Agent Autonomy Approach to Probabilistic Physics-of-Failure Modeling of Complex Dynamic Systems with Interacting Failure Mechanisms

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Outline

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Background

- Probabilistic Physics-of-Failure (PPoF) approach is a powerful method of *component* reliability analysis because it relies on understanding the underlying physical processes
- Taking PPoF approach to the modeling of a *complex dynamic system* is challenging, due to the complexity of system logic and system dynamics, specifically dependencies of failure modes and mechanisms under variable operational conditions.
- Traditional techniques of system reliability[1] including dynamic techniques[2] often do not provide a structured framework for incorporation of *PPoF models* of system components and for capturing *dynamic behavior of complex system*.

Motivation

- New methodology of system reliability modeling is required to make a paradigm shift away from the analysis methods solely driven by field and test data and towards physics-of-failure (PoF) methods.
- Physics-of-Failure (PoF) based modeling technique, needs to be expanded for applications to reliability modeling of **complex engineering systems**.
- The new methodology should be capable of modeling :
  - Interaction and interdependency of failure mechanisms of complex systems
  - Dynamics of environmental conditions and operational inputs from other components
  - Degraded states of the system

[1] *Fault Trees, Event Trees, Reliability Block Diagrams*
[2] *Markov Chains, Stochastic Petri Nets, Dynamic Event Trees, other dynamic techniques*

Research Approach

- "Agent Autonomy" concept used as a solution method for PPoF system modeling.
- Originated from Artificial Intelligence (AI) as a leading intelligent computational inference in modeling of Multi Agents Systems (MAS).
- In agent-oriented approach each agent has the following capabilities:
  - Sense the environment and collect critical information;
  - Define state evolution autonomously and without interference of environment or other agents;
  - Share properties and the current state with other agents.
- The concept of agent autonomy in the context of system reliability modeling was first proposed by Azarkhail [1].
- The current research extends Azarkhail's approach to make agents autonomous with better learning capabilities.

[1] Azarkhail, M., "Agent Autonomy Approach to Physics-Based Reliability Modeling of Structures and Mechanical Systems", PhD thesis, University of Maryland, College Park, 2007.

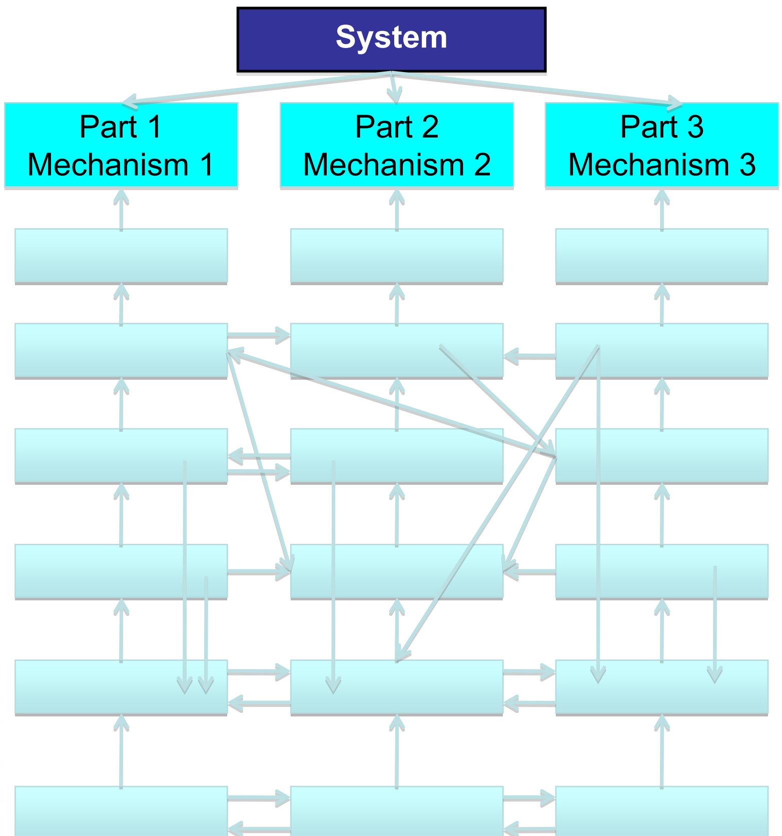
Research Approach (cont.)

- Introduce a new agent classification to better account for degradation and failure processes.
- Identify agent properties within the scope of system evolution in time.
- Introduce agent learning and agent autonomy as the main properties of intelligent agents.
  - The autonomous agents are able to activate, deactivate or completely redefine themselves during the analysis.
  - Agent autonomy makes this approach fundamentally different from all existing methods of PoF-based reliability modeling.
- Present an example of agent-oriented PPoF modeling of complex engineering system to demonstrate the methodology.

[1] Azarkhail, M., "Agent Autonomy Approach to Physics-Based Reliability Modeling of Structures and Mechanical Systems", PhD thesis, University of Maryland, College Park, 2007.

Concept Description

- Each system may be decomposed to failure mechanisms of its components (parts) . Failure mechanisms are described by PoF relationships.
- Consider complex multilevel interdependency of failure mechanisms of the dynamic system gives a specific example.
- The agent-oriented PoF approach provides a structured formalism of modeling this type of interdependency via two-way interactions.



$$T = \min_{i,j}(T_{p_i m_j})$$

Probabilistic Life: Probabilistic Life Model (Mechanistic or Physics of Failure)

Stress or Strength vs. Life: Mechanistic or Physics of Failure Life Model, for Failure Time or Time to Degradation

Stress-Strength Variables: Relationships for Stress variables Causing Degradation or Failure when Strength is exceeded

Enablers: Relationships Connecting Coupling Factors to Stress-Strength Variables

Coupling Factors: Inter Factors - Operational Variables (Internal to the Part)

Coupling Factors: Intra Factors - Environmental / Operational Variables (External to the Part)

Concept Description (Cont.)

Probabilistic-Mechanistic Life Model of Ball Bearing for the Rolling Contact Fatigue - Wear Mechanism (Fatigue Cracking and Formation of Flake-like Wear Particles)

$$\pi(N;n,\kappa,\sigma\,|\,Data) \propto L(Data\,|\,N;n,\kappa,\sigma) \bullet \pi(n,\kappa,\sigma)$$

$$N(Cycles\ to\ Failure) \propto \left(\frac{1}{S}\right)^{n};\quad LnN = \kappa - nLnS$$

$$S \propto \underbrace{g(\Delta P,T)}$$

Finite Element Model

$$T = h(V,T_0,OP)$$

$$P(Load - Hertzian\ Contact\ Stress) \propto g(Design\ Specs, V, Grms, L, M)$$

Design Specs (Material, Surface roughness, Surface defects, Geometrical Tolerances, other), Operating Speed (V), Lubricant oxidation & degradation properties (L)

Duty Cycle / Operating Profile (OP), External Ambient Temperature (T_0), Maintenance (M), Operating Vibration (Grms)

Systems Equations

Probabilistic Life: Mechanistic or Physics of Failure Life Model

Stresses & Strength vs. Life: Mechanistic or Physics of Failure Model, for Failure Time or Time to Degradation

Stresses: Relationships for Stress Agents Causing Overload or Damage when Strength is exceeded

Enablers: Relationships Connecting Coupling Factors To Stresses

Coupling Factors: Describing Inter Environments

Coupling Factors: Describing Intra Environments

Definition of Agents

- Agent considered as a computer replica of:
  - Parameter, characteristic or feature of a hardware component or system;
  - Environmental or operational parameters;
  - Parameter, characteristic or feature of software program;
  - Characteristic or feature of human element.
- This computer replica:
  - contains all properties of the respective parameter, characteristic or feature,
  - mimics how it changes over time, and
  - is able to communicate with other agents by sharing necessary information.

Agent Classification

- The agent structure combines the agents of several types to:
  - Optimize use of available data and information, and
  - Allow bidirectional communication between agents when required to model complex interdependencies.
- Three types of agents are proposed:
  - Type I Micro-Agents,
  - Type II Macro-Agents,
  - Type III Monitoring Agents.
- Each variable of Probabilistic-Mechanistic Life Models is assigned with an agent of a certain type, for example:
  - Type I Micro Agents are assigned to Coupling Factors (Inter and Intra), such as T_0, *V, Grms, L, M*.
  - Type II Macro Agents are assigned to Enablers, Stress and Strength variables *P, T, S, N*.
  - Type III Monitoring Agent is assigned to the system state variable *T* as time to the arrival of the earliest failure.

Agent Classification (Cont.)

- Type I Micro-Agents is the highest granularity of agent autonomy representing single independent variables.

Type I. Micro-Agents	
Group A. Component Design Parameters *(Inter Coupling Factors)*	
1. Material properties	
2. Shape/Geometry/Dimensions	
3. Design & Manufacturing Tolerances	
Group B. Usage Stress Variables and Mission Parameters *(Intra Coupling Factors) /* **Component Performance Characteristics** *(Inter Coupling Factors)*	
Group B1. Operational Conditions	**Group B2. Environmental Factors**
1. Voltage	1.Temperature
2. Power	2. Thermal cycling range
3. Pressure	3. Humidity
4. Vibration	4. Moisture
5. Mechanical Load Characteristic	5. Concentration of reactive substances (salt, acid)
(of any type, e.g. Stress Amplitude)	6. Icing
6. Acceleration	7. Dust, dirt, grease, oil, other contaminants
7. Electromagnetic Impact	8. Radiation
8. Speed	9. Lightning
9. Altitude	10. Atmospheric pressure
Group B3. Human Factors	
Various factors due to human interaction during system operation and maintenance	
Group B4. Component Performance Parameters	
Various parameters / characteristics of a piece part, a component or the system which, due to lack of engineering knowledge, cannot be expressed as a combination of other types of agents (from Groups A, B1 to B3) to form a Type II Macro-Agent (defined below)	

Agent Classification (Cont.)

- Higher abstraction level are called Type II Macro-Agents are defined as a combination of two or more Micro-Agents via PoF based relationship.
  - More complex Macro-Agent may combine several Micro- and Macro-Agents in the similar manner.
  - Example: Type II Macro Agent represents fatigue life N as a function of cyclic stress, where the model parameters *K* and *m* are internal attributes of this Type II agent, and stress amplitude, ΔS, is the input attribute represented by Type I Micro-Agent:

$$N \propto (\Delta S)^m \Rightarrow Ln(N) = K + m \cdot Ln(\Delta S) \qquad (1)$$

- Type III Monitoring Agents collect information about the status of each part, component and the system by aggregating information from Type I and Type II agents into part level status, then further into component level status and finally into the status of the system.

Type II. Macro-Agents *(Enablers, Stress and Strength Variables, Life / Time to Failure)*
Any agent constructed as a combination of two or more Type I Micro-Agents agents of any category (Groups A and B)
Type III. Monitoring Agents
1. System-Monitoring Agents
2. Component-Monitoring Agents
3. Part-Monitoring Agents

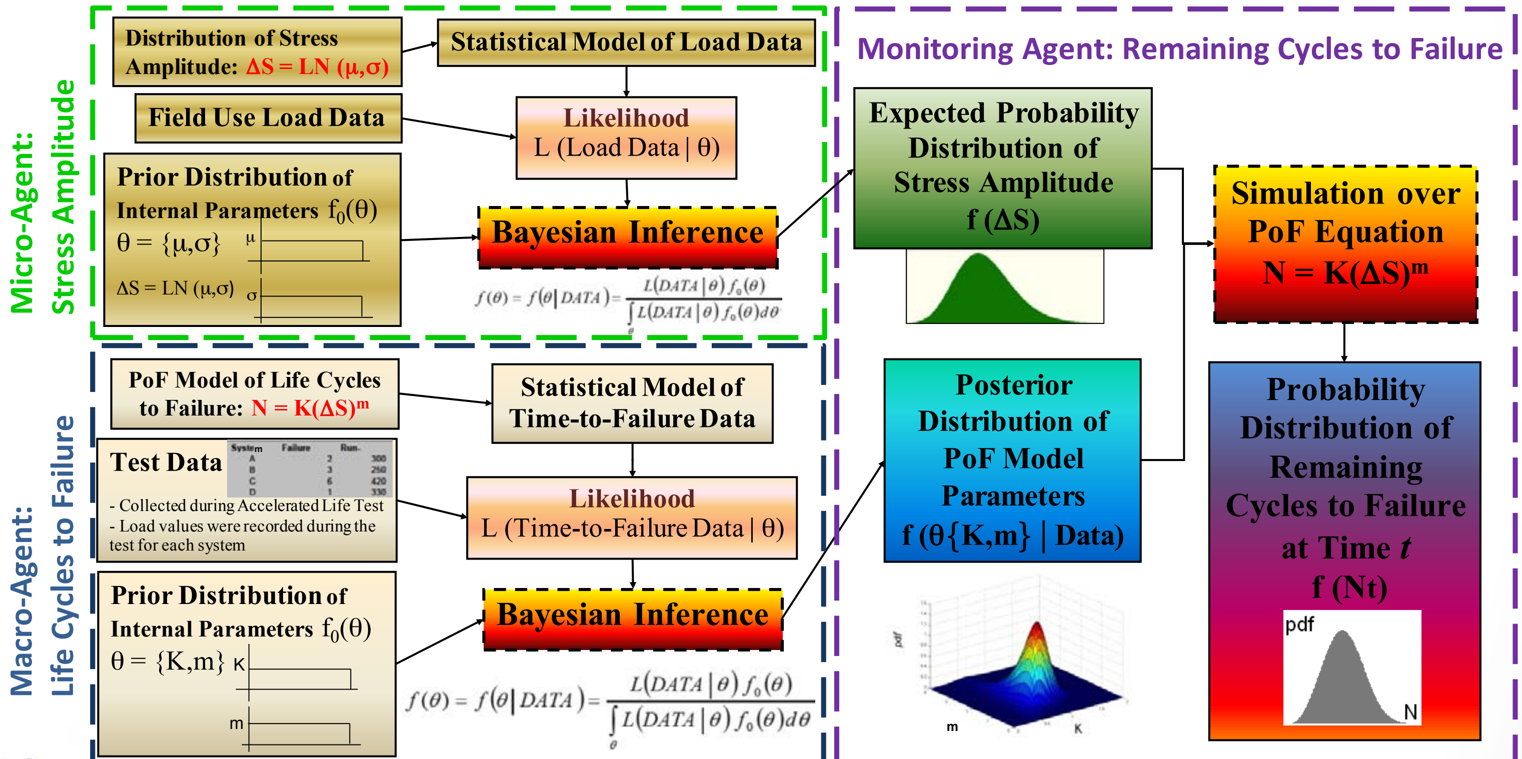
Main Properties of Agents

- Learning
  - The ability of agent to learn from the new data and previous experiences.
  - Learning Property of Type I and Type II agents can be formalized by the means of:
    - Bayesian Inference,
    - Bayesian Fusion approach (for example, Kalman filter, extended Kalman filter),
    - Machine Learning methods (for example, Gaussian Process Regression model),
    - Time Series and Trend Analysis,
    - Bayesian Belief Network (BBN).
  - Type III Monitoring Agents learn and update themselves by aggregating information from Type I and Type II agents.
- Autonomy in Action
  - Self-activation / deactivation capability is another key property of autonomous agents providing then an ability of intelligent reasoning about their current state and further participation in system evolution.

Main Properties of Agents (Cont.)

- Learning

Difference in learning property of three types of agents using a simple example of fatigue life Type II Macro-Agent. Learning property of this agent was developed by means of Bayesian inference.



Case Study

Reliability Model of Gas Turbine Structures

Objective:

- Develop agent-oriented PoF reliability model for structural components of high pressure turbine of a turboprop engine: turbine disks, shaft and roller bearings.

Data collection:

- In-test monitoring and inspection

PoF input:

- Wear and fatigue failure mechanism of high-pressure components were considered;
- Interdependency of failure mechanisms acting on several components was identified (for example, wear and fatigue in the bearings affect progression of fatigue mechanism in the shaft).
- PoF-based relationships developed for the high-pressure turbine bearings from the first principles and considering bearing functionality under applicable operational stresses.

Case Study (Cont.)

PoF input:

- PoF equations for roller bearings:

$$L = B_1 R^k (B_2 R + B_3)^{-10/3} \quad (2)$$

$$N_B = \frac{(S_{pLimit})^{1-(m/2)}}{B_4 (B_5 R + B_6)^m \left(1 - \frac{m}{2}\right)}, m \neq 2 \quad (3)$$

$$S_p = \left[B_4 (B_5 R + B_6)^m \left(1 - \frac{m}{2}\right)(M - L) \right]^{\frac{1}{1-(m/2)}}, m \neq 2 \quad (4)$$

NOMENCLATURE

L = Bearing Life to Spall Initiation
L_1 = Bearing Life to Spall Initiation (for Bearing 1)
L_2 = Bearing Life to Spall Initiation (for Bearing 2)
N_B = Bearing Life to Spall Propagation
N_{B1} = Bearing Life to Spall Propagation (for Bearing 1)
N_{B2} = Bearing Life to Spall Propagation (for Bearing 2)
S_p = Bearing Spall Size after missions M
S_{p1} = Bearing Spall Size after missions M (for Bearing 1)
S_{p2} = Bearing Spall Size after missions M (for Bearing 2)
S_{pLimit} = Critical Size of a Spall
R = Tangential Force on the Turbine Wheel Disks
M = Accumulated Missions
$B_{j(l)}$ = Parameters of Physical Models, j = 1, …, 6 (six parameters), l = 1, 2 (two bearings)
k, m = Material Constants
T_{IT} = BOT (Burnet Outlet Temperature) at start
$\pi(R)$ = probability distribution of R
$\pi(T_{IT})$ = probability distribution of T_{IT}
$\{R_i\}$ = Data (measurements) for R
$\{T_{IT\,i}\}$ = Data (measurements) for T_{IT}
RUL = Remaining Useful Life of the System
RUL_{Bl} = Remaining Useful Life of Bearing l, l = 1,2

Model output:

- Remaining Useful Life (RUL) has been chosen to represent reliability of system of high-pressure turbine components considered in the case study..

Case Study (Cont.)

Agent hierarchy:

- The agents were assigned to the inputs and outputs of physical model of failure. Some examples of Type I Micro-Agents and Type II Macro-Agents

	Type I. Micro-Agents							
ID #	Agent Name	Letter ID	Public Properties					
			Agent Representation	Reasoning / Learning Capability	Affected Component	Time Dependent	Ability to Activate / Deactivate itself Probabilistically
1	**Tangential Force on the Turbine Wheel Disks**	***R***	• Probabilistic* • Monitored during operation to obtain **Data** ***{R_i}*** and distribution **π(R)**	Classical methods of distribution fitting to the **Data** ***{R_i}*** to obtain **π(R)**	Bearing	No	Yes
2	**BOT at start**	***T_{IT}***	• Probabilistic* • Monitored during operation to obtain **Data** ***{T_{ITi}}*** and distribution **π(T_{IT})**	Classical methods of distribution fitting to the **Data** ***{T_{ITi}}*** to obtain **π(T_{IT})**	Disk	No	Yes

Case Study (Cont.)

Type II. Macro-Agents							
			Public Properties				Private Properties
ID#	Agent Name and Quantity	Letter ID	Agent Representation	Equation used for Bayesian Reasoning / Learning	Micro- and Macro-Agents Involved	PoF Model Parameters	Representation of Agent PoF Model Parameters
	Component: **Bearings (2)**						
1 2	**Bearing Life to Spall Initiation (2)**	L_1 L_2	• Probabilistic * • PoF model per **Equation 2** *(below)*	**Equation 2** *(below)* Bearing Life to Spall Initiation	R	k $B_{1(1,2)}$ $B_{2(1,2)}$ $B_{3(1,2)}$	• Probabilistic** • Prior Distributions $\pi_{0(1,2)}(k, B_1, B_2, B_3)$ • Estimated from Data $\{L_{1i}, L_{2i}, R_i\}$
3 4	**Bearing Life to Spall Propagation to Critical Size (2)**	N_{B1} N_{B2}	• Probabilistic * • PoF model per **Equation 3** *(below)*	**Equation 4** *(below)* Bearing Spall Size $S_{pi1,2}$ after missions M_i	R S_{pLimit}	m $B_{4(1,2)}$ $B_{5(1,2)}$ $B_{6(1,2)}$	• Probabilistic** • Prior Distribution $\pi_{0(1,2)}(m, B_4, B_5, B_6)$ • Estimated from Data $\{M_i, R_i, S_{p1i}, S_{p2i}\}$

Type III. Monitoring Agents - Component-Monitoring Agents					
			Public Properties		
ID#	Agent Name and Quantity	Letter ID	Component	Agent Representation	Method of Agent Learning
1 2	**Remaining Useful Life of the Bearing (2)**	**RUL_{B1}** **RUL_{B2}**	Bearing (2)	Probabilistic* $RUL_{B(1,2)}$ = $= L + N_{B(1,2)} - M$	Simulation (Monte Carlo or Latin Hypercube)
Type III. Monitoring Agents - System-Monitoring Agent					
				Public Properties	
	Agent Name	Letter ID	Components Included	Agent Representation	Method of Agent Learning
3	**Remaining Useful Life of the System**	**RUL**	Bearings (2) Shaft (1) Disks (1)	Probabilistic * $RUL = Min\{RUL_{B1}, RUL_{B2}, RUL_S, RUL_D\}$	Simulation (Monte Carlo or Latin Hypercube)

Summary and Conclusions

- Developed an agent classification to allow representation of all levels of system component/part interactions and degradation.
- Agent representation is based on PoF model of the piece parts, components and the system according to the first principles of physical failure mechanisms.
- The agents are defined as intelligent and autonomous entities, due to their learning ability, reasoning capability and self-activation / deactivation.
- Several methodologies of probabilistic agent learning were proposed, including Bayesian inference and Bayesian Fusion (via Kalman filter or extended Kalman filter).
- Methods such as sensitivity analysis is used to support self-activation / deactivation property of intelligent agents.
- Agent-oriented PPoF modeling of a complex hardware system was demonstrated.