurement vector

\(w_k\) : Model error vector

\(v_k\) : Measurement error vector

\(Q_k\) : Model error covariance matrix

\(R_k\) : Measurement error covariance matrix
State Definition & Measurement Set

- **Dynamic states**: $x(t)$
  - Generator torque angle
  - Generator frequency
  - Internal control variables
  - etc.

- **Algebraic states**: $y(t)$
  - Voltage magnitude
  - Voltage phase angle
  - Device internal states
  - etc.

- **Electromechanical dynamics**

- Additional measurements can be used:
  - Frequency
  - Change of rate of frequency
DSE Solution Algorithms – Kalman Filter

- Assumptions:
  - System noise and measurement noise are Gaussian
  - System model and measurement model are linear
  - Optimal solution under these assumptions

- Two Step Algorithm:
  - Prediction Step: estimates state variables and their uncertainties
  - Correction Step: updates state variables using measurement set. Gives more weight to states with higher certainty.

\[
\begin{align*}
\hat{x}_{k-1} & \quad \text{Prediction Step} \\
& \quad \text{System model} \\
\hat{x}_{k|k-1} & \quad \text{Correction Step} \\
& \quad \text{Measurement Model} \\
\hat{x}_k & \quad \text{Measurement}\n\end{align*}
\]

\[
\begin{align*}
\hat{x}_{k-1} & \quad \hat{x}_{k|k-1} & \quad \hat{x}_k \\
P_{k-1} & \quad P_{k|k-1} & \quad P_k
\end{align*}
\]
## Other Filtering Algorithms Assessment

<table>
<thead>
<tr>
<th></th>
<th>Extended Kalman Filter</th>
<th>Unscented Kalman Filter</th>
<th>Ensemble Kalman Filter</th>
<th>Particle Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy</strong></td>
<td>The 2nd best with 0% diverged</td>
<td>33% diverged</td>
<td>The best with 0% diverged</td>
<td>20% diverged (PF 2000)</td>
</tr>
<tr>
<td><strong>Efficacy of interpolation</strong></td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td><strong>Number of samples needed</strong></td>
<td>None</td>
<td>Small</td>
<td>Medium</td>
<td>Large</td>
</tr>
<tr>
<td><strong>Sensitivity to missing data</strong></td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td><strong>Sensitivity to outliers</strong></td>
<td>Low</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td><strong>Computation time (non-parallel)</strong></td>
<td>Shortest</td>
<td>Same order as EKF</td>
<td>longer than EKF</td>
<td>Same order as EnKF</td>
</tr>
</tbody>
</table>

*Source: PNNL*
DSE Solution Algorithms – WLS

- Integrate differential equations using an integration method, e.g. trapezoidal rule

\[
\frac{d(x(t))}{dt} = f(x(t)) \quad \rightarrow \quad x(t) - x(t - h) = \frac{h}{2} \{f(x(t)) + f(x(t - h))\}
\]

- Integration transforms differential equations into algebraic
- Measurements are expressed as a function of the states of the system

\[z = h(x) + e\]

- Weighted Least Squares Solution
- Same rules on linear vs nonlinear(hybrid) implementation apply
DSE Comments

- Suitable for monitoring generator and load dynamics
  - Enables estimation of device internal not measurable variables
- More sensitive to numerical issues
- Wide area application of DSE
  - Centralized architecture implementation is challenging
    - Requires very small communication delays
    - Requires significant computational efficiency
  - Distributed architecture makes more sense
- DSE applications
  - Protection and control
  - Real-time stability assessment
### State Estimation Technology Summary Table

<table>
<thead>
<tr>
<th>SE</th>
<th>Uses PMU Data</th>
<th>Accuracy</th>
<th>Solution Speed</th>
<th>Technology Readiness Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional</td>
<td><img src="thumbs_down.png" alt="Thumb Down" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Single phase, positive sequence models, time skewness</td>
<td><img src="thumbs_down.png" alt="Iterative Solution" /></td>
<td><img src="thumbs_up.png" alt="Commercial products" /></td>
</tr>
<tr>
<td>Linear</td>
<td><img src="thumb_up.png" alt="Thumb Up" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Phase angle measurements, time-tagged</td>
<td><img src="thumb_up.png" alt="Direct Solution" /></td>
<td><img src="thumbs_up.png" alt="Ongoing demos" /></td>
</tr>
<tr>
<td>Hybrid</td>
<td><img src="thumb_up.png" alt="Thumb Up" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Limited, if any, improvements</td>
<td><img src="thumbs_down.png" alt="Iterative Solution" /></td>
<td><img src="thumbs_up.png" alt="Commercial products" /></td>
</tr>
<tr>
<td>Three-Phase</td>
<td><img src="thumb_up.png" alt="Thumb Up" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Captures system imbalances &amp; asymmetries</td>
<td><img src="thumb_down.png" alt="Increases problem size" /></td>
<td><img src="thumb_up.png" alt="Few demos" /></td>
</tr>
<tr>
<td>Distributed</td>
<td><img src="thumb_up.png" alt="Thumb Up" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Facilitates use of detailed models</td>
<td><img src="thumb_up.png" alt="Reduces problem size" /></td>
<td><img src="thumb_up.png" alt="Few demos" /></td>
</tr>
<tr>
<td>Dynamic</td>
<td><img src="thumb_up.png" alt="Thumb Up" /> <img src="thumb_up.png" alt="PMU-Data" /></td>
<td>Captures system dynamics – Numerically sensitive to model accuracy</td>
<td><img src="thumbs_down.png" alt="Computationally challenging – increases problem size" /></td>
<td><img src="thumbs_down.png" alt="Few demos, still in R&amp;D level" /></td>
</tr>
</tbody>
</table>
Conclusions

- Present state estimators are based on 1970’s technology
- Biased state estimation
- Synchrophasor technology enables Advances in State Estimation both Algorithmic and Architectural
  - Linear State Estimation
  - Distributed State Estimation
  - Dynamic State Estimation

Why retrofit old technology?
Let’s move forward!
Together...Shaping the Future of Electricity