INTEGRATED VEHICLE
HEALTH MANAGEMENT

Probabilistic Methods for Diagnosis of Aircraft Systems

Ole J. Mengshoel

Ole.J.Mengshoel@nasa.gov
Carnegie Mellon Silicon Valley &
Intelligent Systems Division
NASA Ames Research Center

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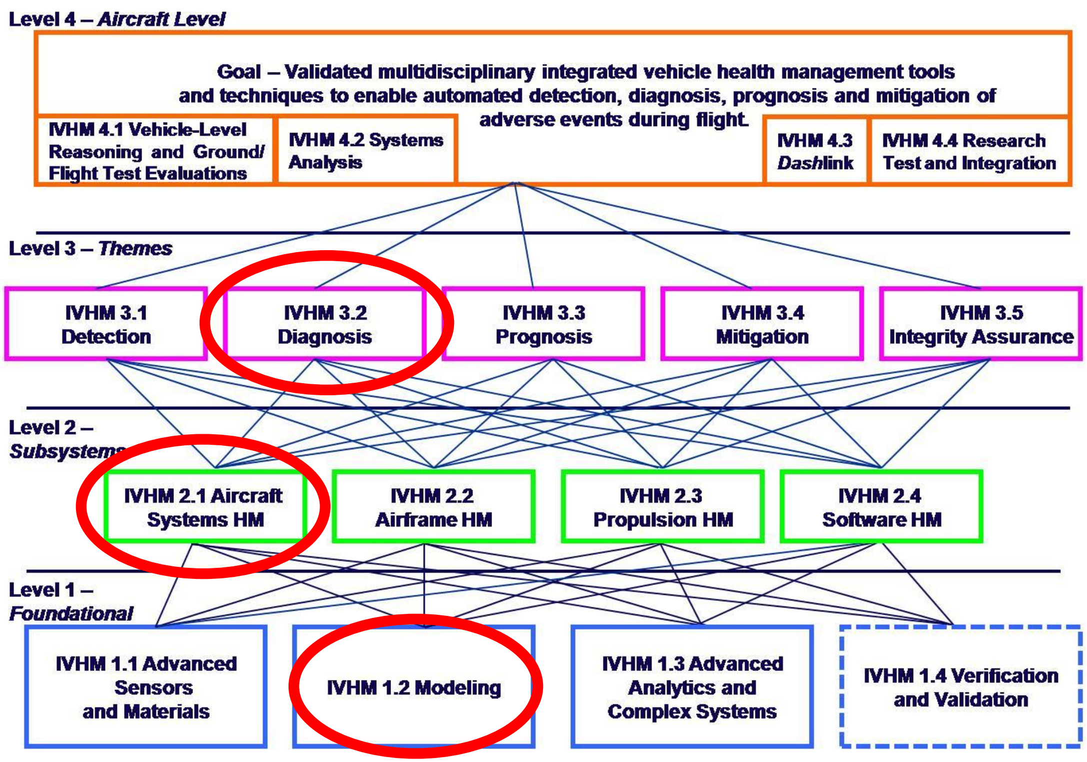
Outline

- Problem Statement
- Background
- IVHM milestones(s) being addressed
- Approach
- Results
- Conclusions
- Future Plans



Problem Statement

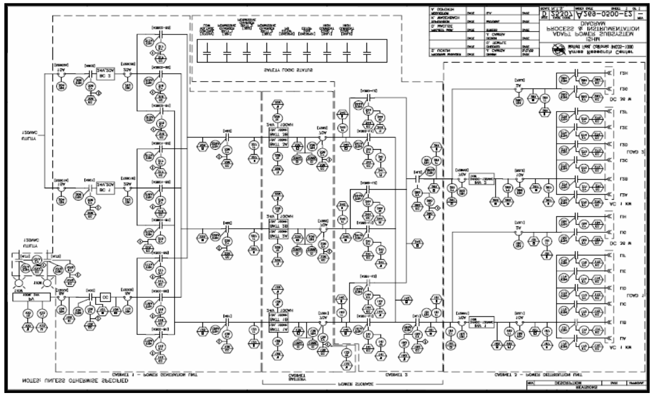
- Diagnosis of complex engineered systems using model-based techniques is complicated by several challenges
  - Hybrid system behavior
  - Model construction
  - Real-time performance
- **Goal**: Develop Bayesian methods for on-line diagnosis of complex engineered systems with real-time performance constraints
- **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

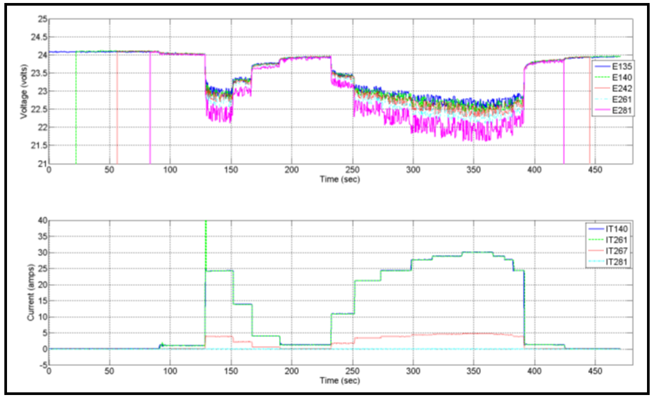
Background: Electrical Power Systems Accidents

- 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.
- Swissair 111 crashed into the Atlantic Ocean on September 2, 1998, killing all 229 people onboard. It was determined that *wires short-circuited* and led to a fire.
- On January 14, 2005, an Intelsat operated communications satellite suffered a total loss after a sudden and unexpected *electrical power system anomaly*, likely the result of high current in the battery circuitry triggered by an electrostatic discharge.
- 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.
- On January 7, 2008, a Boeing 747 *lost main power* on its descent into Bangkok, and had to rely on battery backup.

The Modeling Challenge

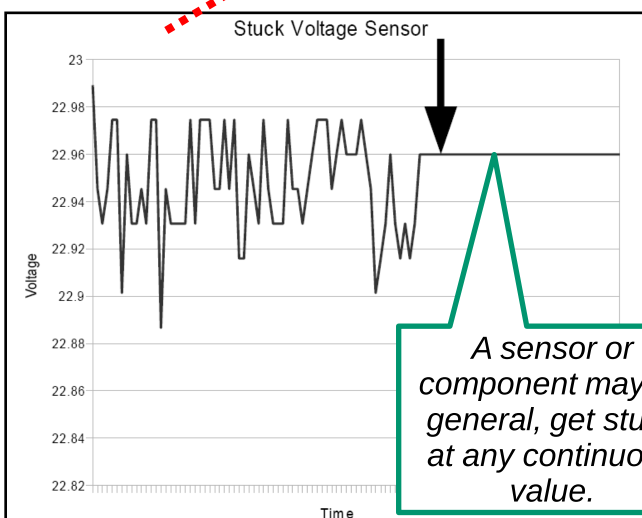
- Uncertainty in EPSs
  - Components and sensors may fail
  - Sensor noise
  - Load-dependent noise
- Many possible modes
  - Due to relays (switches), circuit breakers, certain failures
- Need for high diagnostic accuracy
  - Avoid single-fault assumption
- Large, complex systems are often
  - Difficult to model
  - Tedious to extend and update



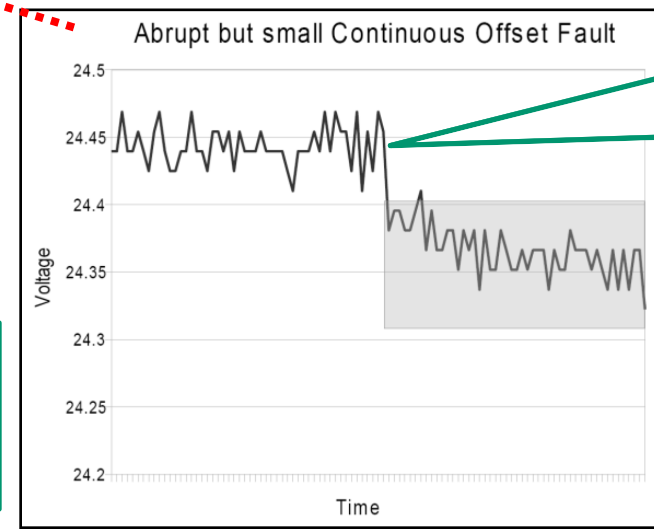


The Hybrid Systems Challenge

- 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*



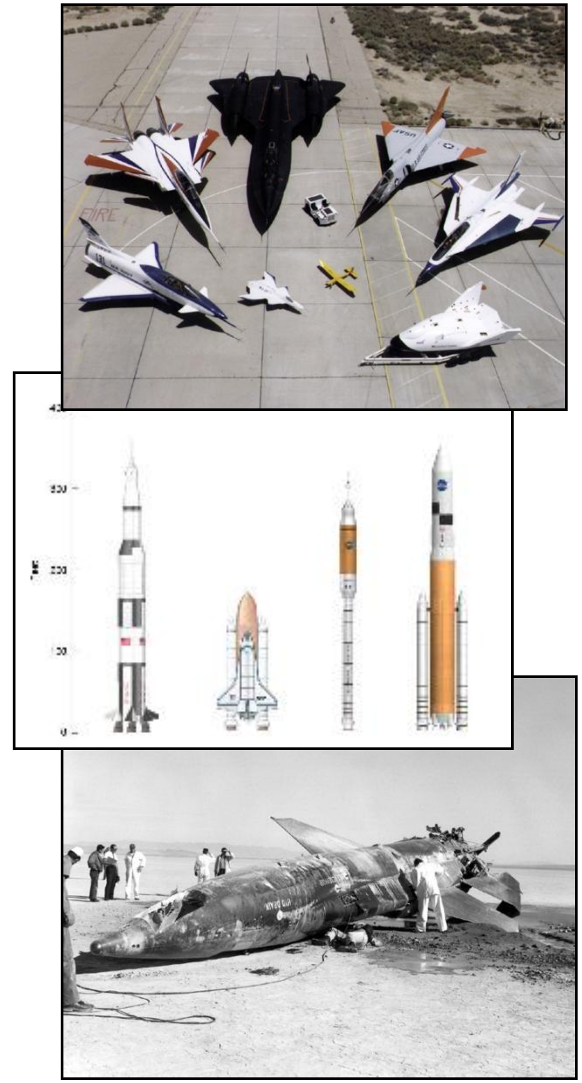
A sensor or component may, in general, get stuck at any continuous value.



A sensor or component may, in general, see an arbitrarily small and faulty drop or increase in its value

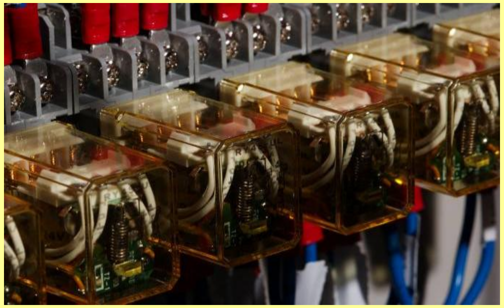
The Real-Time Reasoning Challenge

- 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]



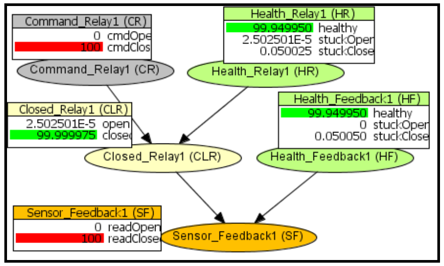
Electrical Power Systems at NASA

- 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/

IVHM Milestone

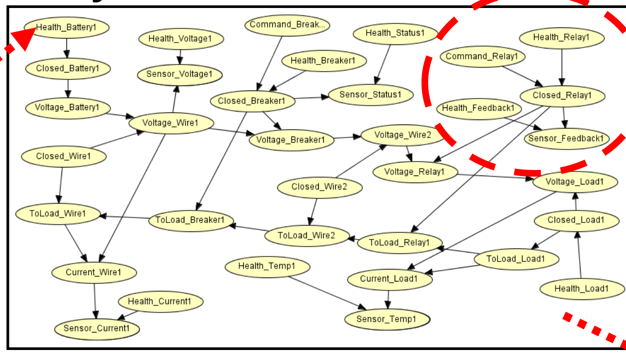


- Milestone 1.2.2.2 – Bayesian Methods and Hybrid Reasoning Techniques:
  - ii) Investigate the modeling of at least three faults types such as continuous, intermittent (transient), cascading, and/or dynamic faults, using Bayesian networks. The selection of the fault types will be informed by the Adverse Events Table as well as the capabilities of the testbed in which the novel approach will be validated. Demonstrate, in experiments, better than 85% accuracy for diagnosing the selected fault types. (FY09Q4).
- Milestone 1.2.2.2 flows into Milestone 2.1.2.1 – Validation Methodologies and Tools for the Diagnosis of Failures
- Principal Investigator : Ole J. Mengshoel (Carnegie Mellon Silicon Valley/NASA ARC)
  - Joint work with: S. Poll (NASA ARC), B. Ricks (University of Texas at Dallas), K. Cascio (UCLA), M. Chavira (UCLA/Google), A. Darwiche (UCLA), D. Garcia (SGT/NASA ARC), T. Kurtoglu (MCT/NASA ARC), D. Nishikawa (NASA ARC), S. Uckun (NASA ARC/PARC)

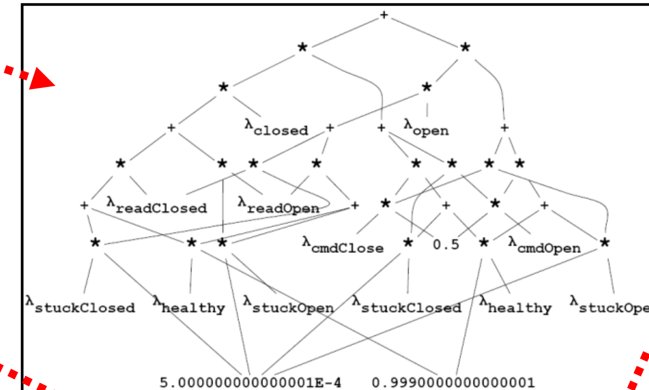
Probabilistic Diagnosis Approach

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

Bayesian network

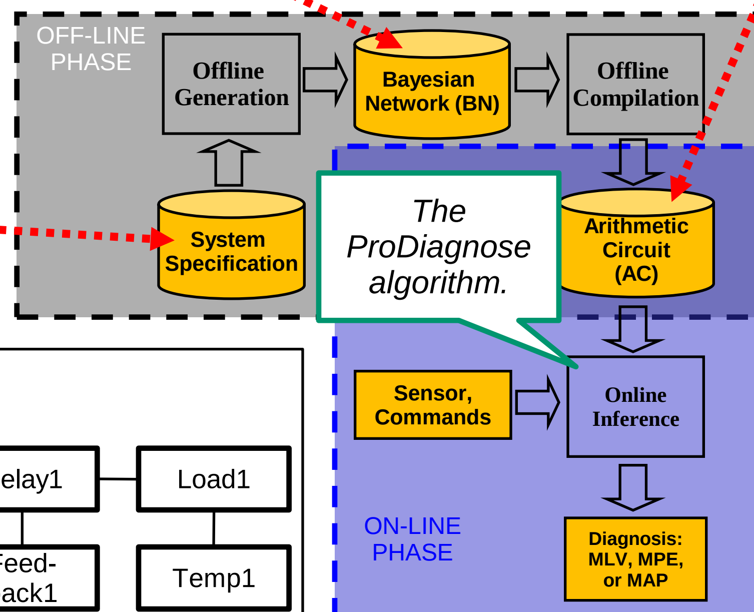


Arithmetic circuit

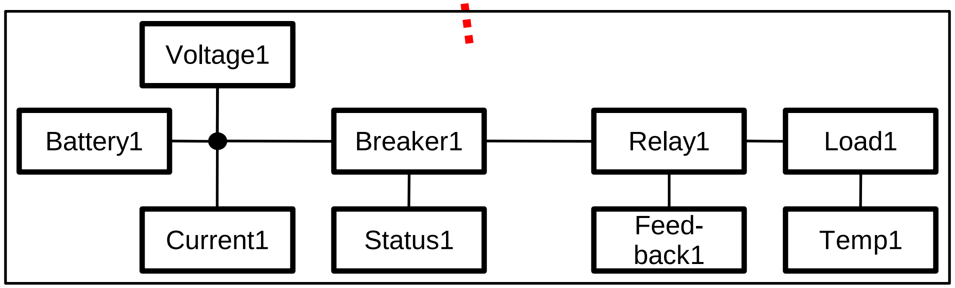


Specification language

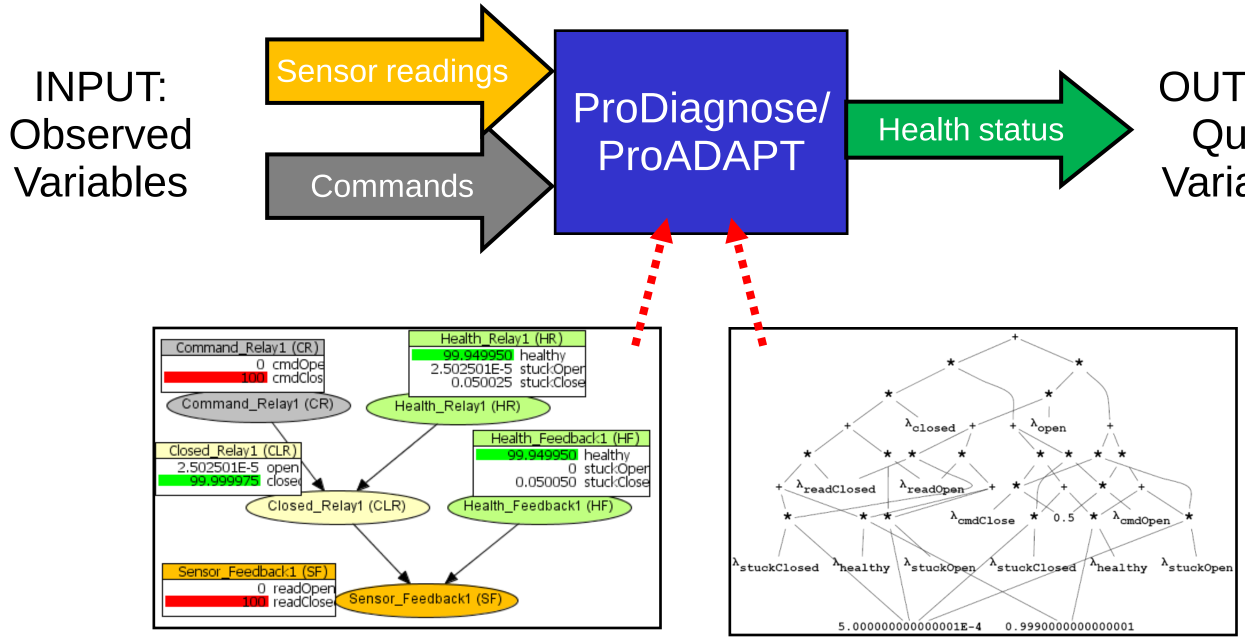
Battery1	: battery	: 0.0005;	
Wire1	: wire	: 0.0000	: Battery1;
Voltage1	: sensorVoltage	: 0.0005	: Wire1;
Current1	: sensorCurrent	: 0.0005	: Wire1;
Breaker1	: breaker	: 0.0005	: Wire1;
Status1	: sensorTouch	: 0.0005	: Breaker1;
Wire2	: wire	: 0.0000	: Breaker1;
Relay1	: relay	: 0.0005	: Wire2;
Feedback1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

These are the fault types considered in this talk.

- Independent faults
  - Abrupt
    - Permanent
      - Discrete
      - Continuous (parametric)
    - Intermittent
  - Incipient
- Dependent faults
  - Common cause
  - Cascading

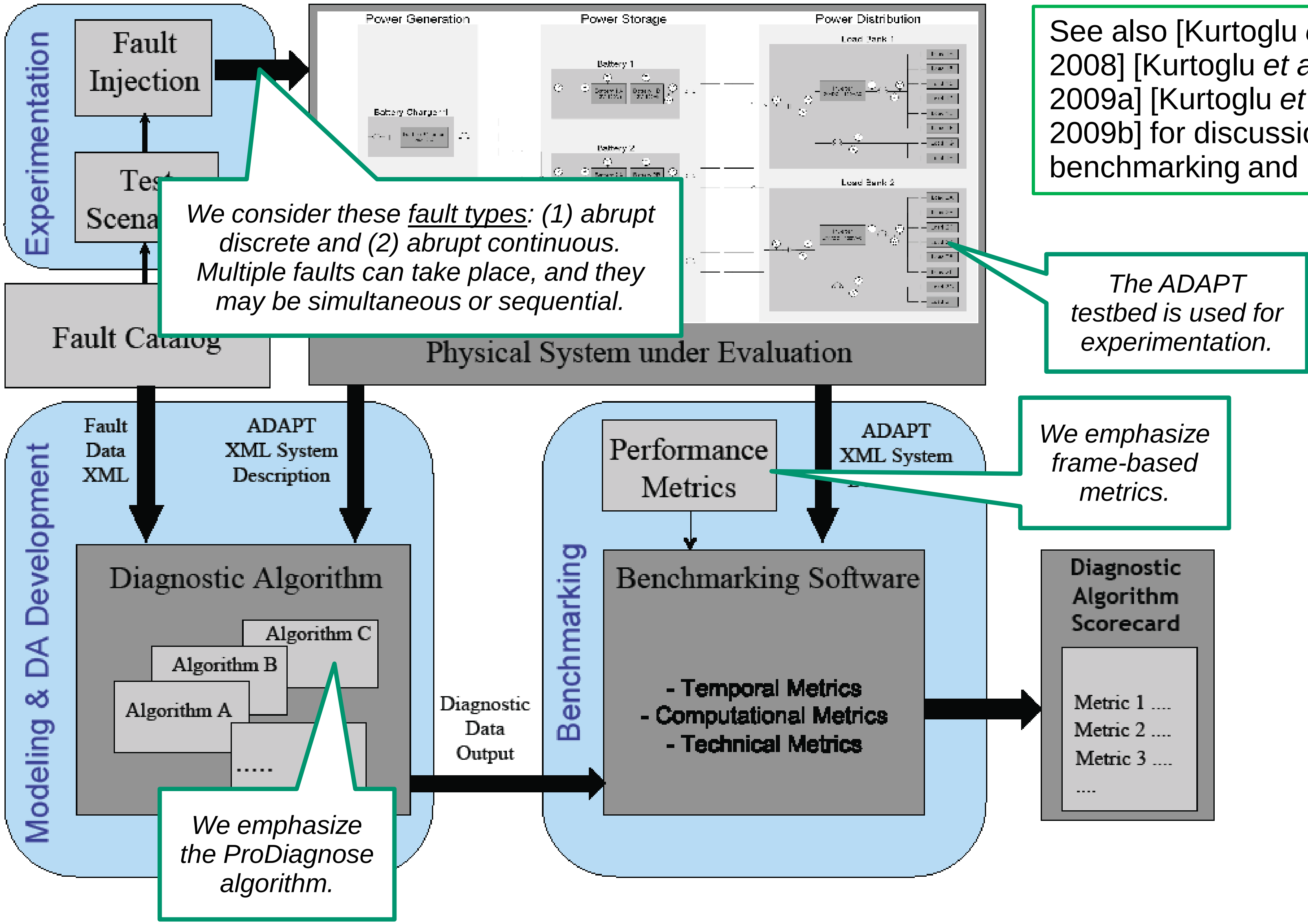
Component	Fault Description
Battery	Degraded
Boolean Sensor	Stuck at Value
Circuit Breaker	Tripped Failed Open Stuck Closed
Inverter	Failed Off
Relay	Stuck Open Stuck Closed
Sensor	Stuck at Value Offset
Pump(Load)	Flow Blocked Failed Off
Fan(Load)	Over Speed Under Speed Failed Off
Light Bulb(Load)	Failed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

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

Related Research

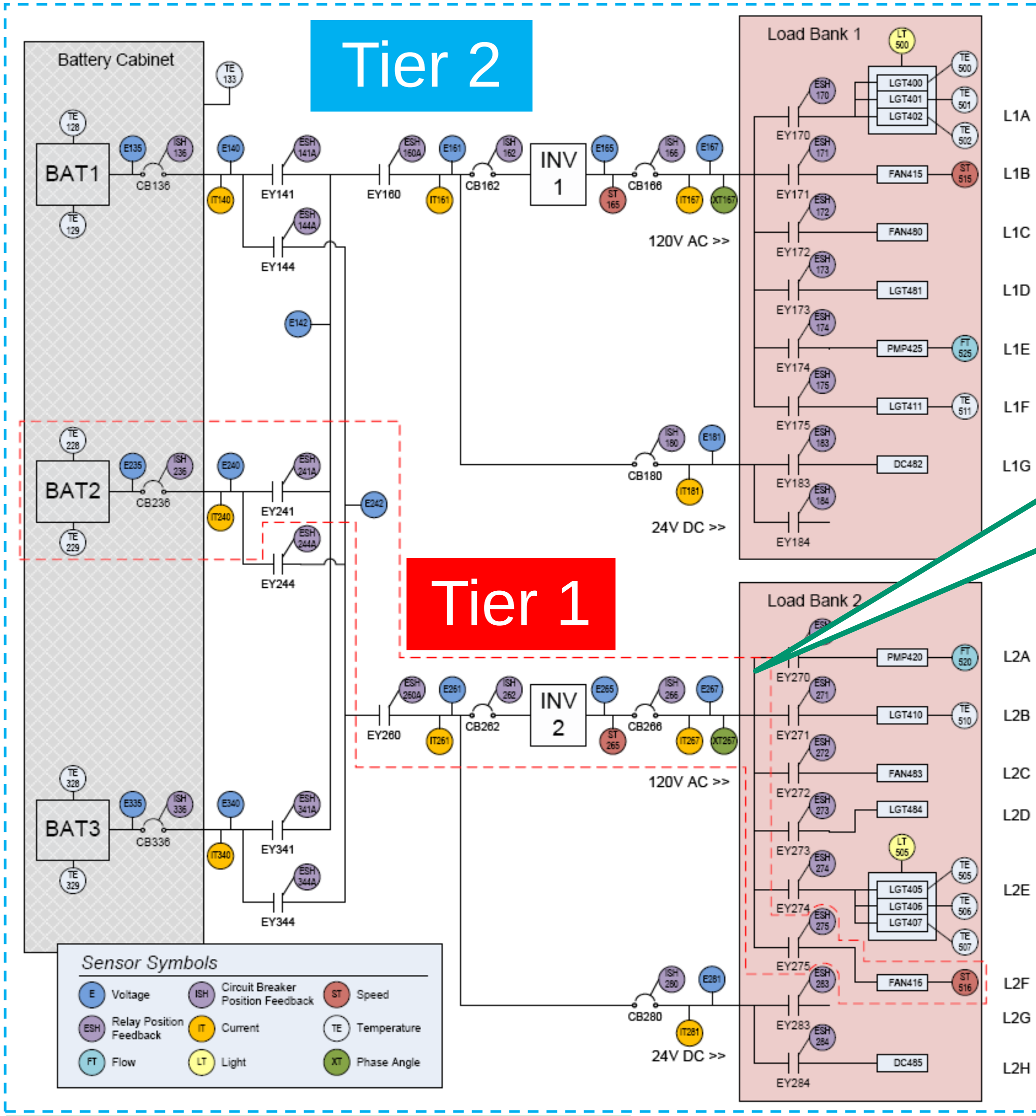
- Using Bayesian networks
  - hybrid (discrete + continuous) BNs:
    - clique tree based [Spiegelhalter & Lauritzen, 1988] using linear Gaussians [Olesen, 1993]
    - particle filtering [Koller & Lerner, 2000]
  - discrete BNs:
    - fault diagnosis in terrestrial EPSs [Yongli *et al*., 2006], [Chien *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]

Benchmarking Architecture



See also [Kurtoglu *et al.*, 2008] [Kurtoglu *et al.*, 2009a] [Kurtoglu *et al.*, 2009b] for discussion of benchmarking and metrics.

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

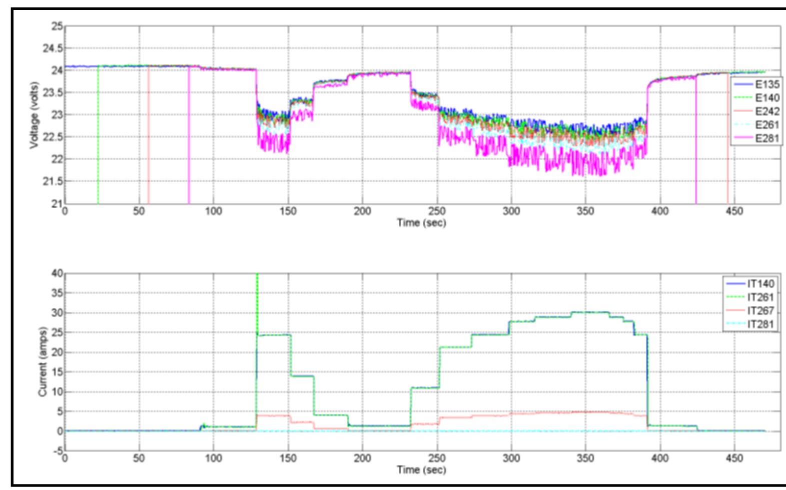
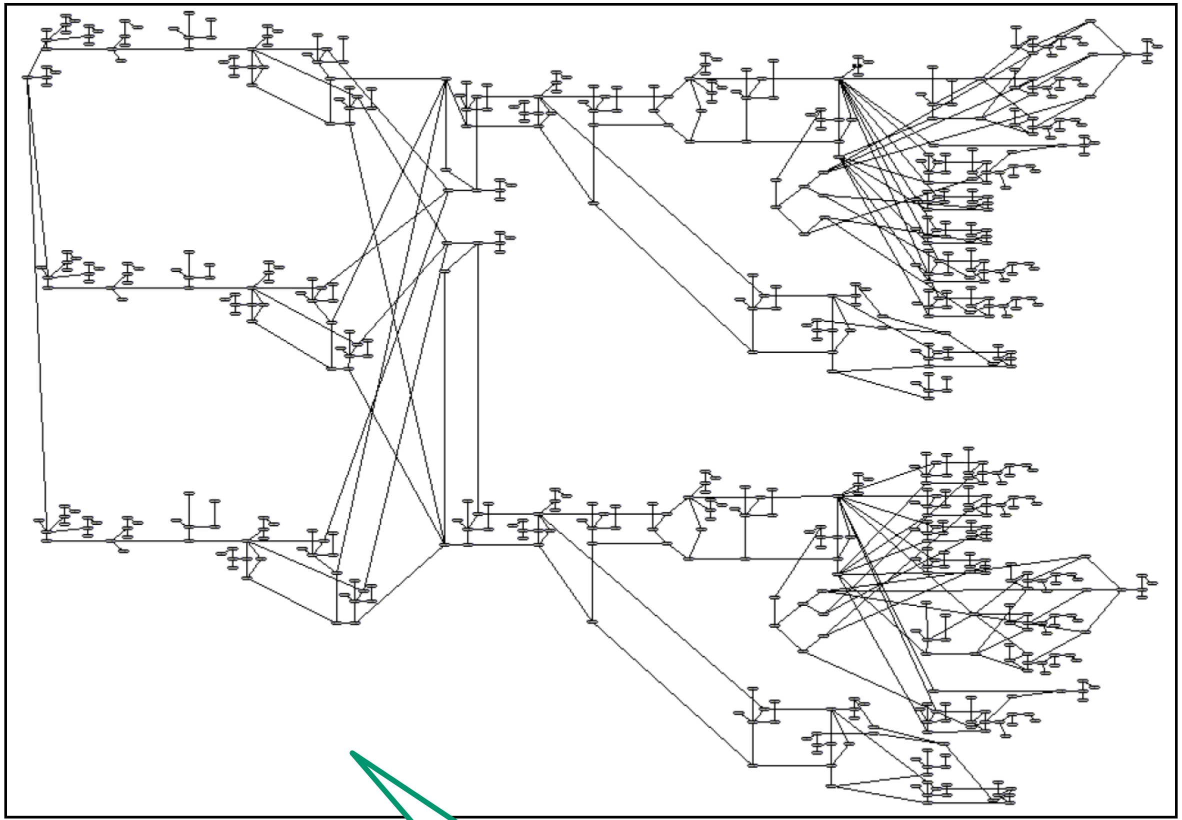


Figure from [Kurtoglu *et al*., 2009b].

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	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

Metrics for Diagnostics

1. **Detection Accuracy**: The ratio of correctly classified experiments (scenarios) to the total number of experiments.
2. **Classification errors**: The Hamming distance between the true component mode vector and the diagnostic algorithm's component mode vector.
3. **False Negatives Rate**: The ratio of experiments where a fault is missed while the system was actually faulty.
4. **False Positives Rate**: The ratio of experiments where a fault is announced by the DA while the system was actually non-faulty, or where a fault is announced too early.
5. **Mean CPU Time**: Average CPU load during an experiment, averaged over all experiments.
6. **Mean Time To Detect**: The period of time from the beginning of a fault injection to the moment of the first “high” detection signal.
7. **Mean Time To Isolate**: The period of time from the beginning of a fault injection to the start of the last persistent “high” isolation signal.
8. **Mean Peak Memory Usage**: The maximum memory size at every step in an experiment, averaged over all experiments.

Experiments, ADAPT Data (1)

- 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

	ADAPT DXC Tier 1			ADAPT DXC Tier 2		
Metric	**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, ADAPT Data (2)

ProADAPT1: The May 2009 version of ProADAPT.

DXC-09 ADAPT Industrial Track Tier 2						
	ProDiagnose (ProADAPT1)	**FaultBuster**	**HyDE**	**RODON**	**Stanford**	**Wizards Of Oz**
False Positives	7.32%	81.43%	0.00%	54.17%	32.16%	51.06%
False Negatives	13.92%	24.00%	30.00%	9.72%	5.19%	9.59%
Classification Errors	76	130	121.57	84.01	110.55	159.25
Detection Accuracy	88.33%	42.50%	80.00%	72.50%	85.00%	74.17%
Mean Time to Detect	5973 ms	14099 ms	17610 ms	3490 ms	3946 ms	30742 ms
Mean Time to Isolate	11988 ms	37808 ms	21982 ms	36331 ms	14103 ms	47625 ms
Mean CPU Time	2922 ms	5798 ms	29612 ms	80261 ms	963 ms	23387 ms
Mean Peak RAM Usage	6539 KB	10261 KB	20515 KB	29878 KB	5912 KB	7498 KB

ProDiagnose: Latest ADAPT Tier 2 Results Using DXC-09 Industrial Track Tier 2 Scenarios		
	ProADAPT1	**ProADAPT2**
False Positives	7.32%	0.00 %
False Negatives	13.92%	1.25 %
Classification Errors	76	20
Detection Accuracy	88.33%	99.17 %
Mean Time to Detect	5973 ms	2096 ms
Mean Time to Isolate	11988 ms	10961 ms

ProADAPT2: The September 2009 version of ProADAPT .

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.

Next Steps in Research

- **FY10:** Using the Bayesian modeling approach, and reflecting the fault types and test bed(s) investigated in FY09, the team plans to develop Bayesian methods and/or models for varying operating conditions and:
  - demonstrate fault detection/diagnosis on at least three faults types such as discrete, continuous, abrupt, transient, or cascading faults
  - examine tradeoff between accuracy and diagnosis time
- We aim to demonstrate, in experiments, better than 95% accuracy for diagnosing faults in sub-scale experiments in real-time (FY10Q4).

- **Beyond FY10:** Demonstration on vehicle of interest to NASA; Consideration of both learning and reasoning; Integration of diagnosis and reconfiguration; Integration with other (and multiple) sub-systems; Integration into control loop; …

Summary

- ***Diagnostic challenges*** 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.*

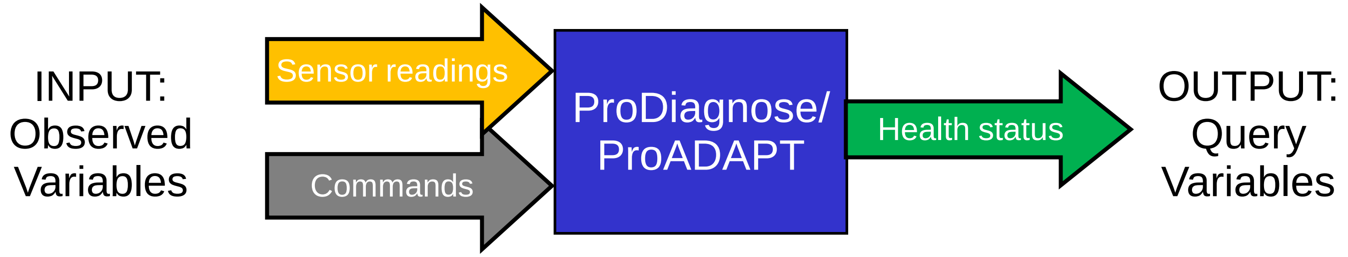
Web and Publications

- Further details:
  - 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.

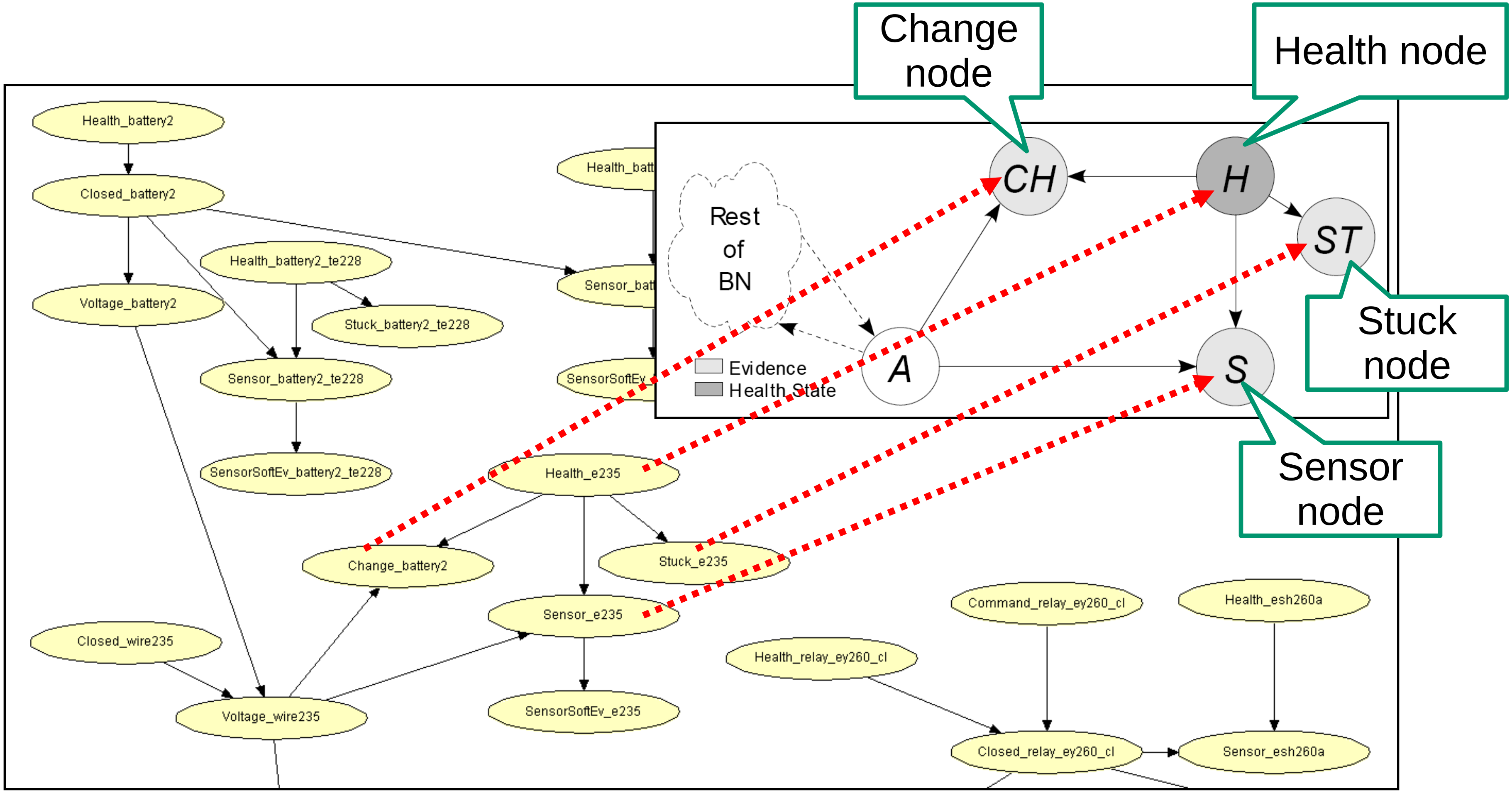
Background Material

Bayesian Network Node Types

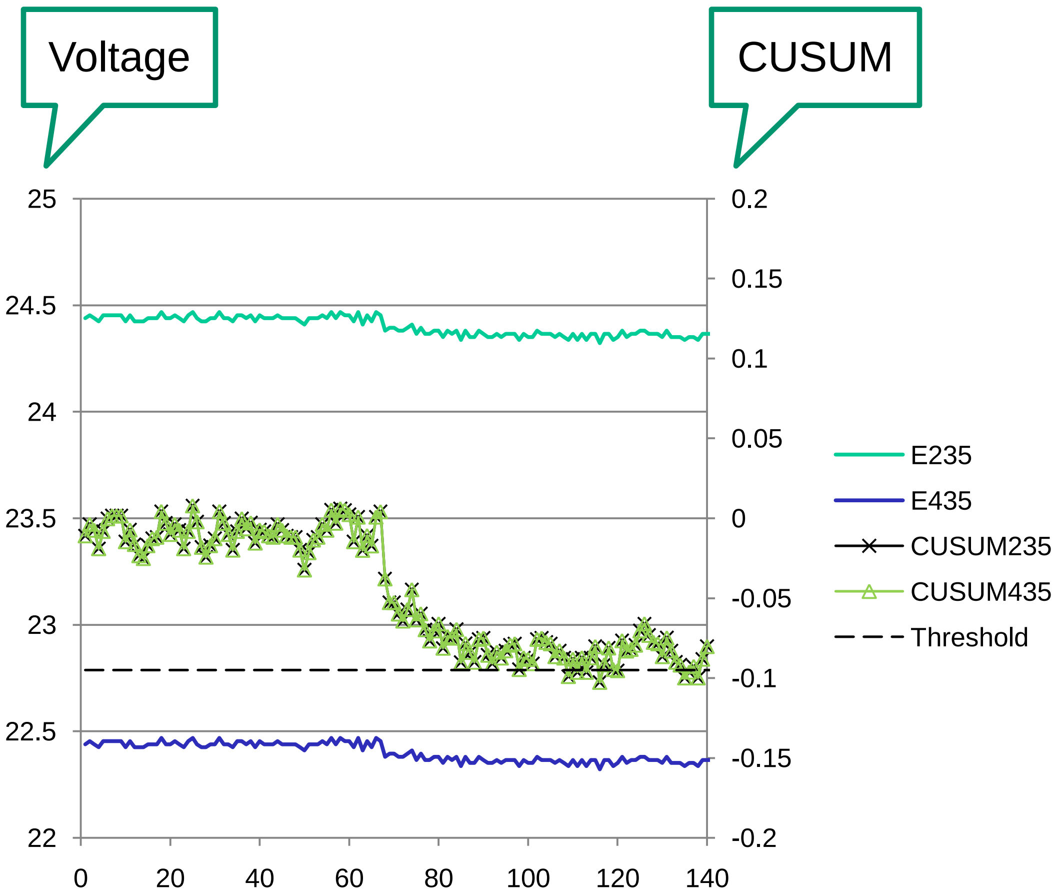


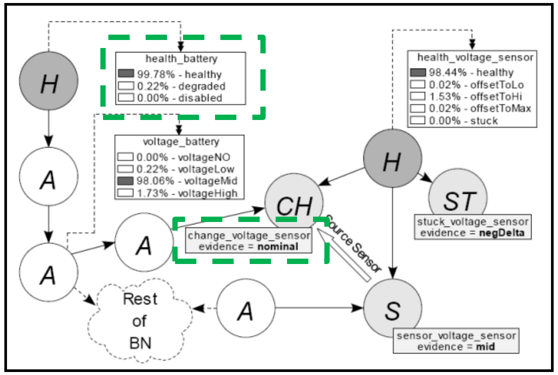
- A command node $C \in \mathbf{C}$, derived from ***C(t),*** represents a command given to a component. An example is a command to open or close a relay.
- A sensor node $S \in \mathbf{S}$ represents the current reading of a sensor. The state of *S* is
  - discretized from a real-valued sensor reading *S(t)*, or
  - the actual state of 0 or 1 for a boolean position sensor *S(t)*.
- A health node $H \in \mathbf{H}$ represents the current health state, normal or abnormal, of a component or sensor.
  - The states of ***H*** are computed using an exact or approximate (i) marginal, (ii) most probable explanation (MPE), or (iii) maximum aposteriori probability (MAP) query.
  - Abnormal states are output as one candidate in the candidate set ***D(t)***
- A stuck node $ST \in \mathbf{ST}$ represents the stuck state of a sensor. A sensor becomes stuck when its reading is the same over a period of time, regardless of what the underlying process state is.
- A delta node $D \in \mathbf{D}$ represents the discretized difference (delta) between the current sensor reading *S(t)* and its previous reading *S(t – 1).*
- A change node $CH \in \mathbf{CH}$ represents overall trends in sensor readings (long term behavior), computed CUSUMs.

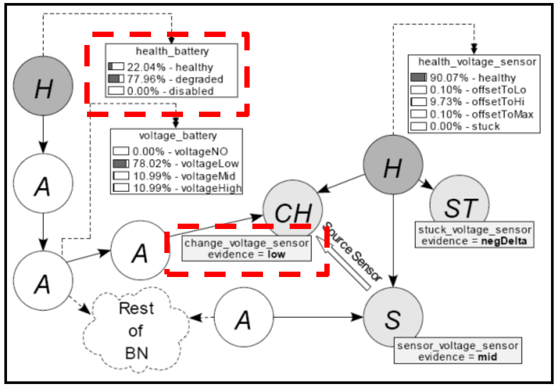
CUSUM – Continuous Faults (1)



CUSUM – Continuous Faults (2)







$$CUSUM(t) = S(t) - \left(w_0 S(t) + w_1 S(t-1) + w_2 S(t-2) + w_3 S(t-3)\right) + CUSUM(t-1)$$

$$CUSUM(t) = S(t) - \left(0.45 \times S(t) + 0.25 \times S(t-1) + 0.24 \times S(t-2) + 0.06 \times S(t-3)\right) + CUSUM(t-1)$$