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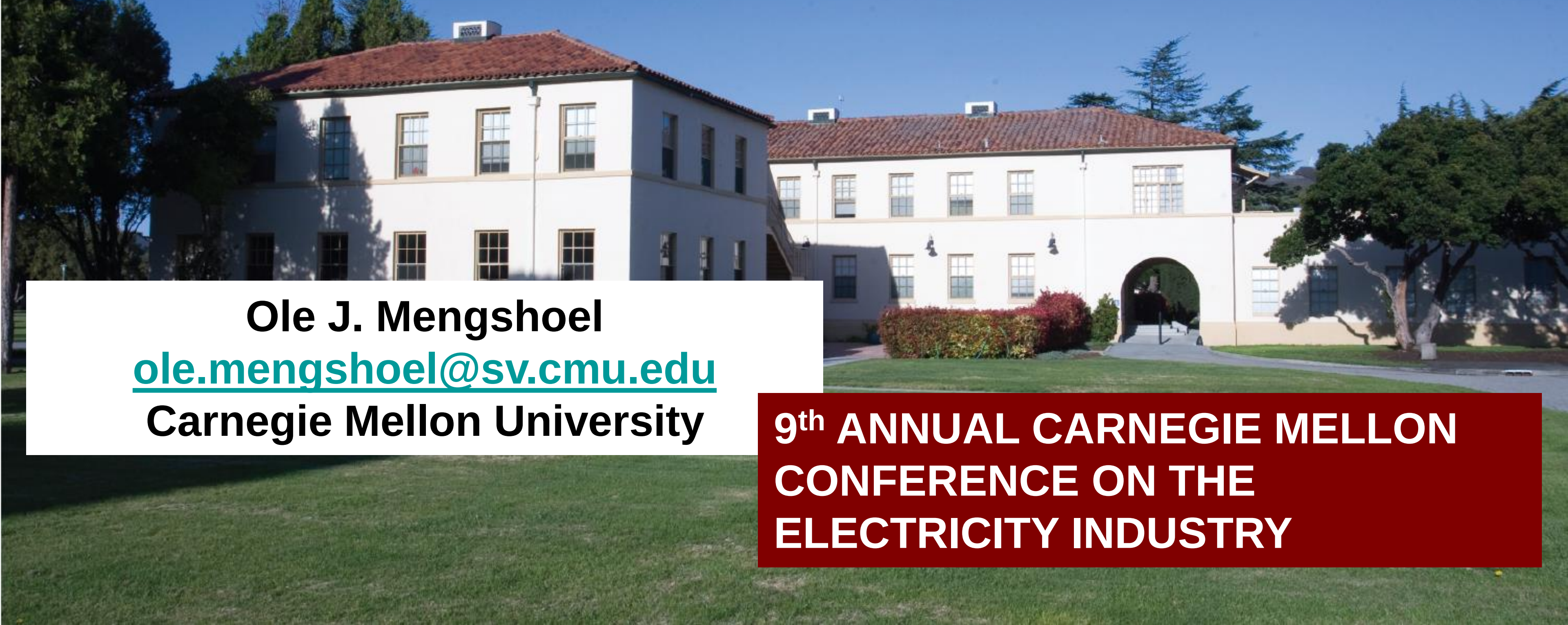
Probabilistic State Estimation: A Foundation for Distributed Energy Management?



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- Power Flow Control: Gabriela Hug, Javad Mohammadi, Soummya Kar
- Probabilistic State Estimation: Erik Reed, Dongzhen Piao, Priya Sundararajan, Briana Johnson, Hao Chen

Overview - Presentation

Bayesian Networks (BNs)

- Representation of joint probability distribution
- Compilation of Bayesian networks to arithmetic circuits/junction trees
- Computation of marginals and most probable explanations

Probabilistic State Estimation using Bayesian networks

- System architecture
- Probabilistic state estimation using Bayesian networks
- Experiments with the IEEE test systems

The Road Ahead

- A role for probabilistic state estimation, and probabilistic graphical models more broadly, in distributed energy management?
- Your questions, comments, and inputs!

Bayesian Networks and Junction Trees: Probabilistic State Estimation

Multi-Variate Probability Models

Marginal Independence
- Too simple for many applications

Naïve Bayes (NB)
- Strong conditional independence assumption

Tree-augmented Naïve Bayes (TAN)
- Slight generalization of NB

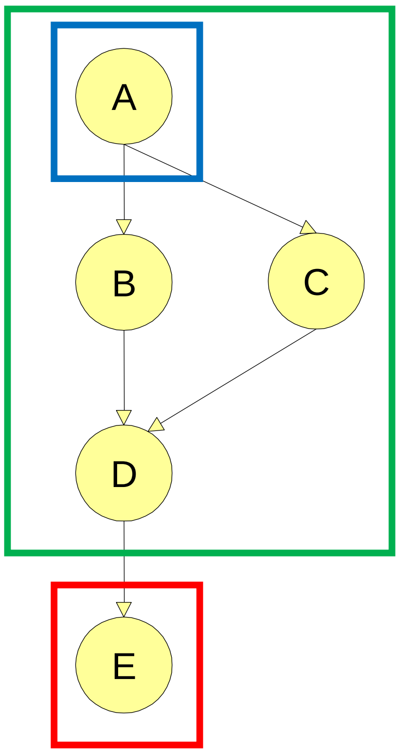
Bayesian network (BN)
- Restriction to DAGs; CPT exponential in the number of parents
- Special cases include Markov chains and trees

Joint Probability Table
- General, but unrealistically large for non-trivial applications

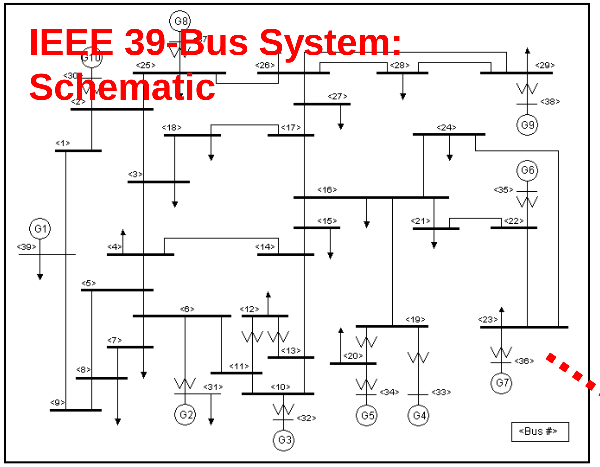
Degree of complexity

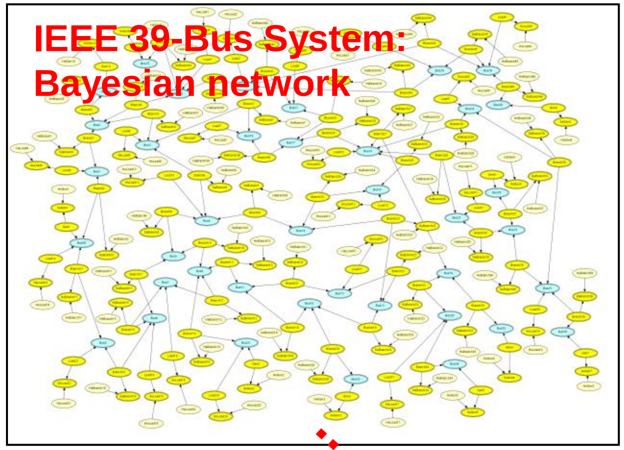
Bayesian Networks and Probability

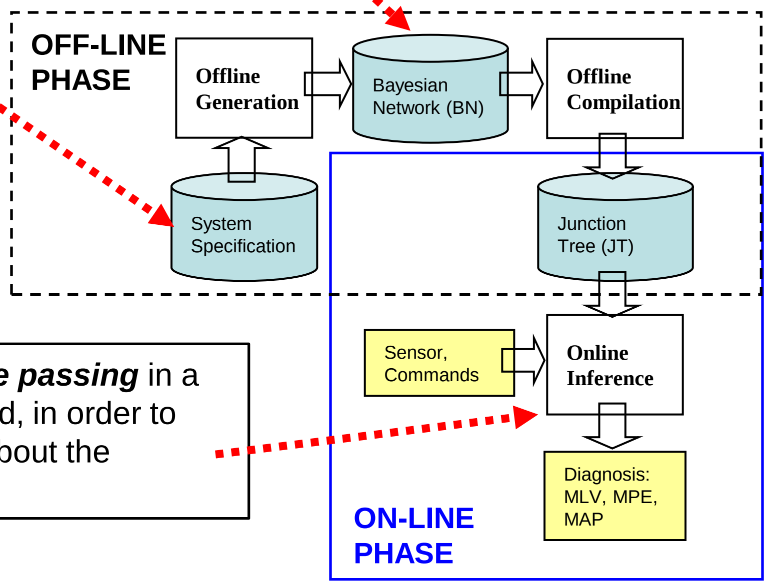
- *Belief updating*: given evidence *e* at node *E* and hypothesis node *A*, infer the posterior probability *Pr(A | E=e)*
  - Most likely value (MLV): Pick, among the states of *A*, a state with max posterior probability
- *Belief revision*: given evidence *e* at node *E* and hypothesis nodes *A, B, C,* and *D*, infer posterior probability *Pr(A=a, B=b, C=c, D=d | E=e)* of explanation
  - the most probable explanation (MPE)
  - *k* most probable explanations (*k*MPE)



Probabilistic State Estimation: Overview

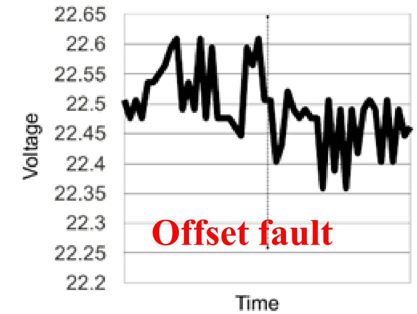


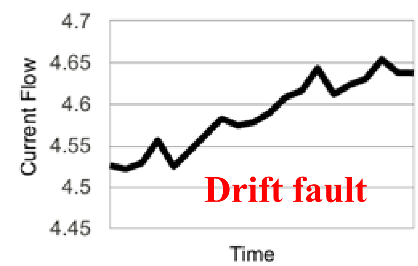




For state estimation, ***message passing*** in a junction tree may be performed, in order to answer a probabilistic query about the posterior distribution Pr(***X*** | ***e***).

Examples of Power System Faults:





Probabilistic State Estimation: A Foundation for Distributed Energy Management?

Overview – Probabilistic State Estimation

<u>Goal of ARPA-E project</u>: Explore benefits achieved by using Distributed Flexible AC Transmission Systems (D-FACTS devices)

- Security-Constrained OPF (SCOPF) for electricity networks, in which the transmission lines are potentially instrumented with D-FACTS
- Objective of SCOPF: Minimize generation cost while maintaining system security

<u>Goal of current research</u>: Improve capabilities of probabilistic state estimation techniques

- Investigate probabilistic state estimation techniques that enable improved support for the SCOPF techniques developed
- Develop and test novel probabilistic graphical approaches, which enable generalized state estimation
- Use different test systems for use cases and experiments

A Small 4-Bus Use Case

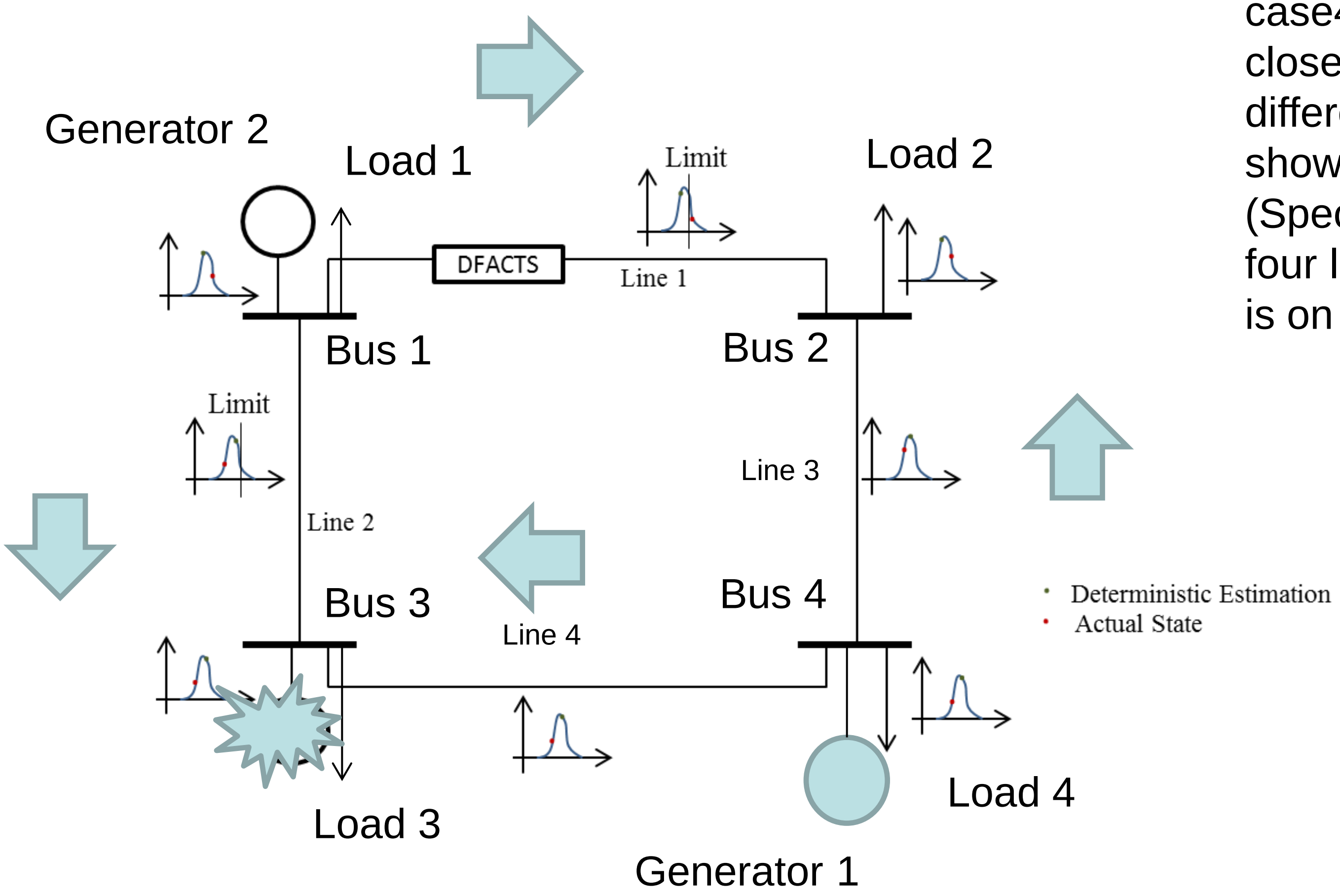
A use case is illustrated on the next slide:

- Curves show the probability distributions which are the output of the probabilistic state estimator for the indicated values (power injections, power flows).
- The red dots indicate the actual state and the green dots the state estimated by the deterministic state estimator.
- The line limits (or rating) are shown by vertical lines for the two critical lines 1 and 2. The DFACTS pushes power from line 2 to line 1.

The state estimation indicates that both power flows are below their limit. However, the probabilistic state estimation might indicate that one has to be careful:

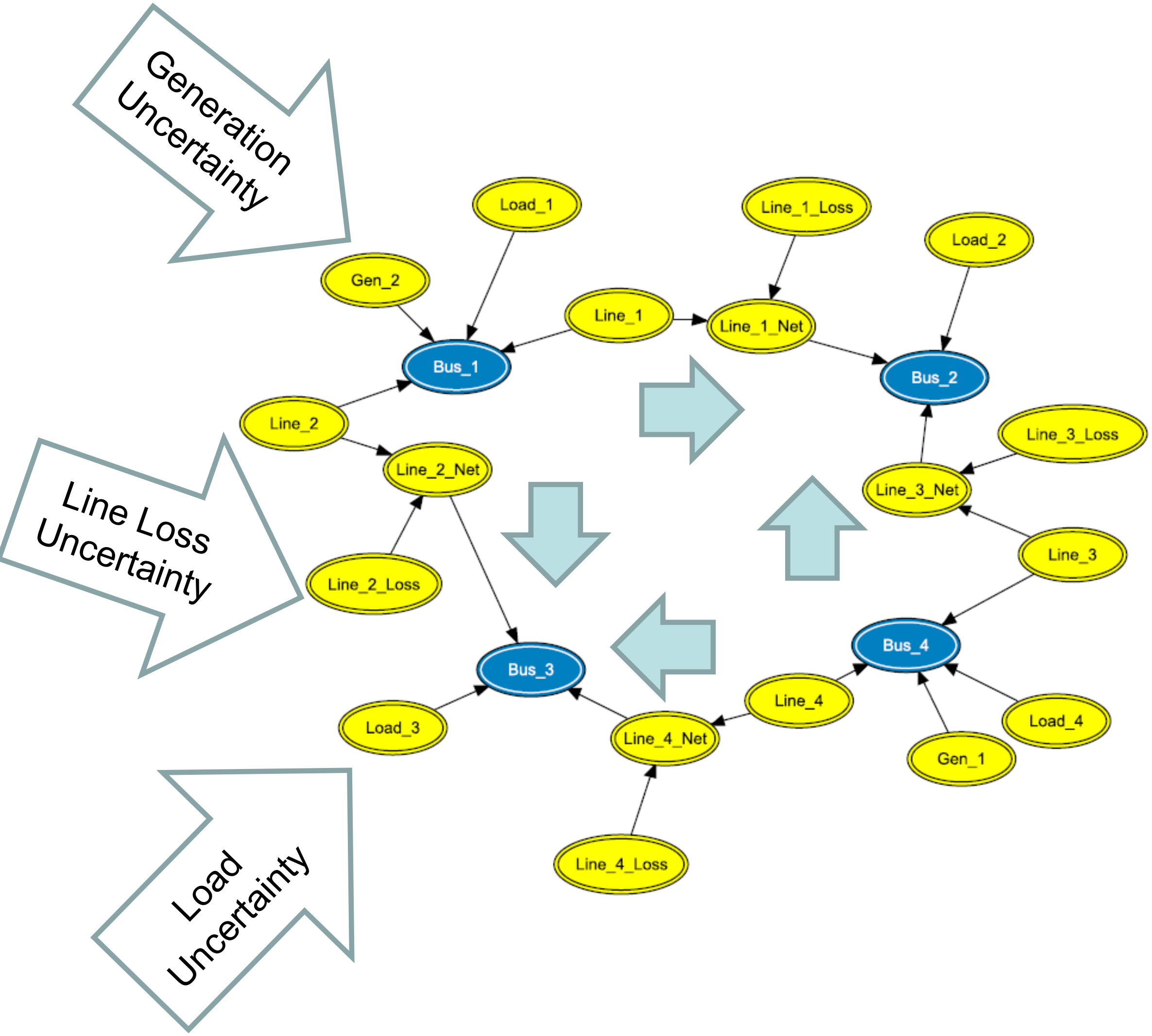
- A line could actually end up being overloaded and it would have been better to not push so much power to Line 1. E.g. such a situation is indicated by the red dots as a potential actual state of the system.
- The probability distributions for the system state can be used to adjust the DFACTS settings to reduce probability that any line is overloaded.

4-Bus Use Case



The example follows, for simplicity, the 4-bus circuit case4gs in MatPower very closely. Note, it is a bit different from what we showed in the 2-pager. (Specifically, there are now four loads and Generator 2 is on a different bus.)

Bayesian Network (BN) and DFACTS



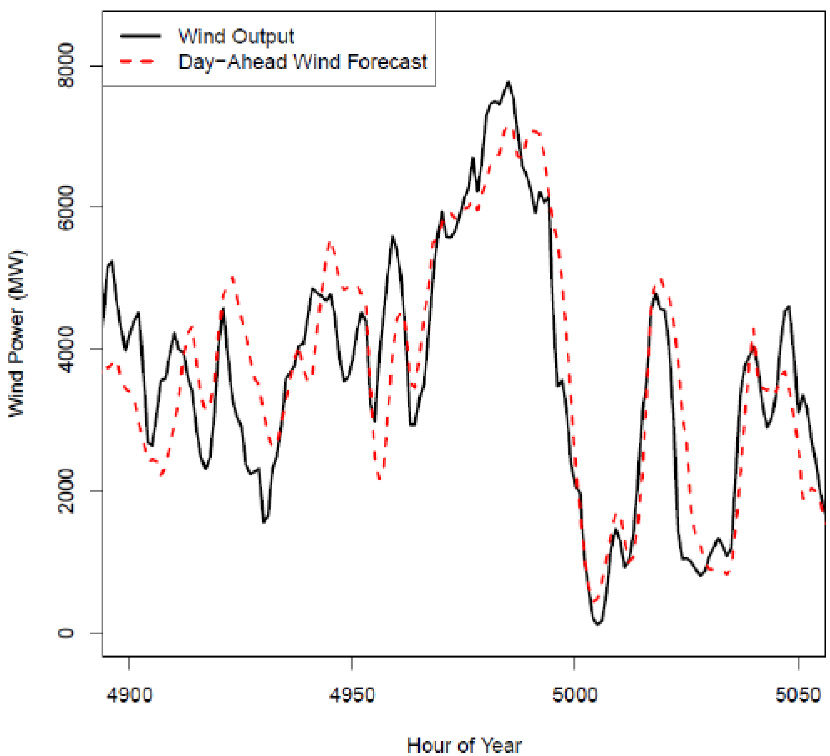
Whether DFACTS is on/off impacts the parameters of the Bayesian networks, not its structure.

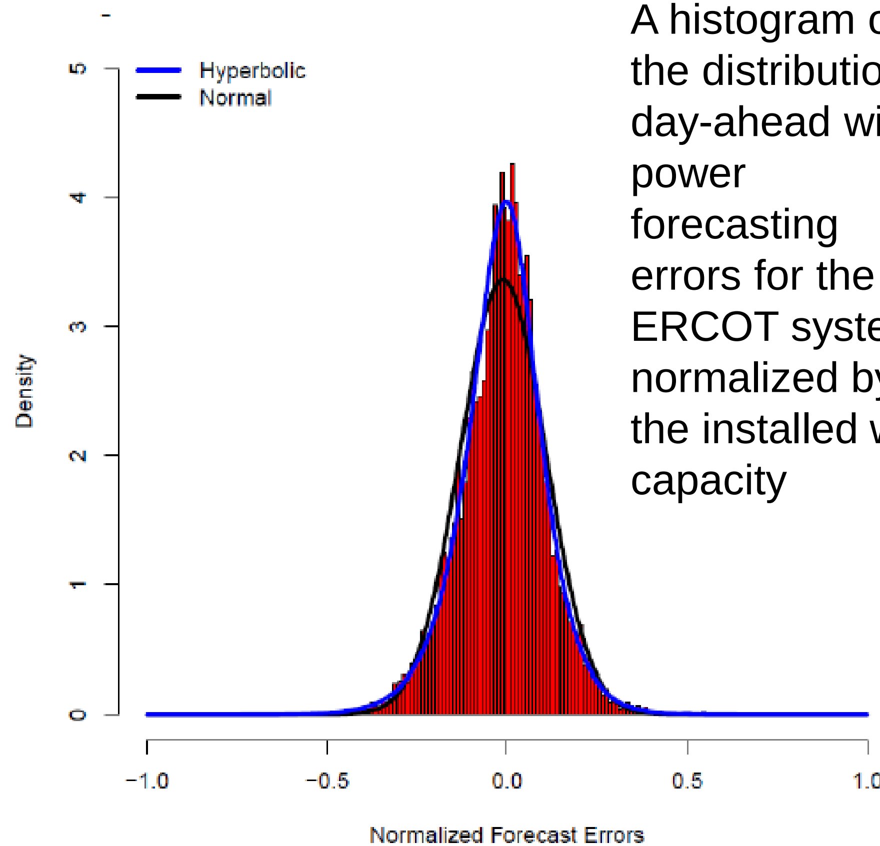
Note 1: Power flow is according to light blue edges, not the black edges in the BN.

Note 2: Main types of uncertainties are shown. Remaining nodes types are: additive and power conservation.

Note 3: Important correlations (aka “common causes”) are not represented, but could be.

Wind Generation: Probability Parameters



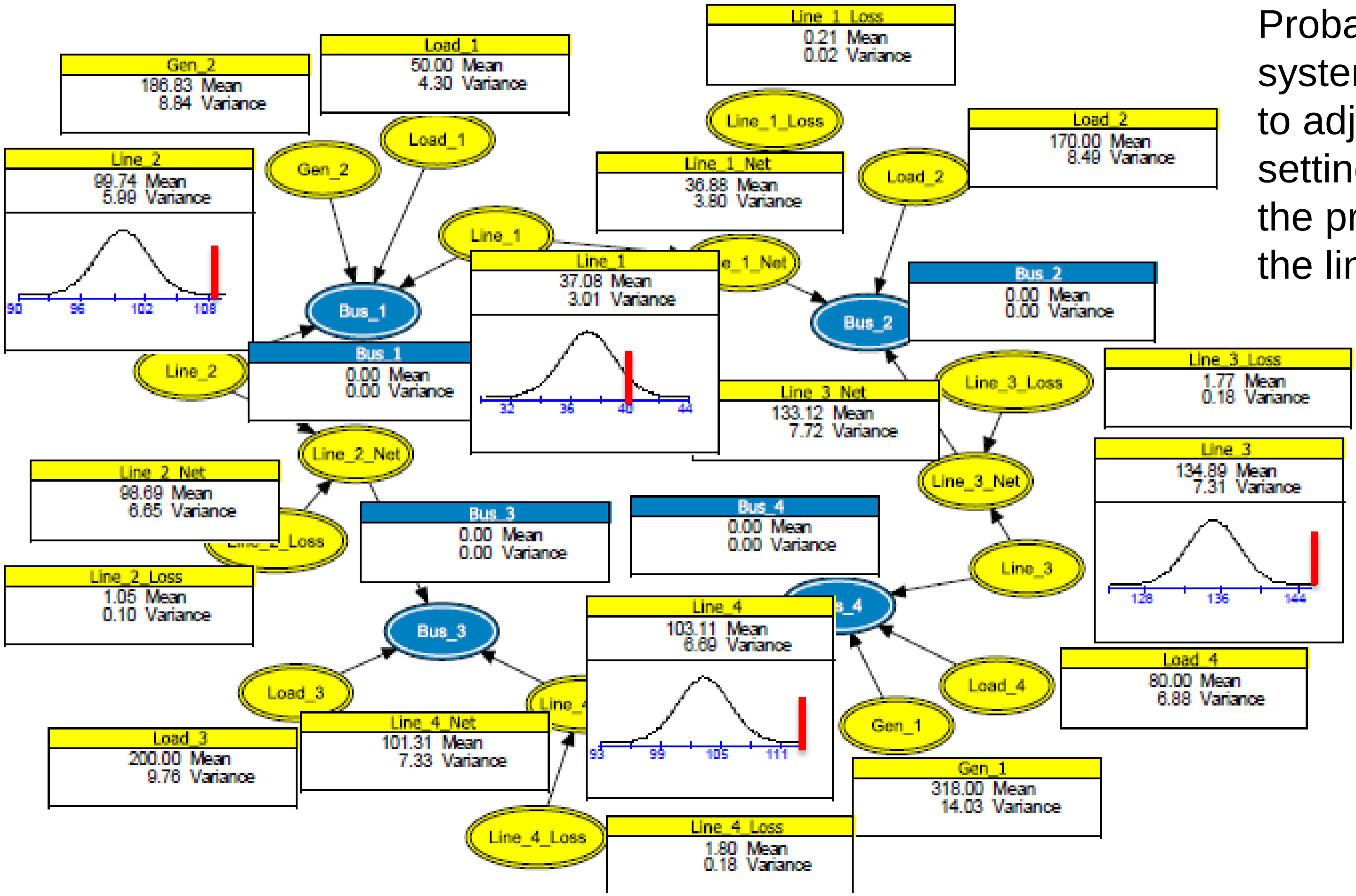


A histogram of the distribution of day-ahead wind power forecasting errors for the ERCOT system, normalized by the installed wind capacity

μ = -0.012; σ = 0.119;

A Comparison of Wind Power and Load Forecasting Error Distributions, http://www.nrel.gov/docs/fy12osti/54384.pdf

Impact of DFACTS: 4-bus Example



Probability distributions for system state can be used to adjust the DFACTS settings such as to reduce the probability that any of the lines is overloaded.

This is how the Bayesian network is used to perform probabilistic state estimation, based on the representation of case4gs as shown on previous slides. *This is with DFACTS on*.

Integration of DFACTS, SCOPF, and PF for Probabilistic State Estimation (PSE)

- Power Control is achieved by means of Distributed Flexible AC Transmission Systems (DFACTS)

- Security-Constrained OPF (SCOPF):
  1. Minimize generation cost while maintaining system security
  2. Determine the DFACTS settings for transmission lines

- Probability State Estimation (PSE):
  1. Integrate DFACTS settings into Power Flow (PF) model
  2. Parameters computed by PF (in MatPower) are used to generate the Probability State Estimation model - uncertainty due to:
     - Load and generation ramp rates
     - Polling window 3-4s
     - Forecast error: hour ahead and day ahead
     - SCOPF is typically run every 5min or 15 min

Scenario Summary

Traditional state estimation is deterministic and usually based on weighted least square optimization:

- It takes into account uncertainties and inaccuracies in the measurements and is carried out about every 2 min.
- The output is a deterministic state, i.e. the state which based on the measurements and the expected measurements is the most likely state.

The (potential) advantages of probabilistic state estimation over such a deterministic state estimator are:

- It can be more robust, i.e. while traditional state estimation may result in non-convergent or incorrectly converging behavior, this is not the case for our probabilistic state estimation algorithms.
- It provides information about a range of states the system could be in, including states for which the determined settings of the DFACTS devices might have negative or positive impacts onto the system.
- Can it be a basis for distributed approaches?

Probabilistic State Estimation: Towards Distribution

Distributed Coordination in Power Grids

Increased power consumption

More heterogenous power generation

- Specifically, renewables

Fine-grained control of power flow

- Bi-directional flow
- Distributed Flexible AC Transmission Systems

Partially shared state

Market-orientation

Mutually distrusting, improving resilience

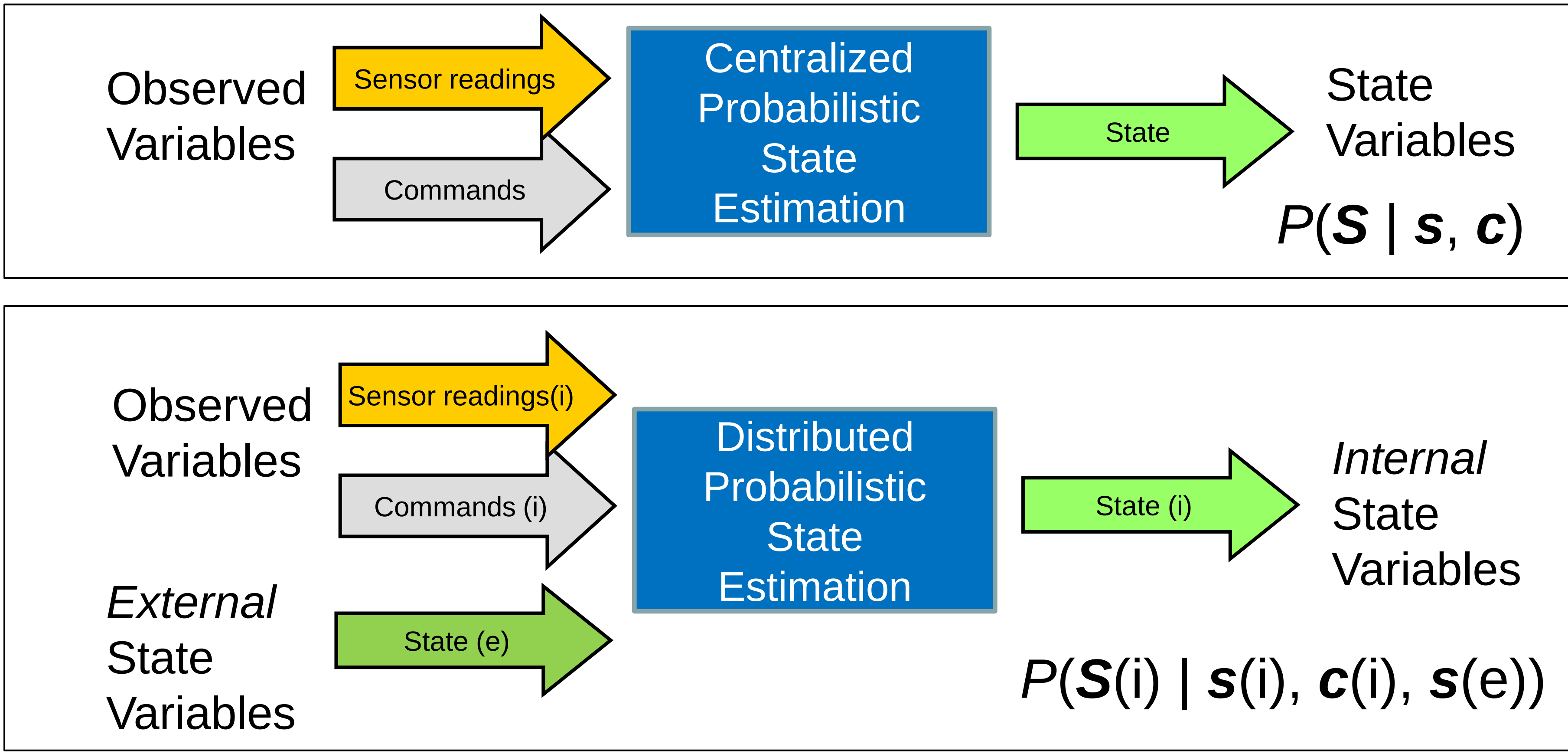
Probabilistic state estimation

- Current, distributed, and forecasted state

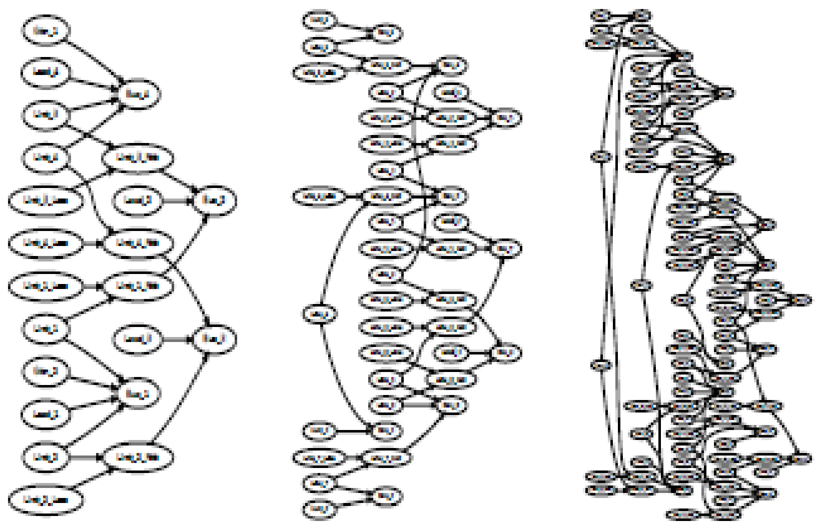
From Centralized to Distributed

Inputs to State Estimation

Outputs from State Estimation



IEEE Test Systems – Bayesian Models



(a) 4-bus (b) 9-bus (c) 14-bus

(b) 300-bus

Models for Centralized PSE

Scalability – Probabilistic State Estimation

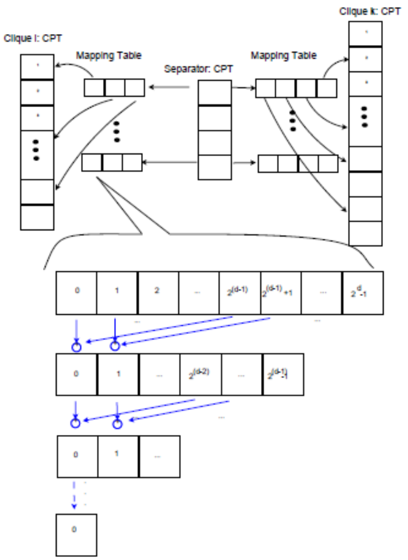
Name	Buses	Branches	Loads	Generators	Nodes	Convert	Compile	Inference
case300	300	411	199	69	1801	3.81	903.22	2.17
case118	118	186	99	54	829	1.23	60.97	1.16
case57	57	80	42	7	346	0.38	4.63	0.46
case39	39	46	21	10	208	0.22	1.31	0.25
case_ieee30	30	41	21	6	180	0.20	1.03	0.22
case30	30	41	20	6	179	0.20	1.05	0.22
case30pwl	30	41	20	6	179	0.20	1.04	0.23
case30Q	30	41	20	6	179	0.19	1.03	0.22
case24_ieee_rts	24	38	17	33	188	0.21	1.05	0.21
case14	14	20	11	5	90	0.10	0.28	0.11
case9	9	9	3	3	42	0.05	0.07	0.05
case9Q	9	9	3	3	42	0.05	0.07	0.05
case6ww	6	11	3	3	45	0.05	0.09	0.06
case4gs	4	4	4	2	22	0.02	0.03	0.03

Table 2: Evaluation of MatPower test systems when converted to BNT Bayesian networks. All computation times (convert, compile, inference refer to the use of junction trees) are in seconds.

- Above: Centralized PSE
- What would Distributed PSE look like?

Key Components of Approach

- Probabilistic State Estimation (PSE) approach:
  - Exact
  - Compilation
  - Multiple-hypothesis, multiple faults, …
  - GPU-friendly
  - Data-driven
- Modeling of IEEE test systems:
  - Probabilistic State Estimation (PSE)
  - Security-Constrained Power Flow Optimization (SC
  - Distributed Flexible AC Transmission Systems (DFACTS)
  - Data and simulation for various IEEE test systems
- Some initial ideas for Distributed PSE



Summary and Questions

Focus: Probabilistic state estimation techniques

- Hypothesis: Deterministic state estimation approaches are reaching their limits
  - Uncertainties associated with renewables and distribution
- Development of probabilistic state estimation techniques
  - Using Bayesian networks; computationally feasible
  - Initial integration with SCOPFS and DFACTS

Questions:

- What information needs to be interchanged between islands, and how often?
- Why, when, and how to synchronize between islands?
- A foundation for distributed coordination?