State Estimation Advancements Enabled by Synchrophasor Technology

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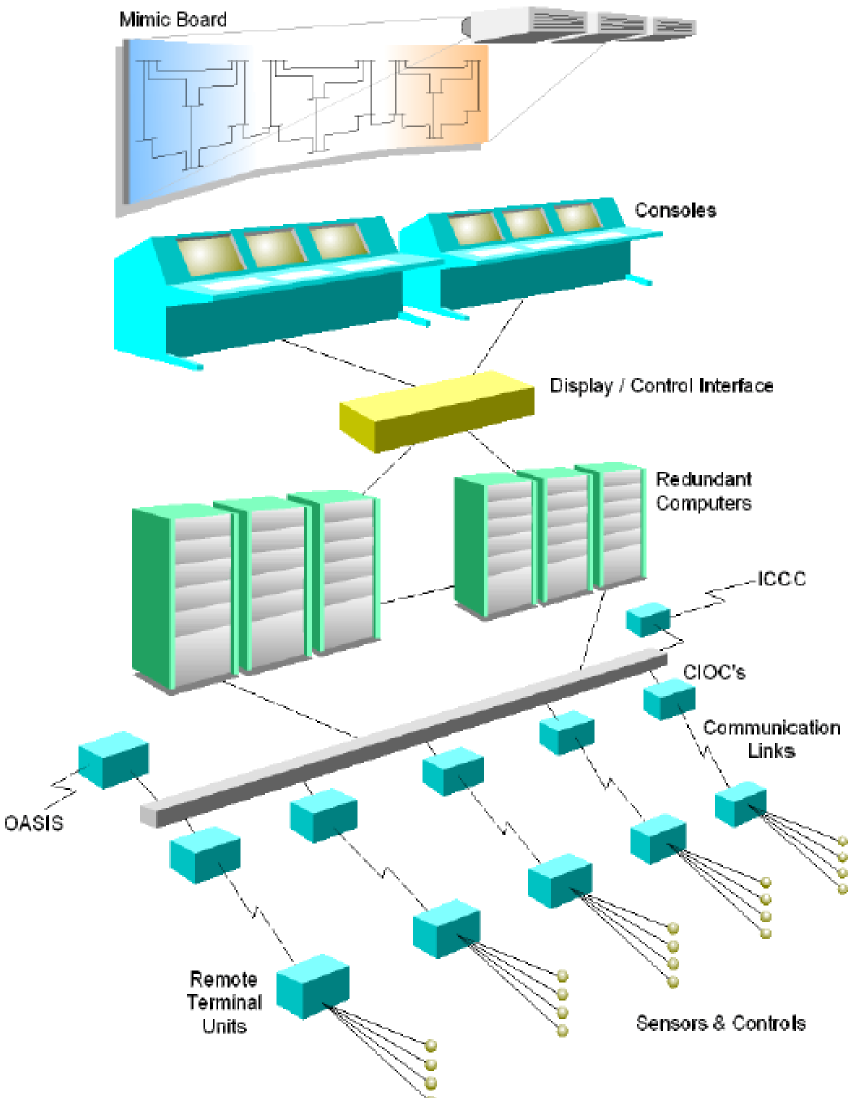
NASPI
March 25 2015
Burlingame, CA

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

Power Systems Operation & Control

Typical Infrastructure



Source: A. P. Sakis Meliopoulos

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.

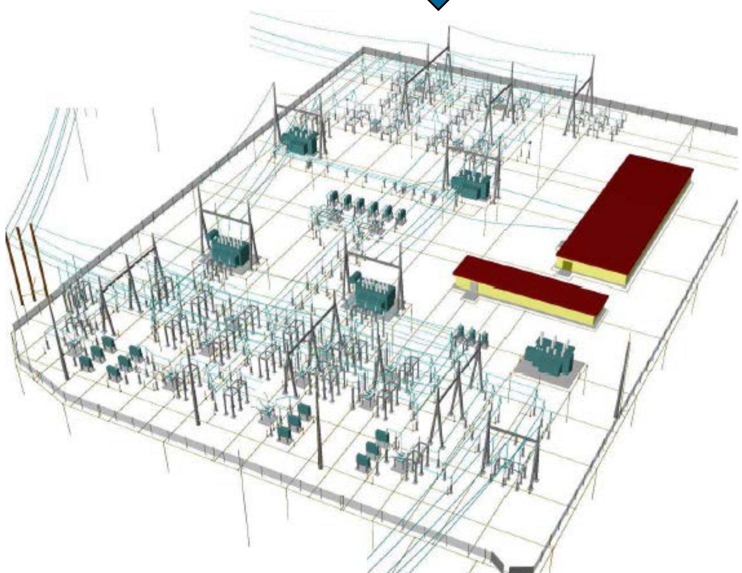
EMS Applications:

- 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

Supervisory Control And Data Acquisition (SCADA)

Source: INEEL

SCADA

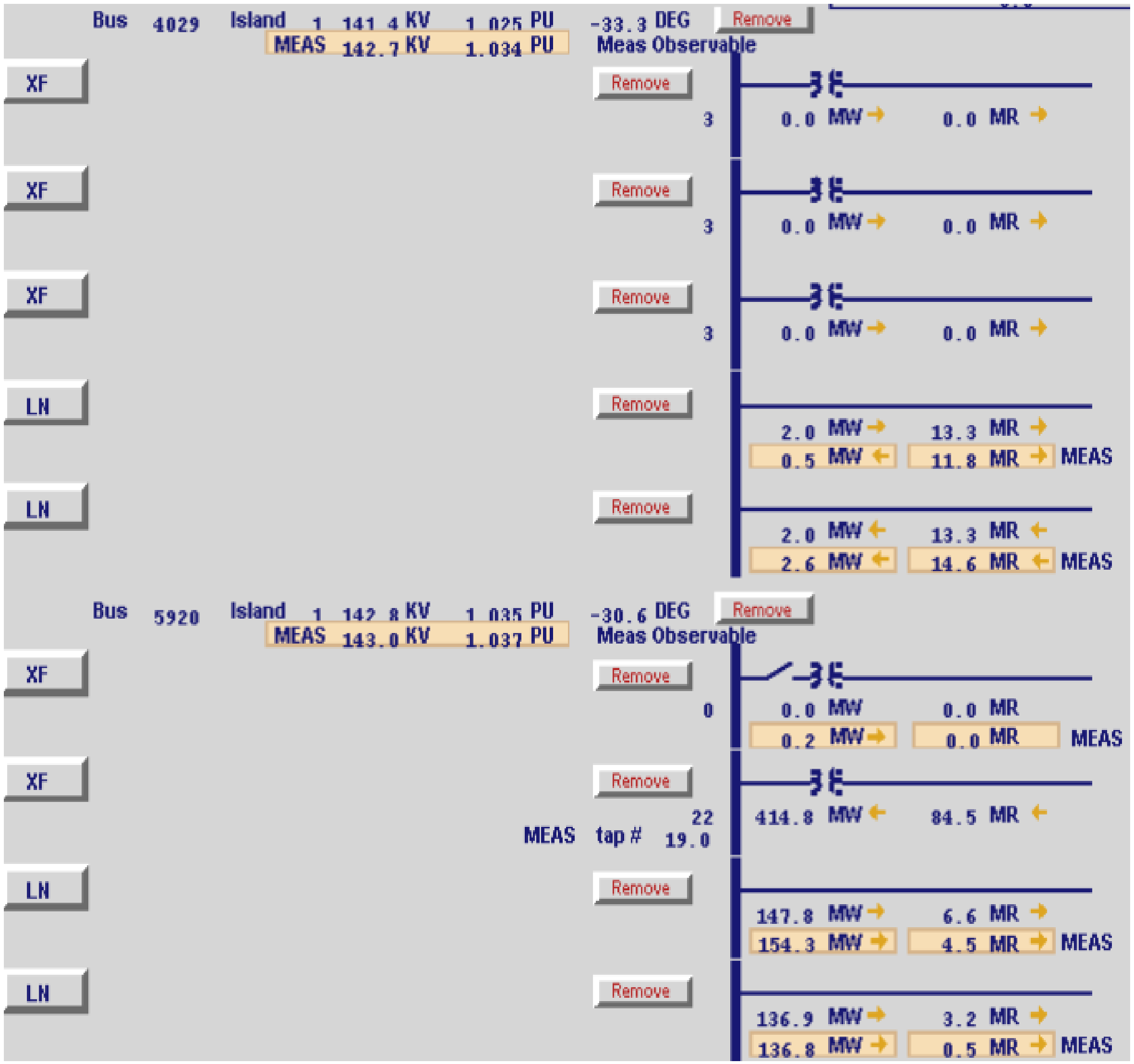


Source: A. P. Sakis Meliopoulos

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

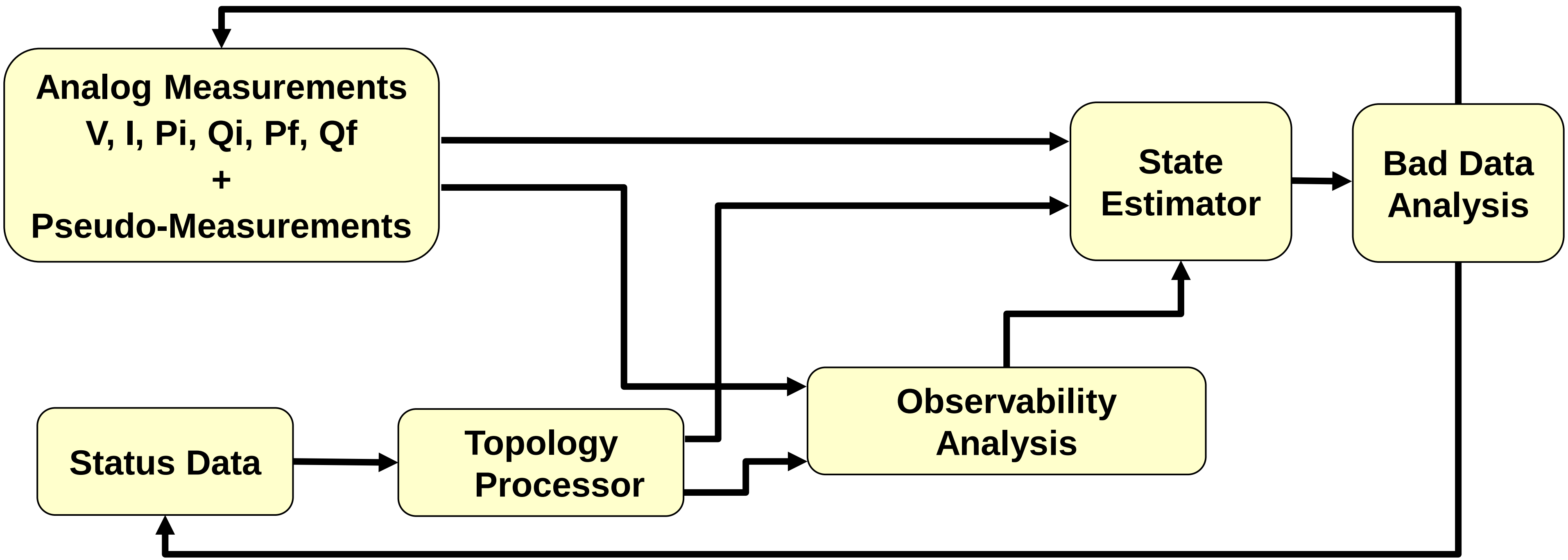
State Estimation



Source: ERCOT

- 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.

State Estimation Flowchart



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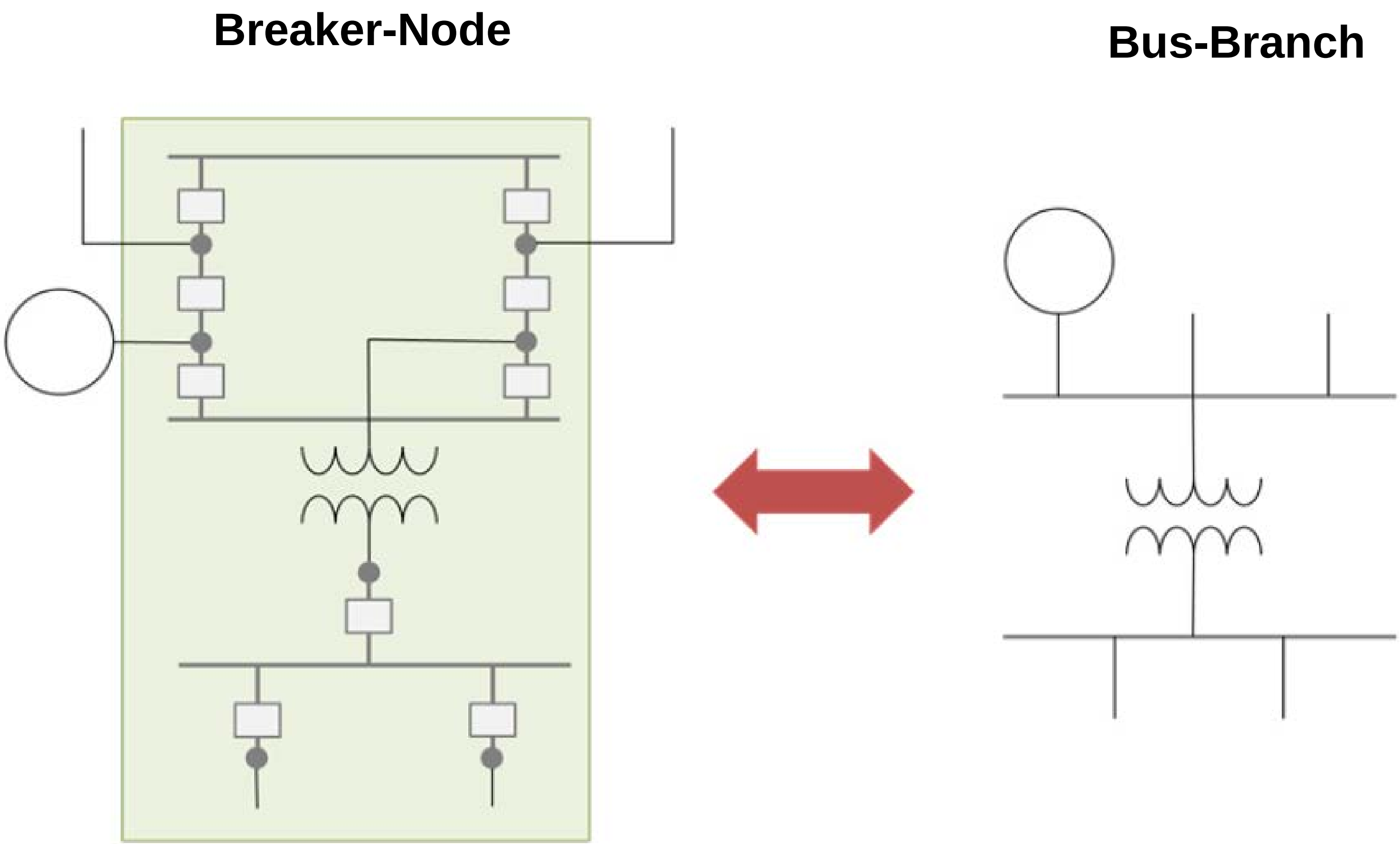
Topology Processor



Source: Siemens PTI

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

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

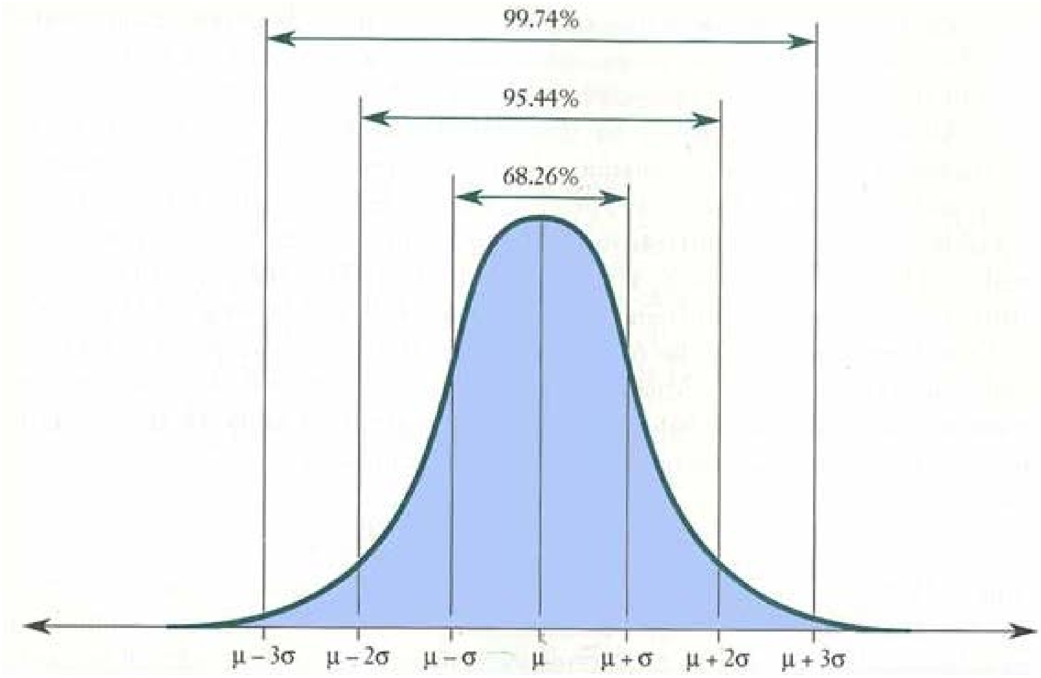
- Measurement Model:

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

  - **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

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

- Linear Case: Direct Solution. Jacobian is constant.

$$\hat{x} = (H^T W H)^{-1} H^T W z$$

- Nonlinear Case: Newton's iterative algorithm:

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

  – where H: Jacobian of **[h([x])]**

Other Solution Algorithms

- Weighted Least Absolute Value

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

  - Linear programming solution

- Min-Max Solution

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

  - 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):

$$\Pr\left[\chi^2 \geq \zeta\right] = 1.0 - \Pr(\zeta, v)$$

  – $\chi^2 = \sum_{i=1}^{m} s_i^2(x)$: Random variable chi-square distributed

  – $\zeta = \sum_{i=1}^{m} (\frac{h_i(\hat{x}) - z_i}{\sigma_i})^2$: Objective function evaluated at the state estimate

  – v=m-n : Degrees of freedom

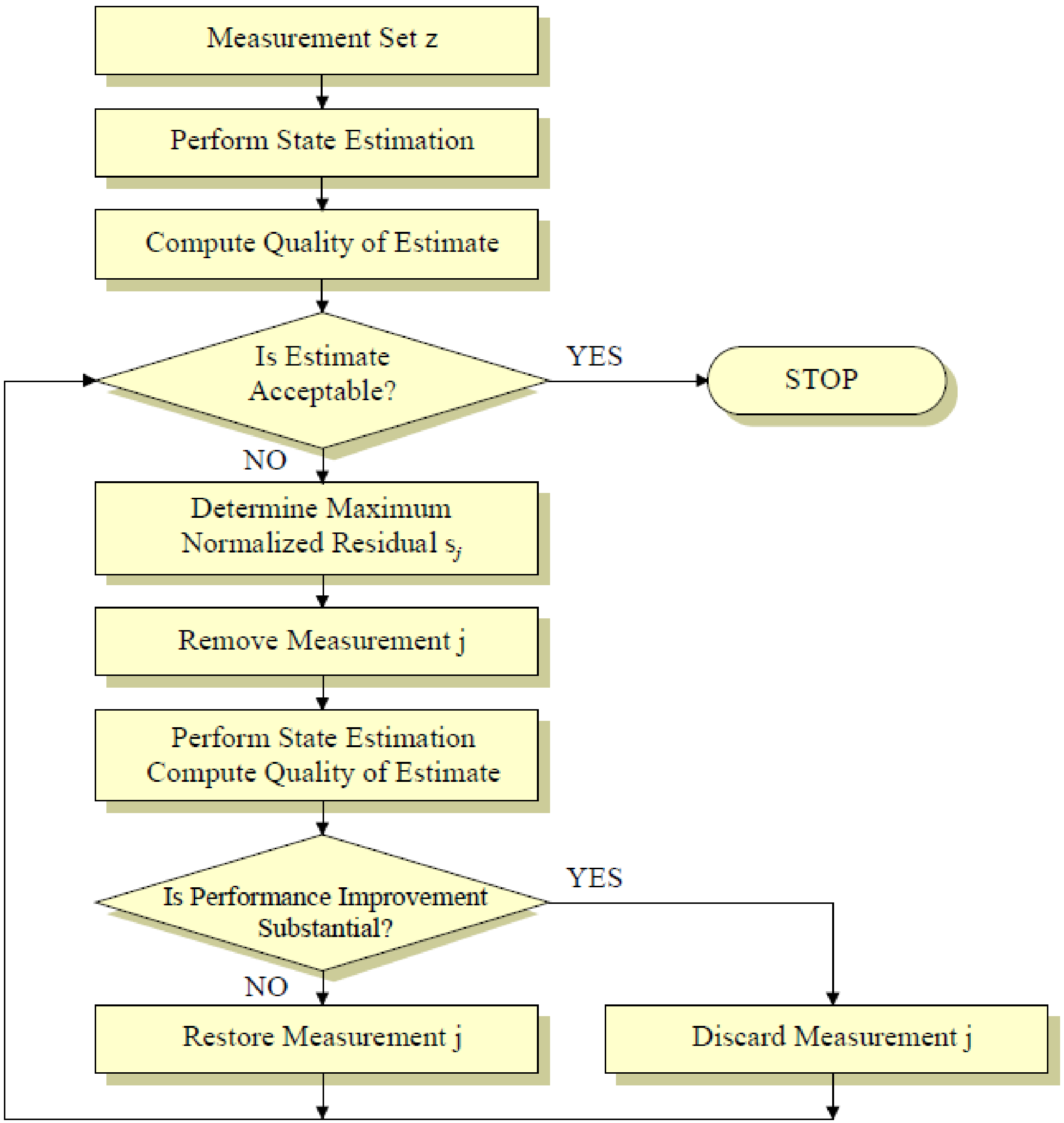
- Covariance matrix of state estimates: $C_x = \left(H^T W H\right)^{-1}$
- Standard deviation of state estimates: $\sigma_{x_i} = \sqrt{C_x(i,i)}$
- Covariance matrix of measurement estimates :

$$Cov_{\hat{b}} = H\left(H^T W H\right)^{-1} H^T$$

- Standard deviation of measurement estimates:

$$\sigma_{\hat{b}} = \sqrt{Cov_{\hat{b}}(i,i)}$$

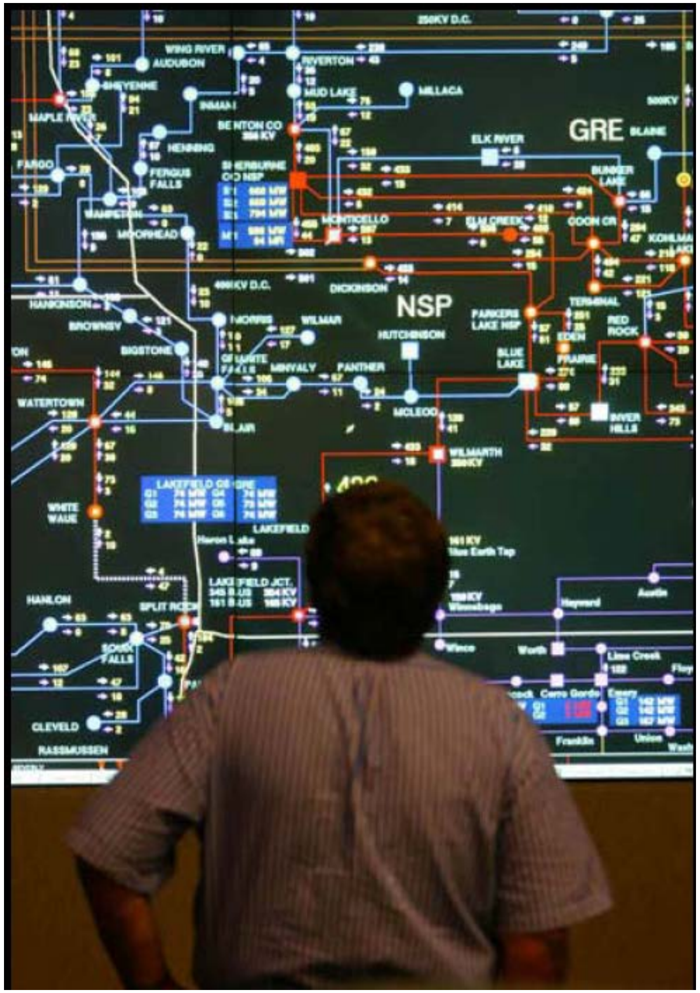
Bad Data Detection, Identification and Rejection



- 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



Source: MISO

Present Implementation

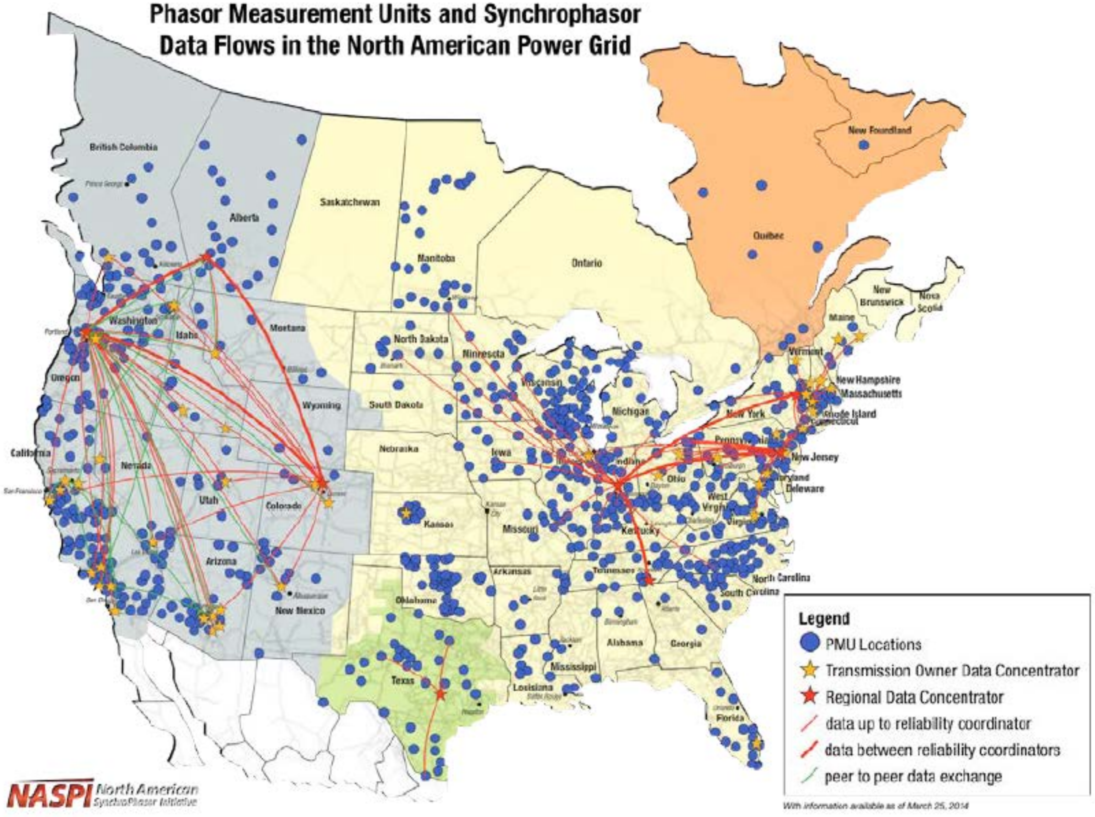
- Single Phase, Positive Sequence Models
  - reasonable modeling assumptions made in the 70's due to computational power constraints
- Voltage & Current Magnitudes, P & Q Measurements
- Non Simultaneous Measurements
- Centralized Architecture

No fundamental changes since 1970's…

Biased State Estimation

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

Synchrophasor Technology – Enabler of Enhanced State Estimation



Source: NASPI

- PMUs provide synchronized measurements with a common, globally valid time reference (UTC time)
- Time Precision 1 μs, 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

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

Computationally demanding state estimation quality check and bad data processing

- 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

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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

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

- 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:

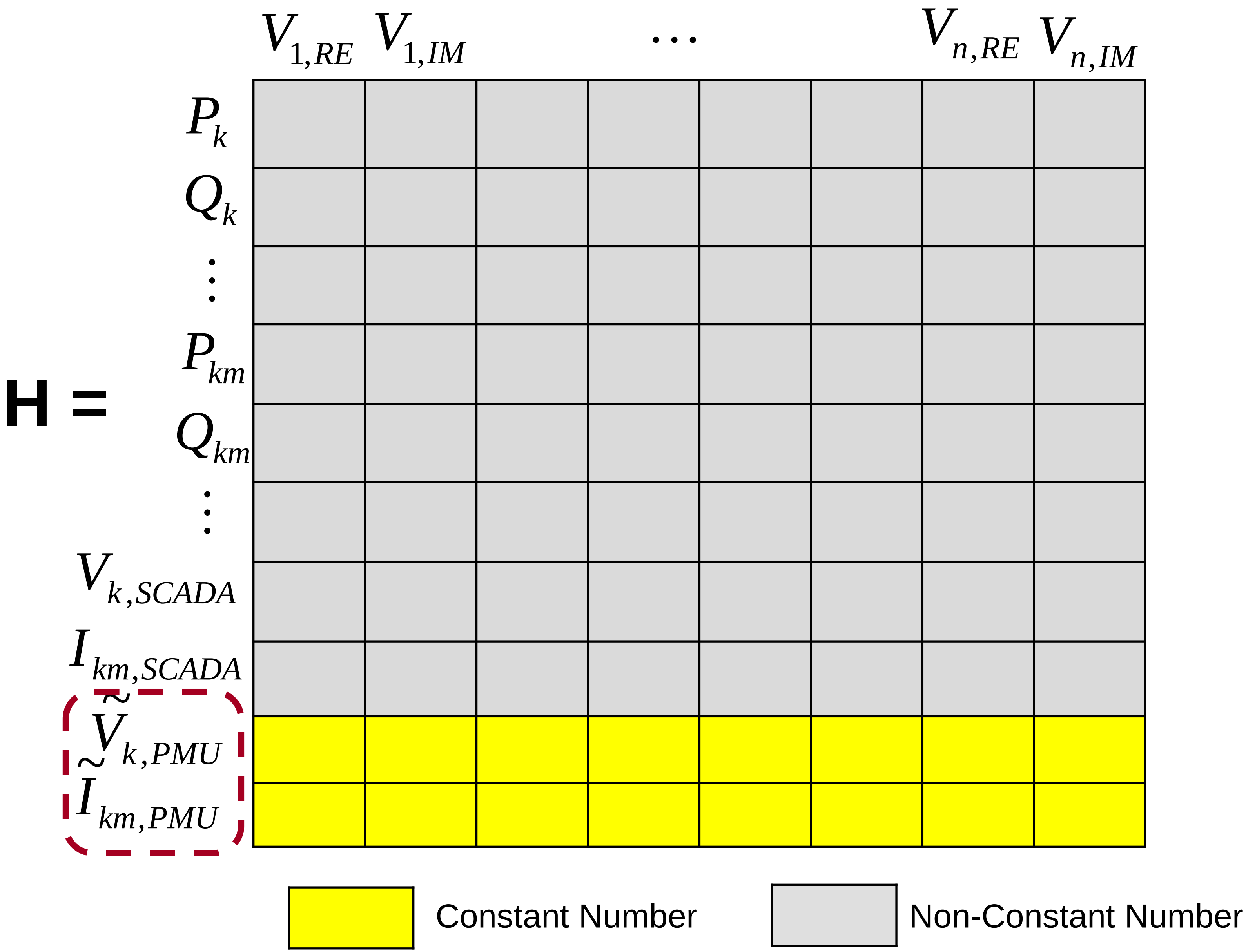
$$Z = h(X) + e \qquad \textbf{Nonlinear}$$

  - Phasor Measurements:

$$Z = H(X) + e \qquad \textbf{Linear}$$

- Solution algorithm: Non-linear WLS (same as in traditional SE)

Hybrid State Estimation – Jacobian Matrix



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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.
  b) Phasor angle measurement picked as reference. Reference set in PDC. Varying reference.
  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

  $\Big\}$ inconsistency

- PMU data down-sampling
- State Estimation Accuracy and Robustness Improvement
  – Number of additional PMU measurements?
  – Critical PMU locations?

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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:

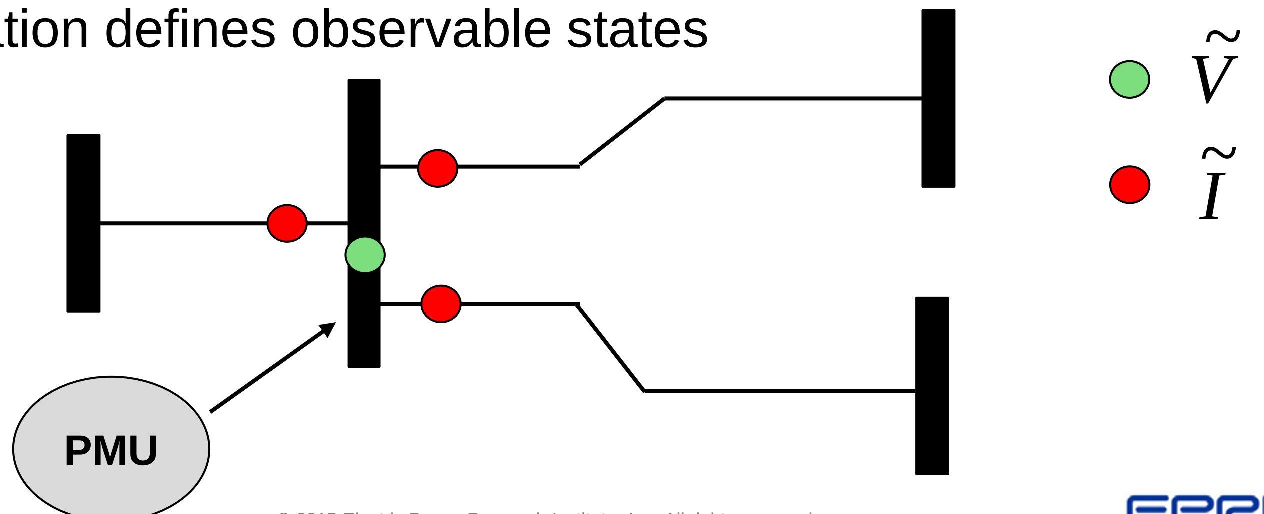
$$Z=H(X)+e$$

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



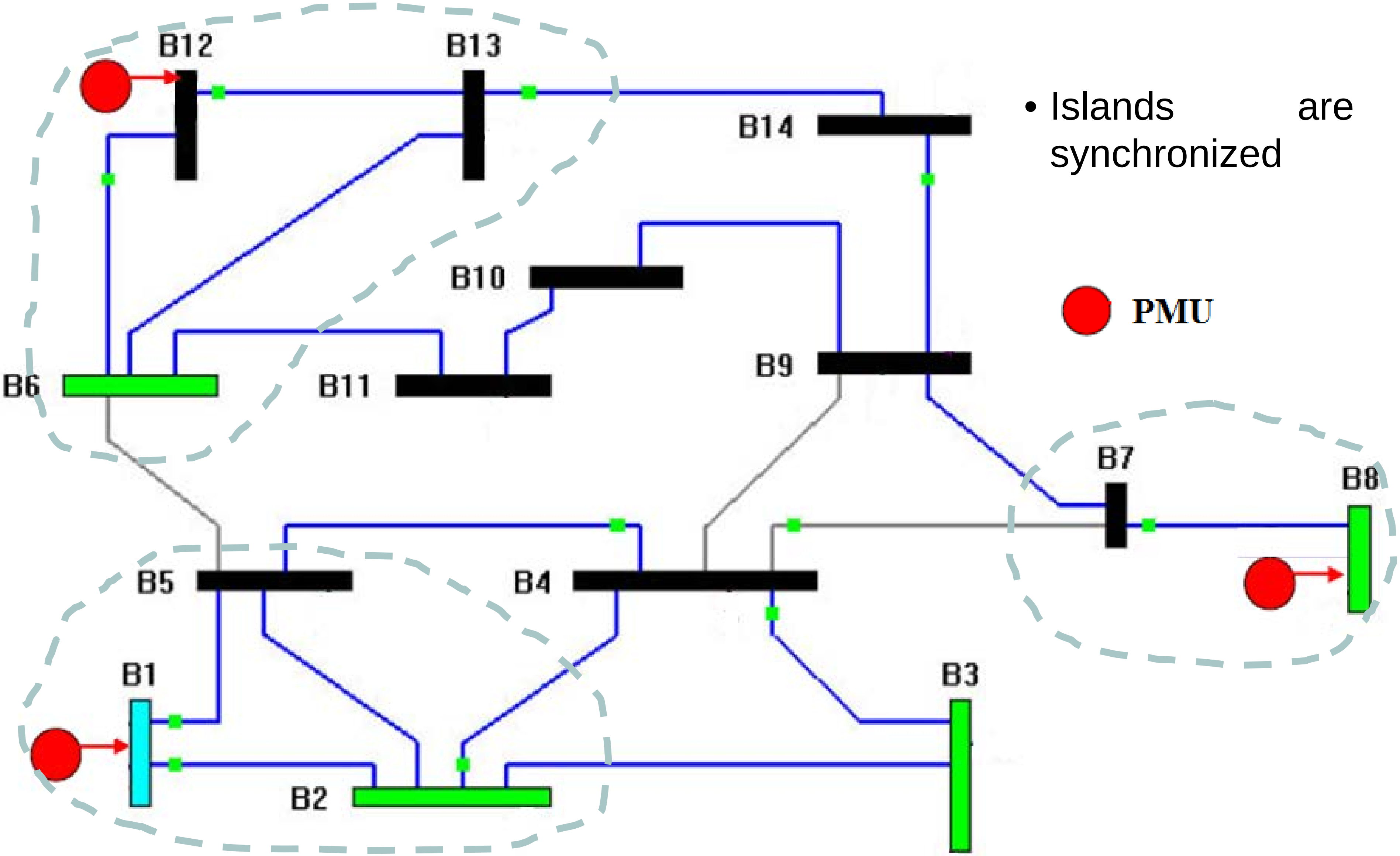
Algebraic Observability

- Number of measurements greater than number of states (m>n). Necessary but not sufficient condition
- System is observable if **H** has also full rank (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



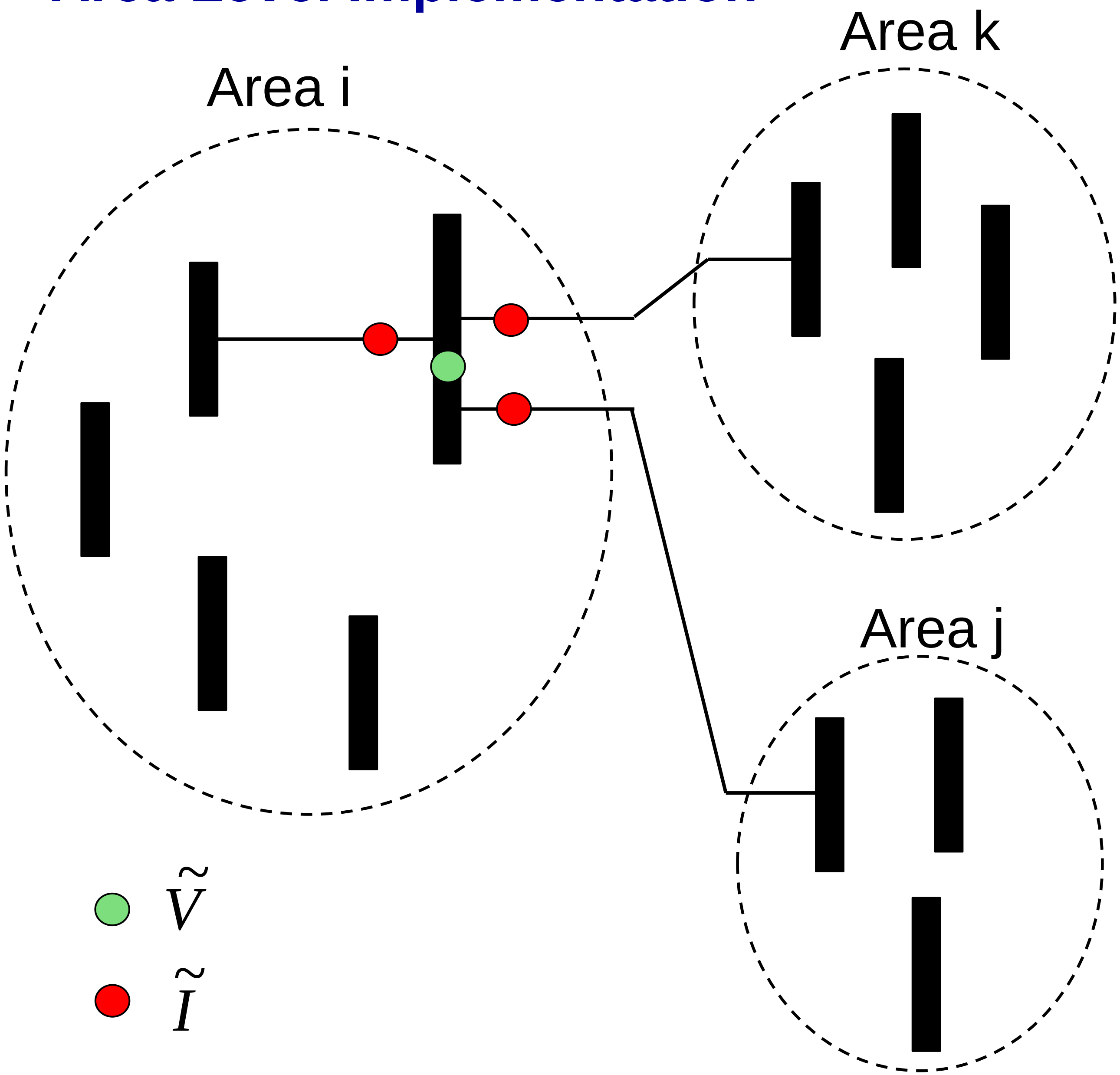
- Islands are synchronized

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

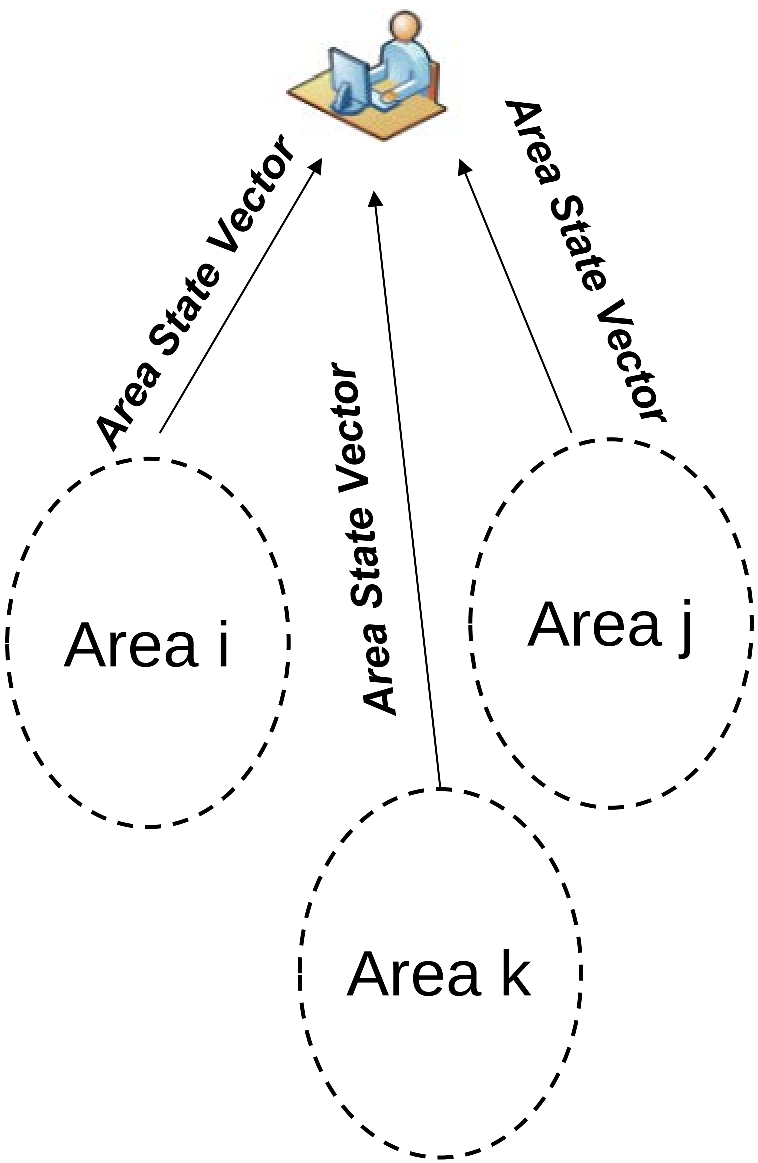


Area State Definition

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

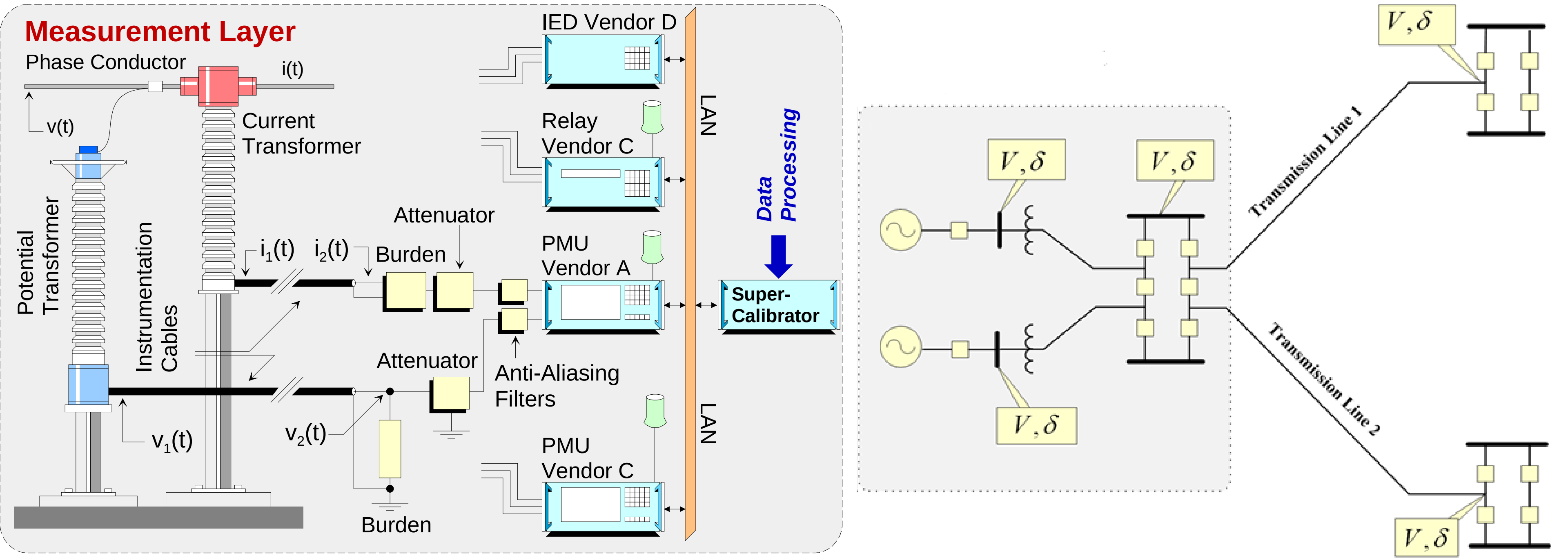
- PMUs are required at the boundary buses for the neighboring buses to be observable

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

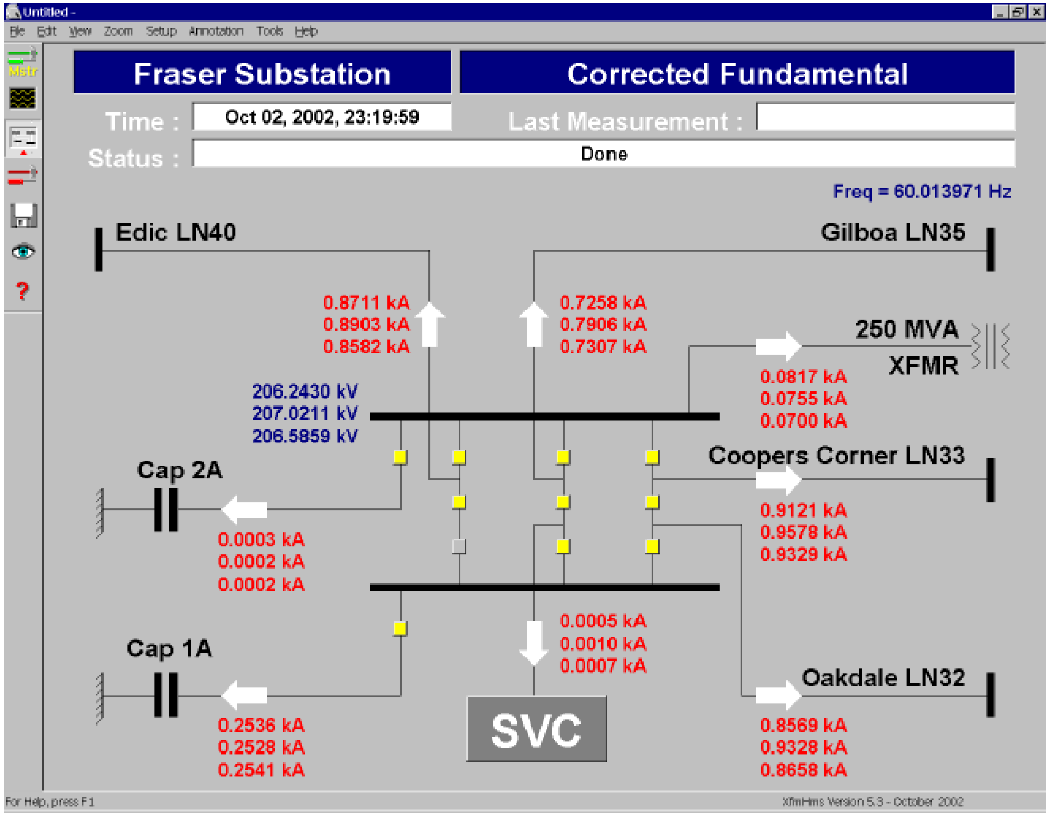
Substation Level Implementation



Source: A. P. Sakis Meliopoulos

- 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

Three-Phase State Estimation



Source: A. P. Sakis Meliopoulos

- 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

Three-Phase State Estimation Formulation

- State Definition – **[x]:** Phase voltage phasors of system's buses

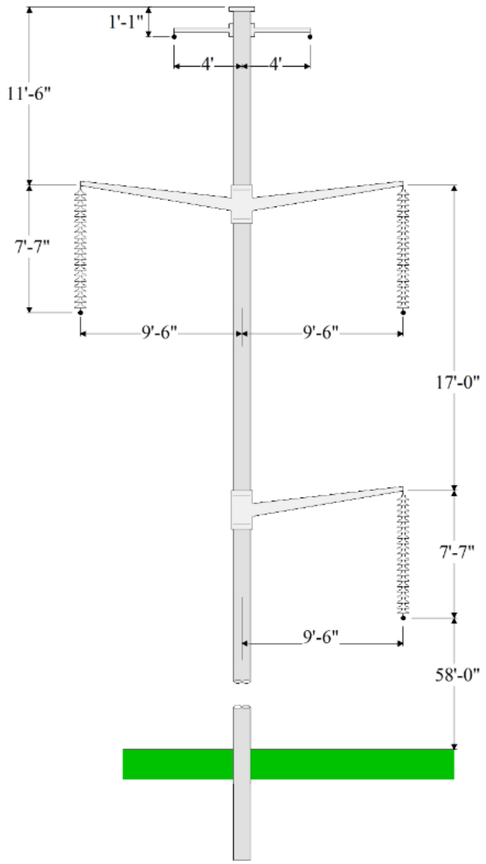
$$[x]=\begin{bmatrix}\tilde{V}_{1,A} & \tilde{V}_{1,B} & \tilde{V}_{1,C} & \cdots & \tilde{V}_{n,A} & \tilde{V}_{n,B} & \tilde{V}_{n,C}\end{bmatrix}$$

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

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

- 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



Source: A. P. Sakis Meliopoulos. Courtesy: Georgia Power

$$Z = \begin{bmatrix} z_{a,a} & z_{a,b} & z_{a,c} \\ z_{b,a} & z_{b,b} & z_{b,c} \\ z_{c,a} & z_{c,b} & z_{c,c} \end{bmatrix} \Rightarrow Z = \begin{bmatrix} z_s & z_m & z_m \\ z_m & z_s & z_m \\ z_m & z_m & z_s \end{bmatrix}$$

- 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

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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:

$$\frac{dx(t)}{dt} = f(x(t), y(t), t) \qquad 0 = g(x(t), y(t), t)$$

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

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Dynamic State Estimation – Mathematical Model

- Discrete nonlinear model:

$$x_k = f(x_{k-1}, w_{k-1}) \qquad w_k \sim (0, Q_k)$$
$$z_k = h(x_k) + v_k \qquad v_k \sim (0, R_k)$$

- Linear model:

$$x_k = A \cdot x_{k-1} + w_{k-1} \qquad w_k \sim (0, Q_k)$$
$$z_k = H \cdot x_k + v_k \qquad v_k \sim (0, R_k)$$

x_k : State vector

z_k : Measurement vector

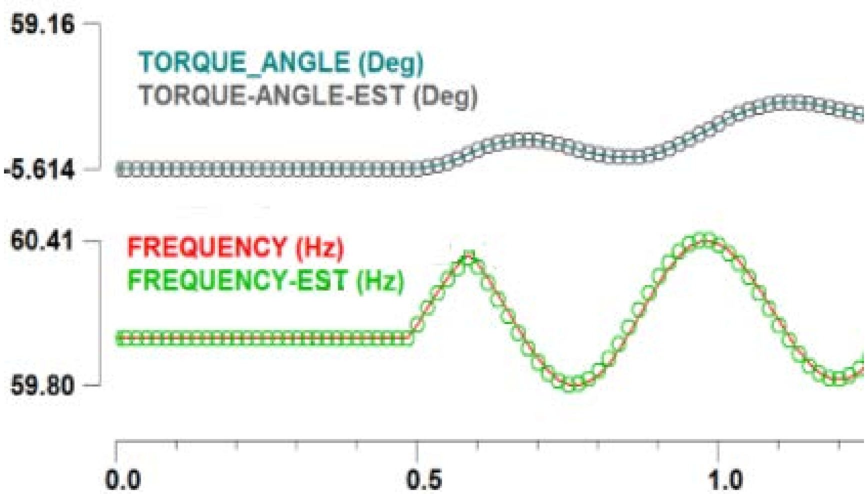
w_k : Model error vector

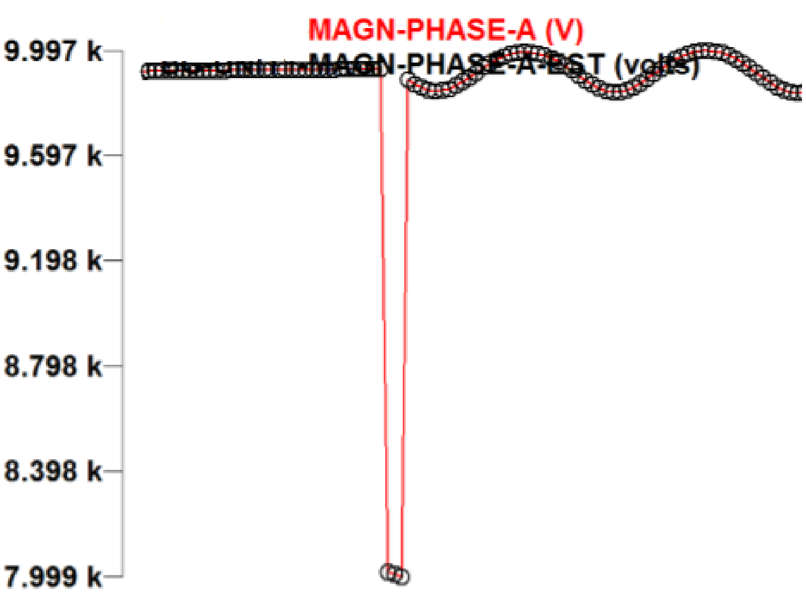
v_k : Measurement error vector

Q_k : Model error covariance matrix

R_k : Measurement error covariance matrix

State Definition & Measurement Set



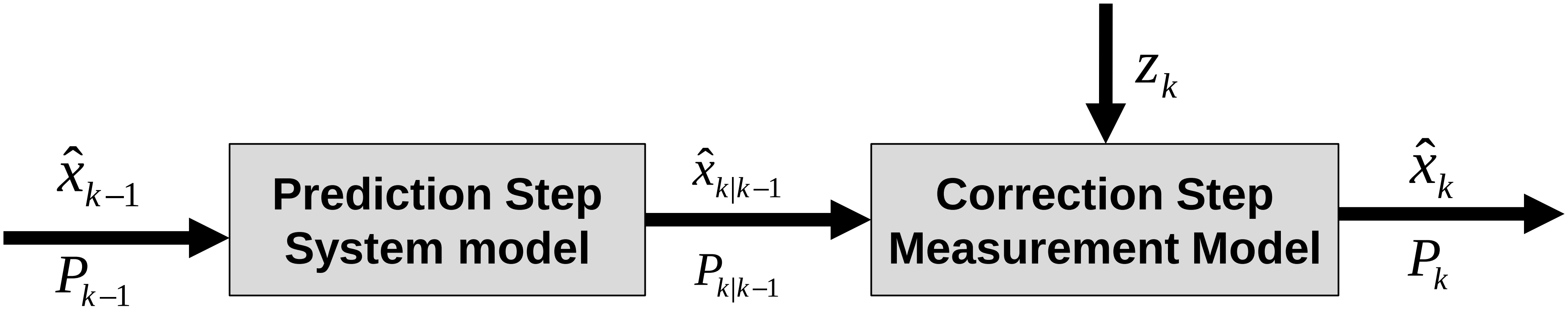


- Dynamic states: $x(t)$
  - Generator torque angle
  - Generator frequency
  - Internal control variables
  - etc.
- Algebraic states: $y(t)$
  - Voltage magnitude
  - Voltage phase angle
  - Device internal states
  - etc.
- Electromechanical dynamics
- Additional measurements can be used:
  - Frequency
  - 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.



Other Filtering Algorithms Assessment

	Extended Kalman Filter	Unscented Kalman Filter	Ensemble Kalman Filter	Particle Filter
Accuracy	The 2^{nd} best with 0% diverged	33% diverged	The best with 0% diverged	20% diverged (PF 2000)
Efficacy of interpolation	High	High	Low	High
Number of samples needed	None	Small	Medium	Large
Sensitivity to missing data	Low	Low	Low	Low
Sensitivity to outliers	Low	Low	Medium	High
Computation time (non-parallel)	Shortest	Same order as EKF	longer than EKF	Same order as EnKF

Source: PNNL

DSE Solution Algorithms – WLS

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

$$\frac{d(x(t))}{dt} = f(x(t)) \quad \Longrightarrow \quad x(t) - x(t-h) = \frac{h}{2}\{f(x(t)) + f(x(t-h))\}$$

- 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

SE	Uses PMU Data	Accuracy	Solution Speed	Technology Readiness Level
Traditional		 Single phase, positive sequence models, time skewness	 Iterative Solution	 Commercial products
Linear		 Phase angle measurements, time-tagged	 Direct Solution	 Ongoing demos
Hybrid		 Limited, if any, improvements	 Iterative Solution	 Commercial products
Three-Phase		 Captures system imbalances & asymmetries	 Increases problem size	 Few demos
Distributed		 Facilitates use of detailed models	 Reduces problem size	 Few demos
Dynamic		 Captures system dynamics – Numerically sensitive to model accuracy	 Computationally challenging – increases problem size	 Few demos, still in R&D level

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