CPS: Small: Collaborative Project: Fault Diagnosis and Prognosis in a Network of Embedded Systems in Automotive Vehicles

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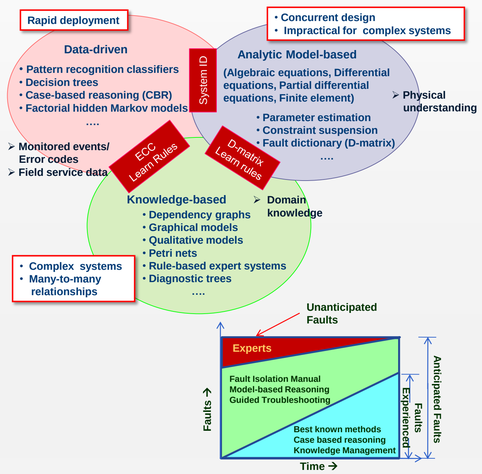
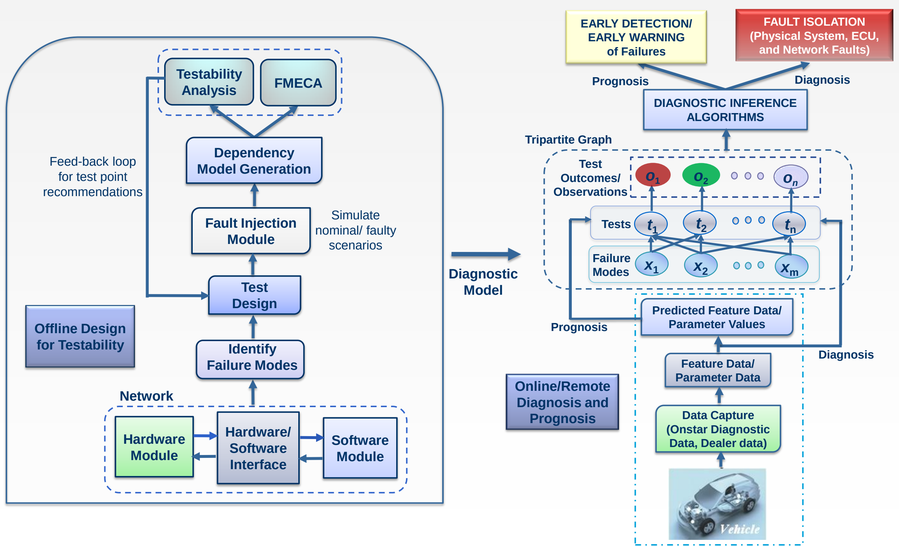
Overview

- Research objectives
  - Diagnosis of physical system, electronic control unit (ECU) and network faults
  - Fault prognosis to predict the remaining useful life (RUL) of physical components based on the inferred failing components and their tracked paths of degradation
- Technical approach
  - Dependency model generation for failure modes, effects and criticality analysis and test point optimization (Simulink®/PSAT + CANoe)
  - Coupled factorial hidden Markov models (CFHMM) + Lagrangian relaxation/Gauss-Seidel + Viterbi for online inference of *multiple, coupled and intermittent* faults
    - Dynamic multiple fault diagnosis (DMFD) with *delayed* observations, dynamic coupled fault diagnosis (DCFD), dynamic fusion of classifiers, dynamic set covering (DSC) and DSC with *delayed* observations (DDSC)
  - Prognosis in *coupled* systems based on failure time, parametric and dynamic signal data
    - Cox proportional hazard model (COX-PHM) and Soft DMFD inference algorithm to estimate the degradations of multiple components coupled by observations
    - Multiple model moving horizon estimation (MM-MHE) algorithm for predicting component survival functions
- Future research: validation of diagnostic and prognostic algorithms on the regenerative braking system in hybrid electric vehicles
- Benefits
  - Reduced mean time to repair
  - Increased vehicle availability
  - Improved customer satisfaction
  - Reduced cost of service and warranty costs

Diagnostic Approaches



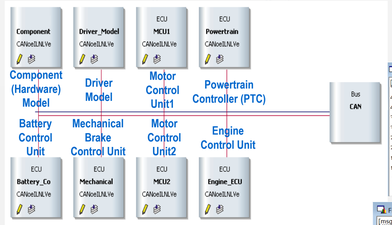
Integrated Diagnostic and Prognostic (D&P) Framework



Application of D&P Framework to Regenerative Braking System (RBS)

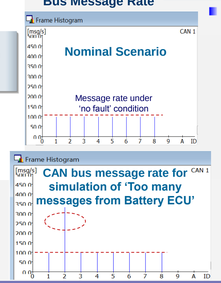
- Cyber-physical challenges
  - Complex system architecture with interactions among multiple subsystems
  - Modeling multiple ECUs in CANoe Software (Vector CANTech Inc.)
  - Enumeration of fault set and design of tests
- Simulation-based fault injection
  - Fault simulations via customized graphical user interface in CANoe software
    - Sensor faults: engine speed sensor fault, battery current sensor fault, battery temperature sensor fault, motor current sensor faults, motor speed sensor faults, vehicle speed sensor fault
    - Parametric faults: clutch inertia fault, wheel inertia fault, wheel radius fault
    - Software logic fault: battery initial SOC fault
    - Network faults: message loss, too many messages sent in a given time frame, data values of a received message are faulty

Simulation Setup of Regenerative Braking System in CANoe

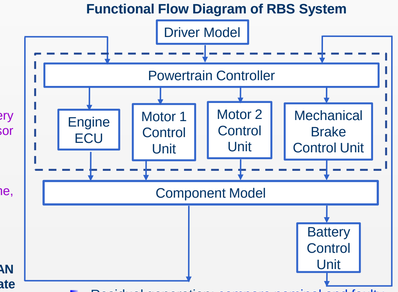


Message ID	Source (S) – Destination (D) Node (ECU)
1, 5	PTC (S) – Motor1 Control Unit (D)
2	Battery Control Unit (S) - PTC (D)
3, 8	PTC (S) – Motor2 Control Unit (D)
4	PTC(S) - Mechanical Brake Control Unit (D)
6, 7	PTC (S) – Engine ECU (D)

Histogram of CAN Bus Message Rate

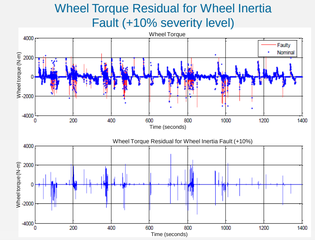


Functional Flow Diagram of RBS System



- Residual generation: compare nominal and faulty scenarios (fault inserted at t=0 seconds)

Wheel Torque Residual for Wheel Inertia Fault (+10% severity level)



Application of D&P Framework to Electric Power Generation and Storage (EPGS) System

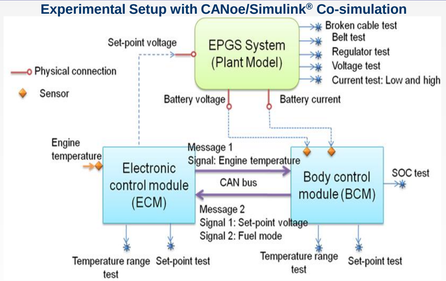
- Enumeration of failure modes: component-level hardware plant faults, software and controller faults

Fault (Fault No.)	
Broken cable (F1)	
Belt slip (F2)	
Voltage regulator (F3)	
Temp. out of range	Temperature fault due to ECM/sensor (F4)
	Temperature fault due to BCM software/communication (F5)
Battery current sensor	High (F6)
	Low (F7)
Battery voltage sensor: Low or High (F8)	
Set-point voltage out of range	BCM software/error in the logic (F9)
	ECM software/communication fault (F10)
Initial SOC estimation fault (F11)	

- Test design

Test (Test No.)	
Broken cable: battery current < -20A for 10 seconds (T1)	
Belt slip: estimated pulley ratio < 3 (T2)	
Voltage regulator: |Battery voltage – Set-point voltage| < 1V (T3)	
Temperature range test: Temp ∉ [-30 – 40 C]	ECM sensor test (T4.1)
	BCM test (T4.2)
Current range test: Current ∉ [-60 – 100 A]	Too low (T5.1)
	Too high (T5.2)
Voltage range test: Voltage ∉ [9 – 16 V]	Too low (T6.1)
	Too high (T6.2)
Set-point voltage test: (Fuel economy mode & Vset > 13 V) || (Normal mode & Vset <=13 V)	Test in BCM (T7.1)
	Test in ECM (T7.2)
SOC range test: Estimated SOC ∉ [40 – 100 %] (T8)	

Experimental Setup with CANoe/Simulink® Co-simulation



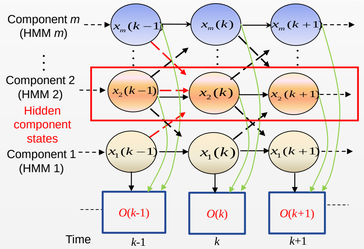
- Fault-test dependency model generation via fault simulations
- Simulation setup
  - US FTP-75 drive cycle for 1315 seconds
  - Fault injection in MATLAB/ CANoe environment
  - Permanent and intermittent faults are injected over time
  - Test outcomes are provided to DMFD algorithm for fault inference

Inference Results via DMFD

Fault No.	Average classification rate	Average false isolation rate
F1	99.7 ± 0.3	0.02 ± 0.03
F2	97.4 ± 6.4	0.4 ± 1
F3	91.8 ± 6.4	0.005 ± 0.004
F9	100	1.1 ± 2.2
F10	99.97 ± 0.04	0
F11	100	0

Dynamic Coupled Fault Diagnosis

- CFHMM framework to diagnose dependent faults occurring over time



- Validated on many real world models
- Improves diagnostic accuracy
- Computationally efficient

- Each component is modeled as a hidden Markov model (HMM): coupled via observations
- Independent HMMs (depends on its own prior state) ⇒ *solved via Viterbi algorithm*
- Dependent faults (depends on prior states of other components) ⇒ *solved via mixed memory Markov model and Viterbi algorithm*
- Iterative block coordinate ascent (Gauss-Seidel) optimization to overcome the complexity due to coupling among faults

Problem: Find maximum *a posteriori* (MAP) solution; fault states are coupled:

$$\hat{X}^K = \arg\max_{X^K=\{\underline{x}(1),\underline{x}(2),\ldots,\underline{x}(K)\}} \Pr\left(X^K \mid O^K, \underline{x}(0)\right) \Rightarrow \max_{X^K} \sum_{k=1}^{K} f_k(\underline{x}(k), \underline{x}(k-1));$$

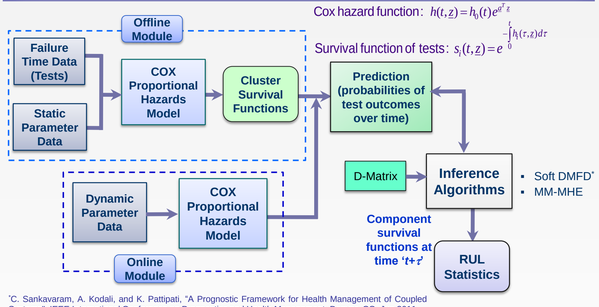
$$\text{where } \underline{x}(k), \underline{x}(k-1) \in \{0,1\}^m$$

A. Kodali, K. Pattipati, S. Singh, "A Coupled Factorial Hidden Markov Model (CFHMM) for Diagnosing Coupled Faults", submitted to *IEEE Transactions on Systems, Man, and Cybernetics: Part A*, Jan 2011.

Prognosis in Coupled Systems

Cox hazard function: $h(t,\underline{z}) = h_0(t)e^{\theta^T \underline{z}}$

Survival function of tests: $s_i(t,\underline{z}) = e^{-\int_0^t h_i(\tau,\underline{z})d\tau}$



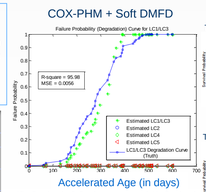
*C. Sankavaram, A. Kodali, and K. Pattipati, "A Prognostic Framework for Health Management of Coupled Systems", IEEE International Conference on Prognostics and Health Management, Denver, CO, Jun 2011.

- Validation of prognosis approach on an **electronic throttle control (ETC)** subsystem

Dealer diagnostic data
- Diagnostic trouble codes (DTCs): 11
- Parameter identifier data (PIDs) : 479 (top 16 PIDs used for analysis via mutual information)
- Repair codes (LCs): 5
- Age of the vehicle

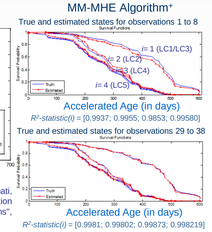
Repair Code	Repair Code Description
LC1	Accelerator Pedal Replacement
LC2	Throttle Body Assembly Replacement
LC3	Accelerator Pedal Position Sensor Replacement
LC4	Powertrain Control Module Replacement
LC5	Throttle Position Sensor Replacement

COX-PHM + Soft DMFD



*B. Pattipati, C.Sankavaram, and K. Pattipati, "Multiple Model Moving Horizon Estimation Approach to Prognostics in Coupled Systems", submitted to IEEE Autotestcon, 2011.

MM-MHE Algorithm*



R^2-statistic(i) = [0.9937; 0.9955; 0.9853; 0.99580]

R^2-statistic(i) = [0.9981; 0.99802; 0.99873; 0.998219]