Visualization of Analytical Processes

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Overview of Visualization of Analytical Processes

- **Challenges and opportunities:**
  - Currently a gap between:
    - Dramatic improvements in hardware and software for gathering, communicating and storing raw data; versus
    - Capacity of humans to act on this data in a meaningful way
  - This gap will only continue to widen in the near future
- **Goals:**
  - Emphasis on large-scale, complex systems represented as probabilistic graphical models
  - Novel, mathematical, computational and visualization methods
  - Analytical processing partly done by the computer, partly by the human
- **Research areas:**
  - Novel feature transformation and data synthesis techniques, based on probabilistic graphical models including Bayesian network
  - Strong coupling of these analytical processes, using Bayesian networks, with visualizations
  - Domain-independent and scalable techniques, using Electrical Power Systems as one major application

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Overview of Talk

- **Previous research**
  - Probabilistic graphical models, Bayesian networks and arithmetic circuits
  - Electrical power system application
- **Research challenge**
  - Visual analytics for large-scale probabilistic graphical models
- **Initial explorations**
  - Coupling of analytical processes, using Bayesian networks, with visualizations
  - Domain-independent and scalable techniques, using Electrical Power Systems as major application

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Previous Research

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Problem Statement

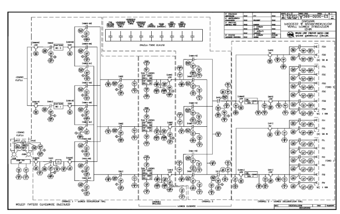
Diagnosis of complex engineered systems using model-based techniques is complicated by several challenges

- Hybrid system behavior
- Model construction
- Real-time performance

Goal: Develop Bayesian methods for on-line diagnosis of complex engineered systems with real-time performance constraints

Target: Demonstrate solutions to challenges using an electrical power system as an example of a complex hybrid system that is ubiquitous to aircraft, spacecraft, and industrial systems

The Modeling Challenge



Uncertainty in EPSs

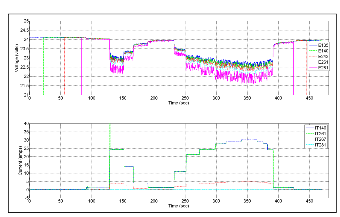
- Components and sensors may fail
- Sensor noise
- Load-dependent noise

Many possible modes

- Due to relays (switches), circuit breakers, certain failures

Need for high diagnostic accuracy

- Avoid single-fault assumption



Large, complex systems are often

- Difficult to model
- Tedious to extend and update

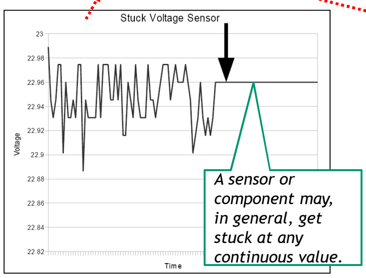
The Hybrid Systems Challenge

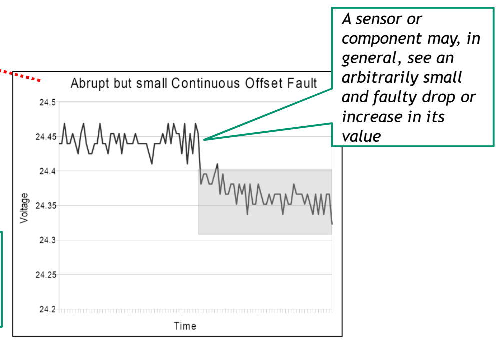
Hybrid systems:

- Discrete: Both healthy and faulty modes
- Continuous: Both healthy and faulty behavior

Fault types in hybrid systems:

- *1.abrupt discrete faults*
- *2.abrupt continuous (parametric) faults*
  - *a) offset*
  - *b) stuck*





The Real-Time Reasoning Challenge

Real-time operating system (RTOS) used in current avionics:

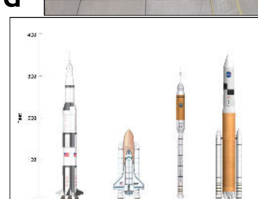
- Task has: period, deadline, and worst-case execution time (WCET)
- Priority-based preemptive scheduling

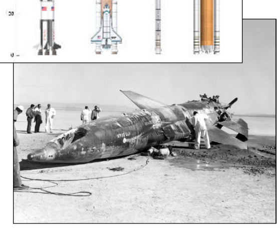
The challenge of embedding AI into hard real-time system:

- Hardness of the computational problems
- High expectation and/or variance of a search algorithm's execution time

The real-time challenge:

- Diagnostic processes need to be designed within RTOS resource bounds
- "Embedding AI into real-time systems" [Musliner et al., 1995]





Electrical Power Networks: Aerospace Applications

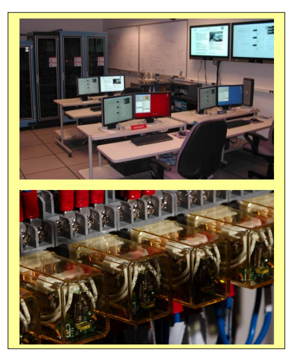
On January 28 1968, a *faulty electrical switch* created a spark which ignited the pure oxygen environment; the fire quickly killed the Apollo 1 crew.

On September 2, 1998, Swissair 111 crashed into the Atlantic Ocean, killing all 229 people onboard. It was determined that *wires short-circuited* and led to a fire.

A *battery failure* occurred on the Mars Global Surveyor, which last communicated with Earth on November 2, 2006. A software error oriented the spacecraft to an angle that over-exposed it to sunlight, causing the battery to overheat.

Electrical Power Systems Testbed

- Electrical power systems (EPSs) are critical in aerospace
- EPS loads include: avionics, propulsion, life support, and thermal management
  - increased EPS use in air- and spacecraft
- ADAPT EPS testbed at NASA Ames:
  - a capability for controlled insertion of faults, giving *repeatable failure scenarios*;
  - a *standard testbed* for evaluating diagnostic algorithms & software; and
  - a *stepping stone* for maturing diagnostic technologies.

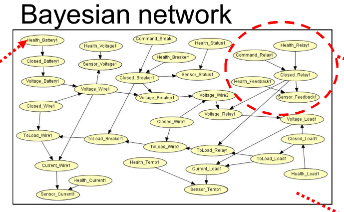


See also http://ti.arc.nasa.gov/projects/adapt

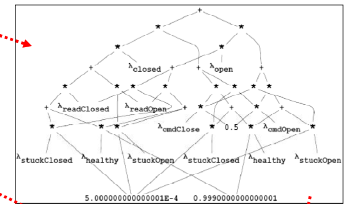
Probabilistic Diagnosis Approach

Each health variable has at least two states (healthy and faulty), thus enabling the diagnoses of zero, one, two, or more faults.

Bayesian network

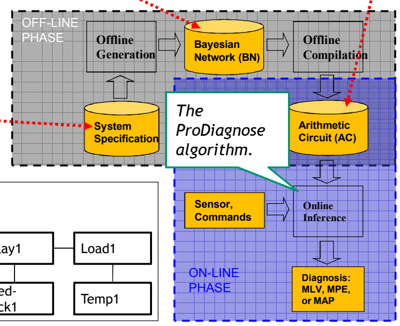


Arithmetic circuit

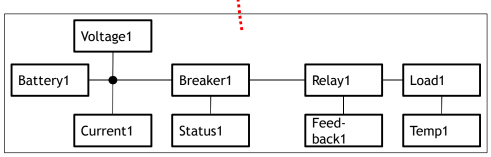


Specification language

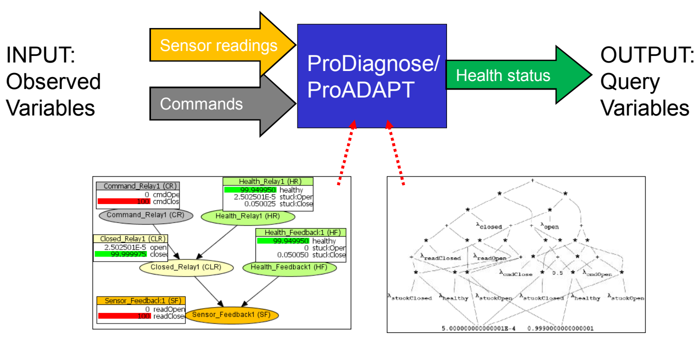
```
Battery1     : battery        : 0.0005;
Wire1        : wire           : 0.0000 : Battery1;
Voltage1     : sensorVoltage  : 0.0005 : Wire1;
Current1     : sensorCurrent  : 0.0005 : Wire1;
Breaker1     : breaker        : 0.0005 : Wire1;
Status1      : sensorTouch    : 0.0005 : Breaker1;
Wire2        : wire           : 0.0000 : Breaker1;
Relay1       : relay          : 0.0005 : Wire2;
Feedback1    : sensorTouch    : 0.0005 : Relay1;
Load1        : load           : 0.0005 : Relay1;
Temp1        : sensorCurrent  : 0.0005 : Load1 ;
```



See [Mengshoel *et al.*, 2008] and [Mengshoel *et al.*, 2009] for BN auto-construction.



Probabilistic On-Line Diagnosis



Probabilistic model for a vehicle's subsystem(s):

- **It represents health of sensors and subsystem components explicitly**
- **It contains random variables for other parts of the subsystem**

A probabilistic approach to:

- ***Diagnosis*: health status of system component nodes**
- ***Sensor validation*: health status of sensor nodes**

Fault Types Investigated

Independent faults

Abrupt

Permanent

These are the fault types considered in this talk.

Discrete

Continuous (parametric)

Intermittent

Incipient

Dependent faults

Common cause

Cascading

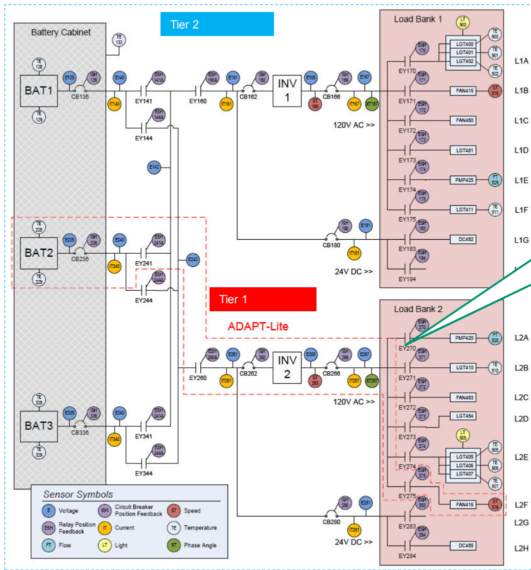
Component	Fault Description
Battery	Degraded
Boolean Sensor	Stuck at Value
Circuit Breaker	Tripped Failed Open Stuck Closed
Inverter	Failed Off
Relay	Stuck Open Stuck Closed
Sensor	Stuck at Value Offset
Pump(Load)	Flow Blocked Failed Off
Fan(Load)	Over Speed Under Speed Failed Off
Light Bulb(Load)	Failed Off

See [Kurtoglu *et al.*, 2009a] and [Kurtoglu *et al.*, 2009b] for discussion of fault types

Related Research

- Using Bayesian networks
  - hybrid (discrete + continuous) BNs:
    - clique tree based [Spiegelhalter & Lauritzen, 1988] using linear Gaussians [Olesen, 1993]
    - particle filtering [Koller & Lerner, 2000]
  - discrete BNs:
    - fault diagnosis in terrestrial EPSs [Yongli *et al.*, 2006], [Chien *et al.*, 2002],
- Not using Bayesian network
  - hybrid bond graphs [Narasimhan & Biswas 2007], [Daigle *et al.*, 2008]
  - general diagnostic engine [de Kleer & Williams, 1987], [Karin *et al.*, 2006], [Bunus *et al.*, 2009]
  - convex optimization [Gorinevsky *et al.*, 2009]

ADAPT Experimental Testbed



Tier 1 experiments were substantially easier than Tier 2 experiments:
- a subset of ADAPT was used
- relays were closed at all times

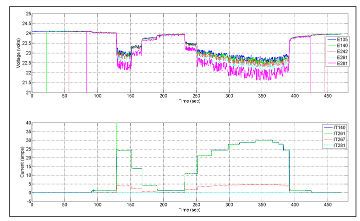
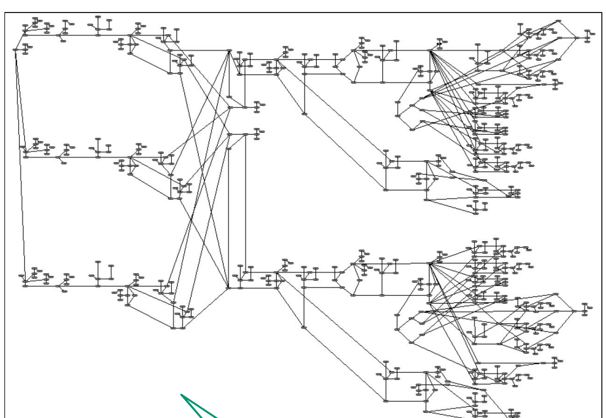


Figure from [Kurtoglu *et al.*, 2009b].

Bayesian Network Model of ADAPT Tier 2



The Bayesian network model of ADAPT Tier 2.

ADAPT EPS					
			ADAPT	Bayesian Network	
Name	Sym	Description	Qty per EPS	Qty per sensor: Nodes	Qty per sensor: Evidence nodes
DC Current Sensor	it	Measures DC current in amps	7	3	2
AC Current Sensor	it	Measures AC current in amps	2	3	2
DC Voltage Sensor	e	Measures DC voltage in volts	12	3	2
AC Voltage Sensor	e	Measures AC voltage in volts	4	3	2
Circuit Breaker Position Sensor	ish	Senses whether a circuit breaker is opened or closed	9	2	1
Relay Position Sensor	esh	Senses whether a relay is opened or closed	24	2	1
Temperature Sensor	te	Measures temperature in Fahrenheit of batteries, battery cabinet, and light bulbs	15	5	3
Speed Transmitter	st	Measures RPM of the large fans	2	5	3
Phase Angle Transducer	xt	Measures the phase shift in degrees between the sine waves of AC current and voltage	2	6	2
AC Frequency Transmitter	st	Measures the AC frequency in Hertz	2	3	2
Flow Transmitter	ft	Measures the flow rate in gallons per hour through a pump	2	5	3
Light Sensor	lt	Measures the intensity in millivolts of incoming light	2	3	2
		TOTAL	83	43	25

Experiments, ADAPT Data

- Two types of scenarios:
  - Tier 1 scenarios: nominal or contained one fault
  - Tier 2 scenarios: nominal or contained single, double, or triple faults
- The ADAPT EPS was used to generate fault and nominal scenarios:
  - Faults were injected simultaneously or sequentially
  - Fault types were additive parametric (abrupt changes in parameter values) and discrete (unexpected changes in system mode)
  - Faults were permanent and included both component faults and sensor faults

Metric	ADAPT DXC Tier 1			ADAPT DXC Tier 2		
	ProADAPT	RODON	HyDE-S	ProADAPT	Stanford	RODON
False positives (FP) rate	*0.0333*	0.0645	0.2000	*0.0732*	0.3256	0.5417
False negatives (FN) rate	*0.0313*	0.0968	0.0741	*0.1392*	0.0519	0.0972
Detection accuracy	*0.9677*	0.9194	0.8548	*0.8833*	0.8500	0.7250
Classification errors	*2.0*	10.0	26.0	*76.0*	110.5	84.1
Mean time to detect T_d (ms)	*1,392*	218	130	*5981*	3946	3490
Mean time to isolate T_i (ms)	*4,084*	7,205	653	*12,486*	14,103	36,331
Mean CPU time T_c (ms)	*1,601*	11,766	513	*3,416*	963	8,0261
Mean peak memory usage (kb)	*1,680*	26,679	5,795	*6,539*	5,912	29,878
Score	*72.80*	59.85	59.50	*83.20*	81.50	70.50
Rank	*1*	2	3	*1*	2	3

9 competitors in Tier 1. 6 competitors in Tier 2.

Experiments, Simulated Data

Inference Time (ms)	MPE		Marginals	
	VE	ACE	CTP	ACE
Minimum	17.25	0.1967	8.527	0.4934
Maximum	38.45	2.779	54.51	5.605
Median	17.63	0.1995	9.204	0.5624
Mean	17.79	0.2370	10.02	0.6981
St. Dev.	1.513	0.2137	4.451	0.6669

ACE is the approach used in ProADAPT.

Comparison between Arithmetic Circuit Evaluation (ACE), Variable Elimination (VE) and Clique Tree Propagation (CTP)

Main conclusions:

All three inference algorithms are quite efficient, thanks to auto-generation algorithm

ACE outperforms VE (for MPE) and CTP (for marginals), both in Mean and St. Dev.

Summary: Bayesian Networks for Diagnostics

- ***Diagnostic challenges*** in aerospace and at NASA:
  - Modeling of large, complex systems
  - Hybrid systems – discrete and continuous behavior
  - Hard diagnostic problems, real time requirements
- Probabilistic diagnosis approach, ***ProDiagnose***, with application to ADAPT electrical power system:
  - Auto-generation of Bayesian network
  - Compilation of Bayesian networks to real-time arithmetic circuits
  - Handling of abrupt discrete and continuous (parametric) faults using discrete and static Bayesian networks
  - Strong performance on electrical power system data from ADAPT testbed

Bayesian Reasoning for Diagnostics: *Operates in a state space of size > 2^{500} in time < 1 ms.*

Proposed Research

Goals and Expected Outcomes

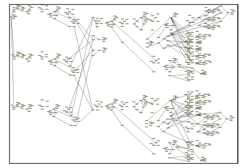
Contributions in learning and reasoning in probabilistic graphical models, including Bayesian networks, that consider their use in visualization and human-computer interaction

Solid mathematical foundation: probabilistic graphical models (Bayesian networks, Markov random fields, factor graphs, …)

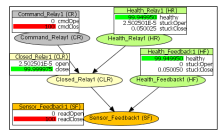
Difficulty for humans to reason under uncertainty, especially under time pressure and stress

- Visualization options
  - Do not visualize uncertainty (determinism - the traditional stance)
  - Visualize uncertainty
- Visualization of uncertainty has recently been shown to improve human performance

Current visualization methods for probabilistic reasoning target domains with “few” random variables - say 1 to 100 range - not in the 100 - 100,000,000 range



versus



Background: Physical Networks

Networks provide opportunities to study visual analytics of large-scale interactions:

Local interactions are relatively well-understood

Inference can, due to sparseness, be made fast

Our main example network: *Electric Power Systems (EPSs)*

Terrestrial power grid (on a national level)

Micro-grids (vehicle, building, neighborhood, …)

Current analysis typically uses deterministic models at two time scales:

Short (several cycles at 60 Hz): dynamic differential equations

Long: steady-state power flow equations; Monte-Carlo simulation

Robustness and scalability issues because of network-wide interactions:

Blackouts in current EPS, due to cascading failures

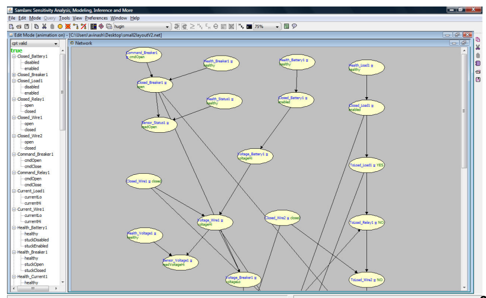
An upgraded national EPS - Smart Grid:

Numerous distributed generator plants (wind, solar, etc.)

Their potential large number, intermittency, and unreliability is causing great concern

Visualizing Bayesian Networks

Bayesian Network Tool	Visual model
Hugin Expert	Nodes, Bar charts
BayesBuilder	Nodes, Bar charts
WinMine	Nodes
BayesianLab	Nodes
Netica	Nodes, Bar charts
MSBNx	Nodes
Analytica	Nodes
GeNIe/SMILE	Nodes, Bar-charts/pie-chart



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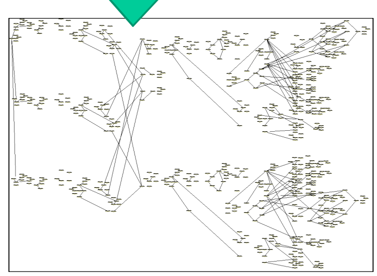
Problem Statement

- Current Bayesian network visualizations, though useful, have several limitations:
  - Difficulty handling large-scale domains
  - Often no support for time series data
  - Often no displaying of information (e.g., Bayesian network) along with the underlying data (e.g., time series).
  - Need to perform visual search to locate interesting information
  - …

Bayesian network for diagnosis of the ADAPT electrical power system: 671 nodes and 790 edges



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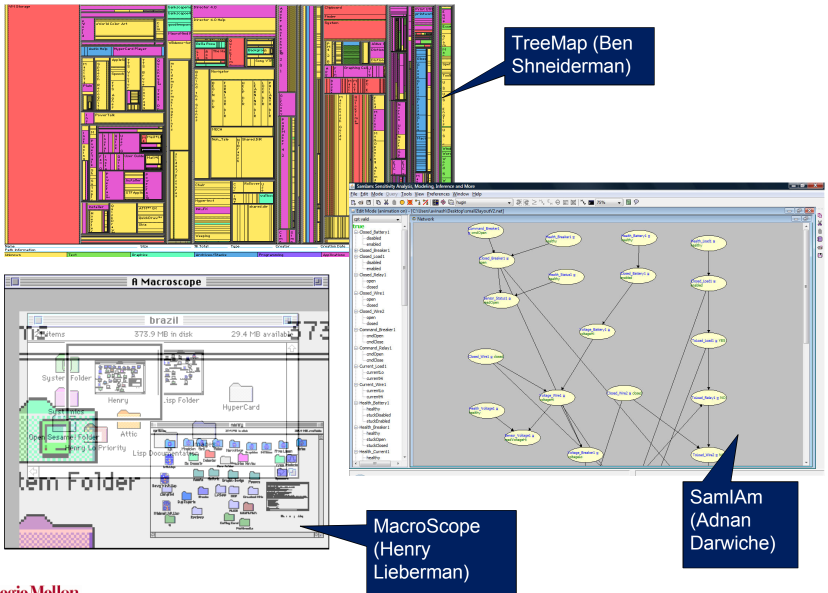
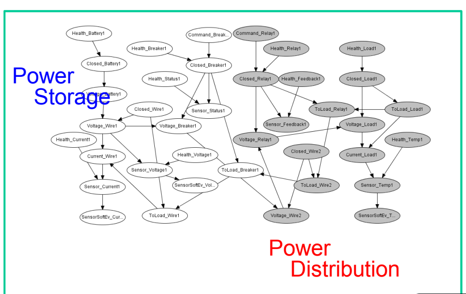
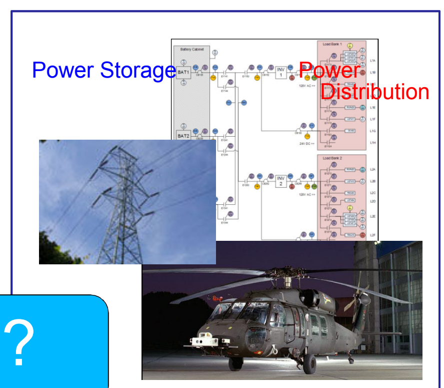
Candidate Visualizations



Visualization of Analytical Processes





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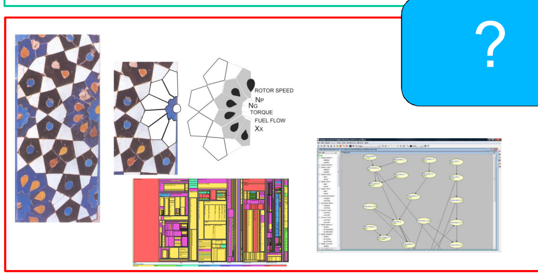
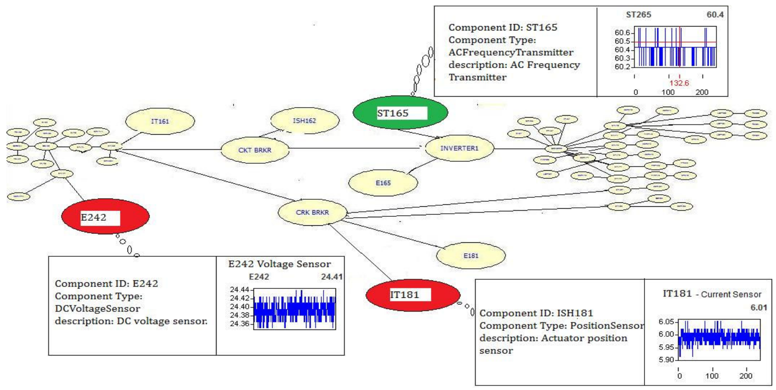
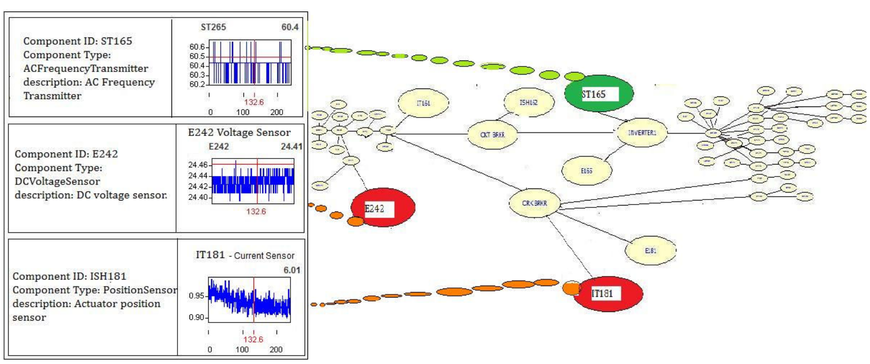


Visualization Exploration (1)



Bifocal XY with color map and zooming.

Visualization Exploration (2)



Bifocal XY with color map, zooming, and comparison.

Application Areas

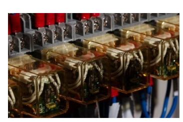
- Aerospace: The C-MAPSS software tool is used to simulate nominal and fault engine degradation over a series of flights. In one C-MAPPS data set, 30 engine and flight condition parameters were recorded at 1 Hz for a number of flights; see https://dashlink.arc.nasa.gov/data/c-mapss-aircraft-engine-simulator-data/ for details. Another C-MAPSS data set, see https://dashlink.arc.nasa.gov/data/turbofan-engine-degradation-simulation-data-set/, contains turbofan engine degradation data.
- Engineering: Water distribution networks can be modeled using the EPANET software; see http://www.epa.gov/nrmrl/wswrd/dw/epanet.html. This software has been used to evaluate algorithms for sensor placement, which have as their goal to quickly detect contaminants [Leskovec, 2007].
- Social network data: Add Health is a longitudinal study, consisting of a representative sample, of adolescents in grades 7-12 in the United States during the 1994-95 school year. The data set contains information on the social, economic, psychological and physical health of participants, along with contextual (or network) data on family, community, school, friendships, etc. See http://www.cpc.unc.edu/projects/addhealth and [Hoff, 2007].
- Homeland security: FODAVA data sets.
- Electrical power networks: See other slides.

Summary: Visualization of Analytical Processes

***Vision**: Improving the visualization of analytical processes, in particular machine learning and inference processes that use probabilistic graphical models, in large-scale systems such as electrical power systems.*

***Tasks:** Abstract large scale-scale networks – such as electrical power systems – into probabilistic graphical representations. Combine algorithmics and visulization to create better methods for understanding, analyzing, and controlling large-scale probabilistic models.*

Faculty: Mengshoel, Selker, and Ilic



- **Identify gaps in current approaches to visual analytics as applied to probabilistic graphical models**
- **Find "common ground" between visualization and probabilistic graphical models**
- **Develop methods that handle large-scale networks, such as electrical power systems, when modeled as probabilistic graphical models**

Web and Publications

- Further details:
  - Intelligent sytems lab: http://mlt.sv.cmu.edu/cis/
  - DASH*link* - Health management technologies in aeronautics: https://dashlink.arc.nasa.gov/
  - ADAPT testbed: http://ti.arc.nasa.gov/projects/adapt/
  - Probabilistic diagnostics: http://ti.arc.nasa.gov/project/pca/
  - Personal: http://ti.arc.nasa.gov/people/omengshoel
- Publications:

  - O. J. Mengshoel, M. Chavira, K. Cascio, S. Poll, A. Darwiche, and S. Uckun, "Probabilistic Model-Based Diagnosis: An Electrical Power System Case Study." Accepted, *IEEE Trans. on Systems, Man and Cybernetics, Part A*, 2009.
  - O. J. Mengshoel, S. Poll, and T. Kurtoglu. "Developing Large-Scale Bayesian Networks by Composition: Fault Diagnosis of Electrical Power Systems in Aircraft and Spacecraft." In *Proc. of the IJCAI-09 Workshop on Self-* and Autonomous Systems (SAS): Reasoning and Integration Challenges*, 2009.
  - B. W. Ricks and O. J. Mengshoel. "Methods for Probabilistic Fault Diagnosis: An Electrical Power System Case Study." In *Proc. of Annual Conference of the Prognostics and Health Management Society*, 2009
  - O. J. Mengshoel, A. Darwiche, K. Cascio, M. Chavira, S. Poll, and S. Uckun, "Diagnosing Faults in Electrical Power Systems of Spacecraft and Aircraft." In *Proc. of the Twentieth Innovative Applications of Artificial Intelligence Conference (IAAI-08)*, Chicago, IL, 2008.
  - O. J. Mengshoel, "Macroscopic Models of Clique Tree Growth for Bayesian Networks". In *Proc. of the 22nd National Conference on Artificial Intelligence (AAAI-07)*. July 2007, Vancouver, Canada, pp. 1256-1262.
  - O. J. Mengshoel, "Designing Resource-Bounded Reasoners using Bayesian Networks: System Health Monitoring and Diagnosis." In *Proc. of the 18th International Workshop on Principles of Diagnosis (DX-07)*, Nashville, TN, May 2007.