



An Information Theoretic Framework and Self-organizing Agent-based Sensor Network Architecture for Power Plant Condition Monitoring: DE-FE0007270

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- **Project Goals**
- **Project Objectives**
- **Technical Approach**
- **Expected Results**
- **Project Elements**
 - Information Architecture
 - Virtual Sensors and Sensor Processing
 - Self-organization
 - System Integration

Project Goals

Realizing the potential of next generation instrumentation systems

Year 1: Develop an *intelligent agent-based information theoretic architecture* to enable robust and flexible health and condition monitoring for advanced power plant applications.

Year 2: Develop self-organizing computational algorithms that *maximize the collection, transmission, aggregation, and conversion of data into actionable information* for monitoring, diagnosis, prognosis, and control of power plants.

Year 3: Demonstrate the viability and efficacy of an agent-based, information-theoretic system for real-time health and condition monitoring of power generation equipment and systems.

Project Objectives

Realizing a sensor network for health and condition monitoring

- Develop the theoretical foundations and the algorithms necessary to **elicit system structure from available measurements**.
- Develop the signal processing, filtering, and inference algorithms and software systems necessary to **detect, diagnose, and prognose** defects, degradation, and faults in power generation systems **at component, subsystem, and system levels**.
- Develop algorithms and software systems that enable a sensor network for condition monitoring of power generation plants to be **adaptive, resilient, and self-healing**.
- Evaluate the effectiveness of these computational algorithms in **maximizing information extracted** from power plant data and **realizing its value** for condition monitoring using a power plant simulation test bed.

Technical Approach

Systems viewed as communication networks

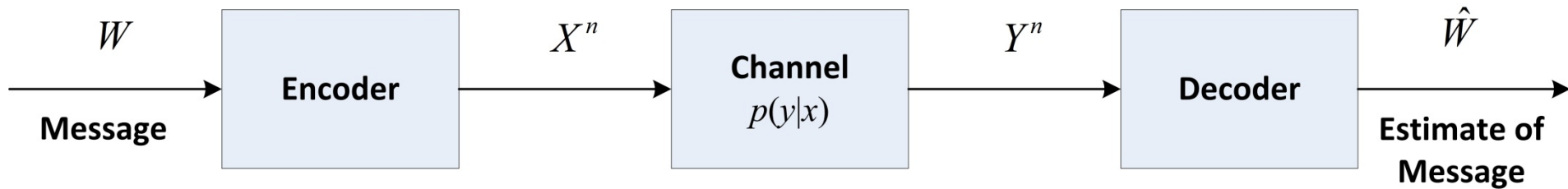
- **System elements are considered as nodes in a communication network;**
 - Elements send “messages” via physical media to other system elements,
 - Elements “process” messages from other elements and alter their states accordingly.
- **Instrumentation provides a means for accessing “messages”;**
 - Messages may be corrupted,
 - Messages may be missing.
- **Proper understanding of the observations requires an understanding of both the processing and the network topology!**

Data and Information are not the same!

- **Information is the amount of surprise contained in data;**
 - Data that tells you what you already know is not informative,
 - Not all data is created equal.
- **The fundamental measure of information is *Shannon entropy*:**
$$H(X) = - \sum_{x \in X} p(x) \log_d p(x)$$

Information Channels

Modeling Information Flow



- Let X and Y be the *input* and *output alphabets*, and let S be the set of channel states. An information channel is then a system of probability functions
- Mutual information between the input and output provides a measure of *channel transmittance*:

$$T(X;Y) = H(X) - H(X|Y)$$

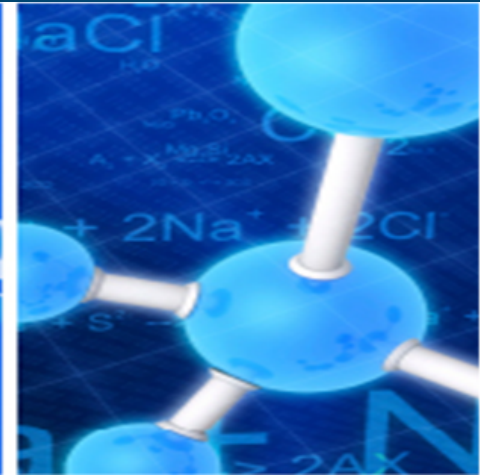
- The maximum over all distributions is known as the *channel capacity*.

- **Determine the “intrinsic” communications topology provided by available observation processes;**
 - Fusing information from multiple sensors,
 - Reconstituting lost or degraded observations,
 - Detect system changes reflected in changing communications topology.
- **Identify “correlative” structure of sensor data;**
 - Identifying relevant (possibly abstract) subsystems,
 - Mesoscopic models and “summary” variables.

Expected Results

Fundamental building blocks for self-organizing sensor network for condition monitoring

- **Accurate, computationally tractable means of computing entropy measures for the processes/components/subsystems/systems of interest.**
- **Distributed and self-organizing method for using entropy measures to identify intrinsic communications structure of power generation systems.**
- **Self-organizing method for combining observations with dynamics/behaviors/events of interest.**
- **Statistical techniques for detecting/classifying/identifying conditions of interest and characterizing severity and prognosis of system performance degradation.**



Information Geometry

Accomplishments

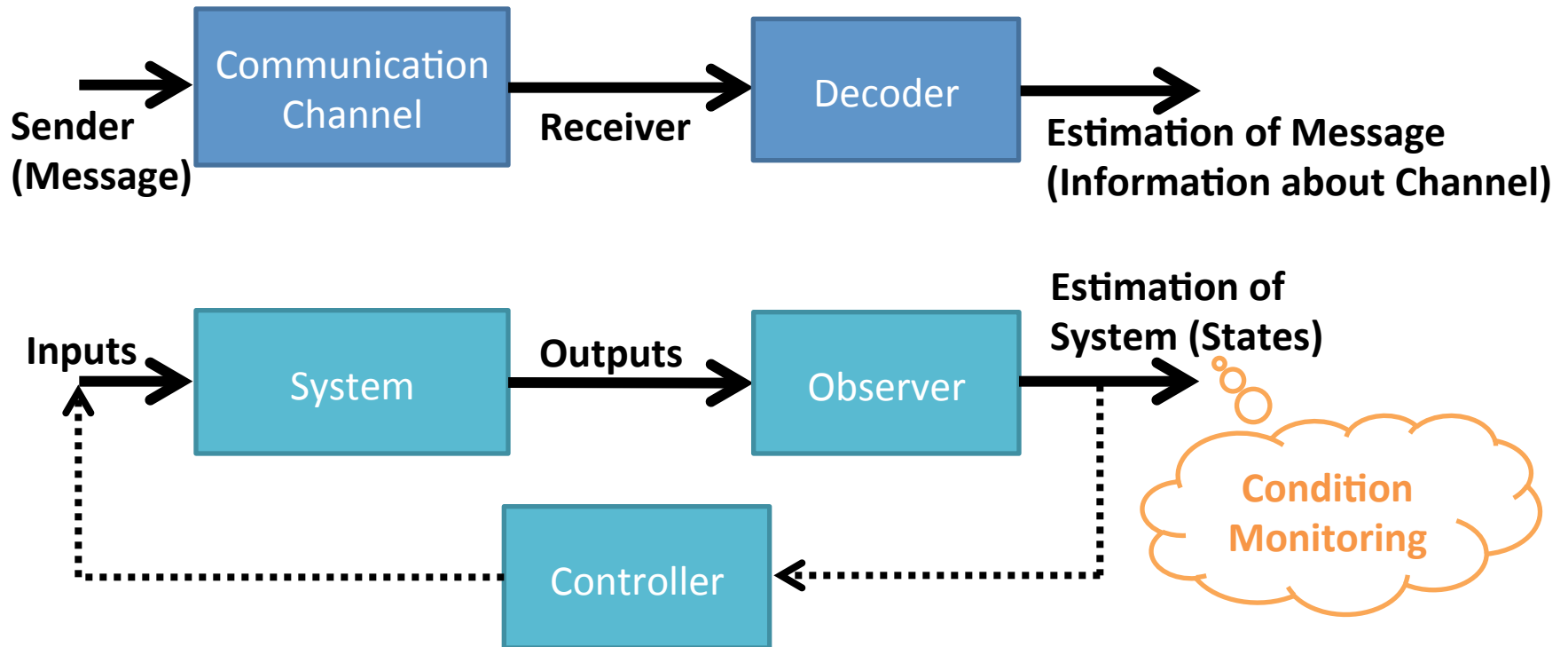
- Approach for the Discovery of system structure for health and condition monitoring of power plant equipment
 - Mathematical framework that uses data from sensors to elucidate the underlying structure of a power plant as it evolves in a consistent and theoretically sound manner
 - Appropriate measures for determining connections between system elements in a meaningful way and for determining relevance to monitoring needs
 - Algorithms to compute these measures in an efficient and reliable manner and for eliciting system structure using these measures

Technical Approach

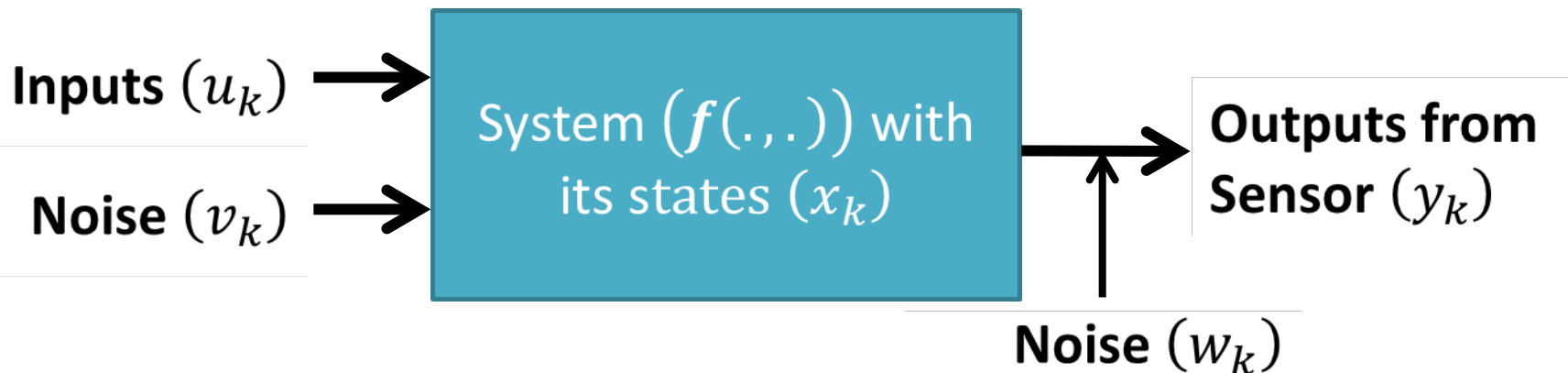
- Components of complex systems “communicate” via internal system dynamics
 - **Information theoretic framework**
 - Capture important aspects of these “communications”
 - Robust to nonlinearity
 - Inherent information hierarchy aids in system partitioning and decomposition
- Equipment monitoring can be described within a control theoretic context
 - **Establish direct connection between information theory and control theory to ensure fundamental soundness of the information theoretic framework**

Communication Channels and Feedback Systems

- Focus on the system structure



Consider the nonlinear I/O system:



- We find that

$$I(y_{1:k}; u_{1:k}) = I(x_{1:k}; u_{1:k}) - I(x_{1:k}; u_{1:k} | y_{1:k})$$

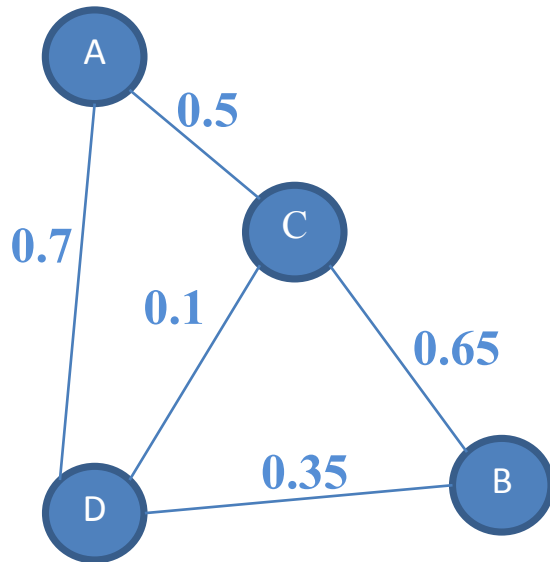
Connection between
Inputs and Outputs

Connection between
Inputs and System

Connection between
System and Outputs
(Inverse relationship)

System Structure Construction

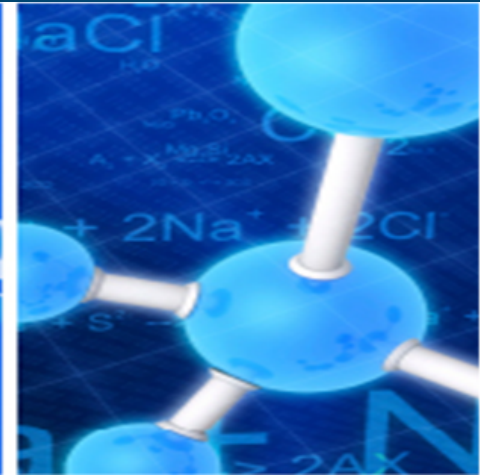
Undirected Weighted Graph



Weighted Adjacency Matrix

	A	B	C	D
A	0	0	0.5	0.7
B	0	0	0.65	0.35
C	0.5	0.65	0	0.1
D	0.7	0.35	0.1	0

- System Structure is used to detect changes associated with possible failures and faults
 - Pre-processing the information matrix
 - No pre-processing
 - Dimension reduction/projection
 - PCA/ICA
 - Diffusion map
 - Analysis approaches
 - Directly analyze information matrix
 - Analyze eigenvalues/eigenvectors
 - Analyze Laplacian matrix
 - Etc.



Self-Organizing Logic

Self-organizing sensor networks support condition monitoring

- Develop **adaptive, resilient, and self-healing** sensor network for condition monitoring of complex systems
 - Techniques, algorithms, and software for *dynamically* discovering the intrinsic communication topology of power generation systems.
 - Techniques, algorithms, and software for associating sensor data streams with operational objectives.
 - Techniques, algorithms, and software for reconstituting lost or degraded sensing and communication capabilities.

Challenges and Opportunities

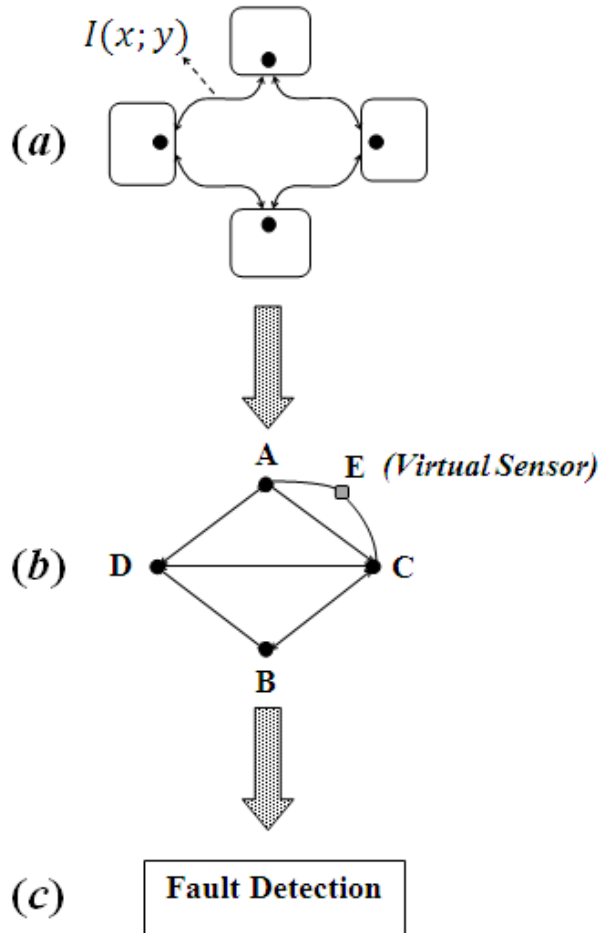
- **Scaling problems associated with centralized methods:**
 - Complexity,
 - Transmission of large amounts of data to central processes (bandwidth, QoS),
 - Computational footprint (cycles, memory).
- **Accommodate existing infrastructure**
- **Lack of detailed a priori understanding of components, processes, and their interactions**
- **Wide variation in operating conditions, system permeability**
- **Ubiquitous computational and (wireless) communication resources**
- **Power management technologies engendering a new class of instrumentation**
 - No umbilical
 - Physically reconfigurable on-the-fly

Technical Approach

- **The aforementioned constraints and opportunities mandate a distributed, agent-based approach and strongly suggest the use of biologically inspired algorithms.**
- **Distributed**
 - Monolithic approaches do not scale well and tend to be “brittle,” i.e. do not accommodate new instrumentation or permit reorganizing existing infrastructure without significant rework.
- **Agent-Based**
 - Agent based approaches are flexible and embed inherent system descriptions. They provide a powerful basis for bottom-up application to complex systems and minimize communication requirements while distributing processing tasks in a realistic manner.
- **Biologically Inspired**
 - Biologically inspired approaches provide the machinery necessary to capture emergent phenomena and thus provide a basis for accommodating unanticipated contingencies. This is crucial for large-scale complex systems where all contingencies cannot be enumerated.

Accomplishments

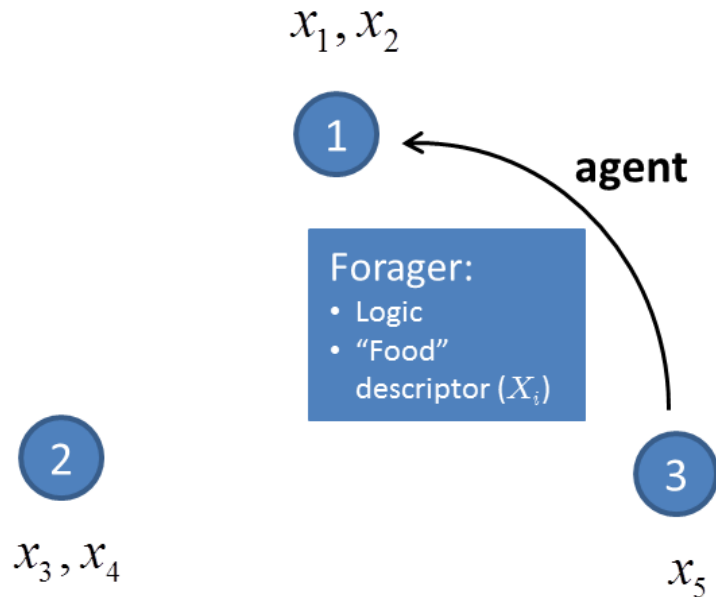
Connecting data to operational needs and objectives



- Discovering the actual topology of the system's intrinsic communication structure.
- Associating information streams with monitoring processes.
- Extracting information from the relevant data streams for fault detection, diagnosis and prognosis.

Network Discovery

The observation of physical system from a foraging perspective



x_i : a time series which is the partial observation of the physical system at node i

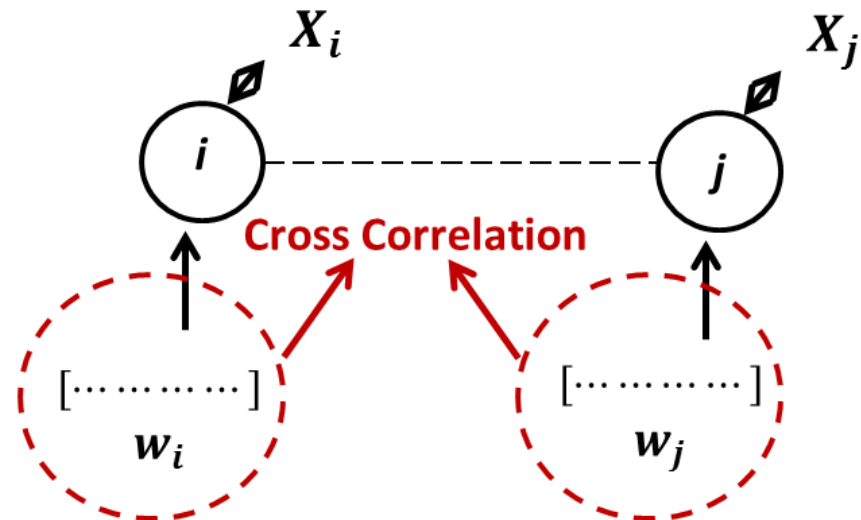
Agent going from node 3 to node 1:

Behavior

- The agent carries some data, described as time series, from its home node to the next one.

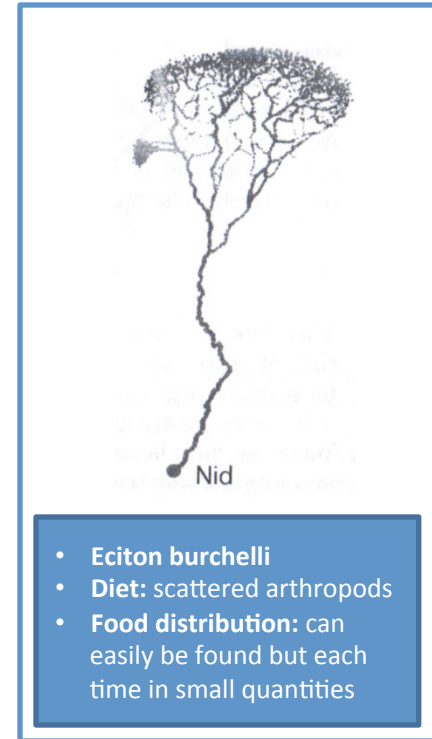
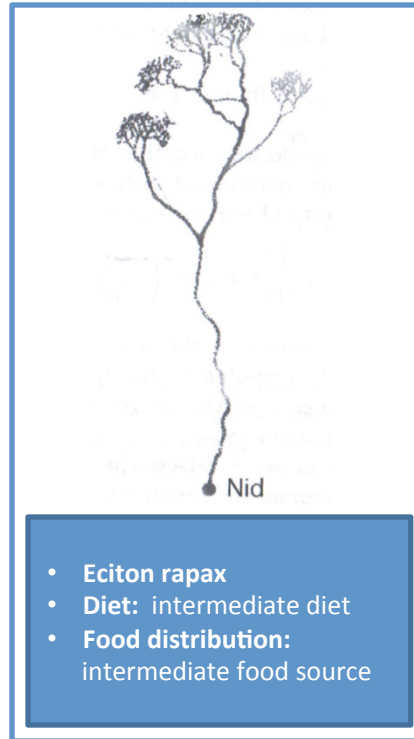
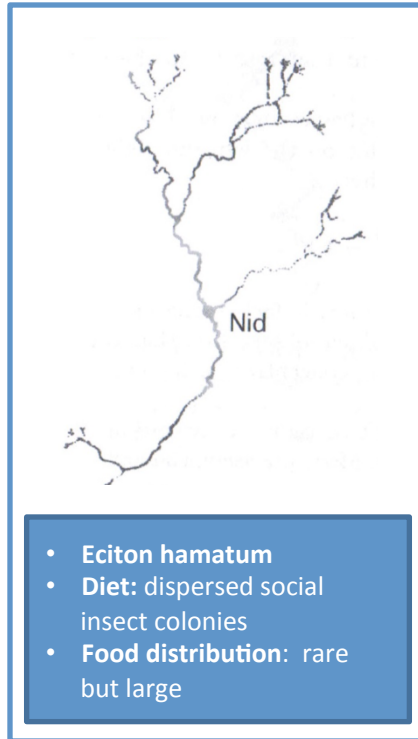
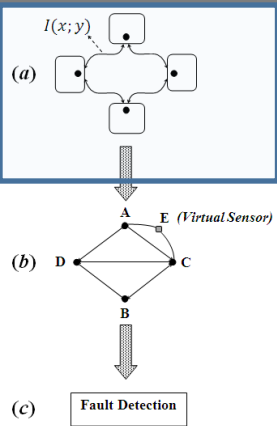
Food Definition

- The Mutual Information between the time series of node 3 and node 1.



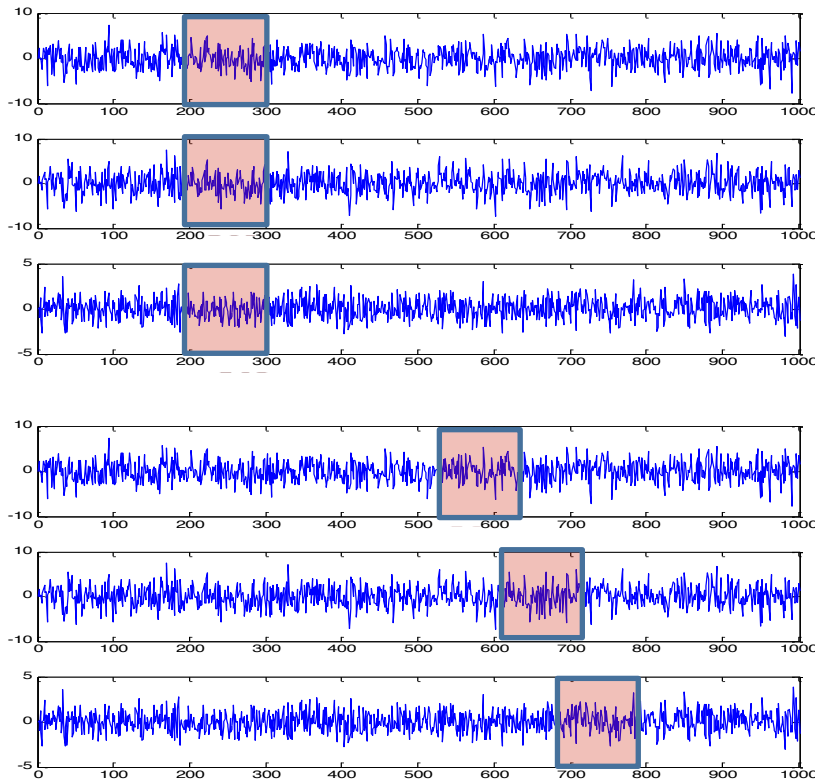
Foraging Behavior

Foraging Patterns of Three Army Ant Species with Different Diets



These behaviors are used as a basis for optimization approaches due to its tendency to find the shortest path, most notably **Ant System** and **Ant Colony Optimization**. These behaviors are adapted to the specifics of the problem at hand.

“Food” for Foragers



$$\Sigma_{w_1, w_2} = \begin{bmatrix} 7.6766 & -0.9311 \\ -0.9311 & 5.4541 \end{bmatrix}$$

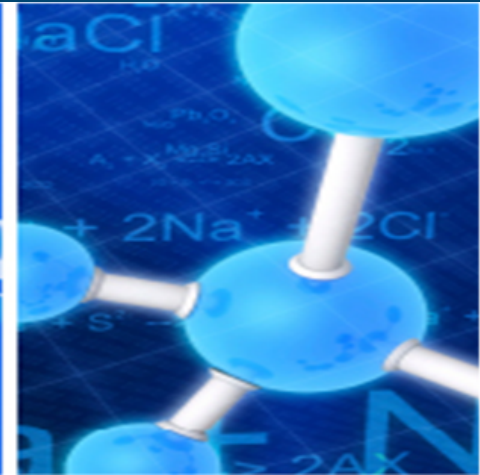
$$\Sigma_{w_2, w_3} = \begin{bmatrix} 5.4541 & -0.0772 \\ -0.0772 & 1.8371 \end{bmatrix}$$

$$\Sigma_{w_3, w_1} = \begin{bmatrix} 1.8371 & 0.3876 \\ 0.3876 & 7.6766 \end{bmatrix}$$

$$\Sigma_{w_1, w_2} = \begin{bmatrix} 9.3388 & -1.4681 \\ -1.4681 & 6.2307 \end{bmatrix}$$

$$\Sigma_{w_2, w_3} = \begin{bmatrix} 6.2307 & -0.0935 \\ -0.0935 & 1.5962 \end{bmatrix}$$

$$\Sigma_{w_3, w_1} = \begin{bmatrix} 1.5962 & -0.2804 \\ -0.2804 & 9.3388 \end{bmatrix}$$



Virtual Sensors

Accomplishments

Realizing the value of information

- **Signal processing, filtering, and inference algorithms and software systems for the detection, diagnosis, and prognosis of defects, degradation, and faults in power generation systems at component, subsystem, and system levels.**
 - Techniques, algorithms, and software for *detecting and identifying anomalies and events of interest.*
 - Techniques, algorithms, and software for characterizing and classifying observed anomalies at the component, subsystem/process, and system levels and providing diagnoses and prognoses for detected events.
 - Develop techniques, algorithms, and software for reconstituting lost or degraded sensing and communication capabilities.

Challenges and Opportunities

What has to be done and what's available to do it...

- **Imperfect or incomplete observation processes:**
 - Noise,
 - Sparsity of sensing (both physical and temporal),
 - Inability to directly instrument all components/processes of interest.
 - **Accommodate existing infrastructure**
 - **Lack of detailed a priori understanding of components, processes, and their interactions**
 - **Wide variation in operating conditions, including sensor failures**
-
- **Ubiquitous computational and (wireless) communication resources**
 - **Power management technologies engendering a new class of instrumentation” => more sensors/higher sampling rates**
 - No umbilical
 - Physically reconfigurable on-the-fly
 - **Substantial repositories of relevant data available for many components and subsystems.**

Technical Approach

Combining a priori knowledge with information from instrumentation

- **Incorporate a priori knowledge of system behaviors and observed phenomena:**
 - Focus on meeting operational needs,
 - Specification of known signatures or precursors,
- **Augment mapping between sensor output and operational needs with “self-discovery” to improve accuracy, timeliness, and robustness:**
 - Verify/augment “known” connections with statistically inferred relationships,
 - Detect/correct erroneous or degraded sensor outputs,
 - Detect and classify/characterize anomalous (unknown) dynamics.
- **Provide “best of breed” techniques to characterize anomalies and provide diagnoses/prognoses for detected events:**
 - Change detection/classification via filtering approaches,
 - Signature detection/matching via model-based signal processing techniques,
 - Infer causal relationships between observations and condition at all relevant levels of spatio-temporal resolution.

Scenario Elements

Diagnostics and Prognostics for Rotating Machinery

- Faults of Interest
 - Mass Unbalance
 - Misalignment
 - Cracking in Rotor Shafts
 - Other elementary faults such as changes in stiffness, damping and static load, ...
- Operating Conditions
 - Rub Impact
 - Oil whip and Oil whirl

Observer/Filter-Based Fault Detection and Diagnosis

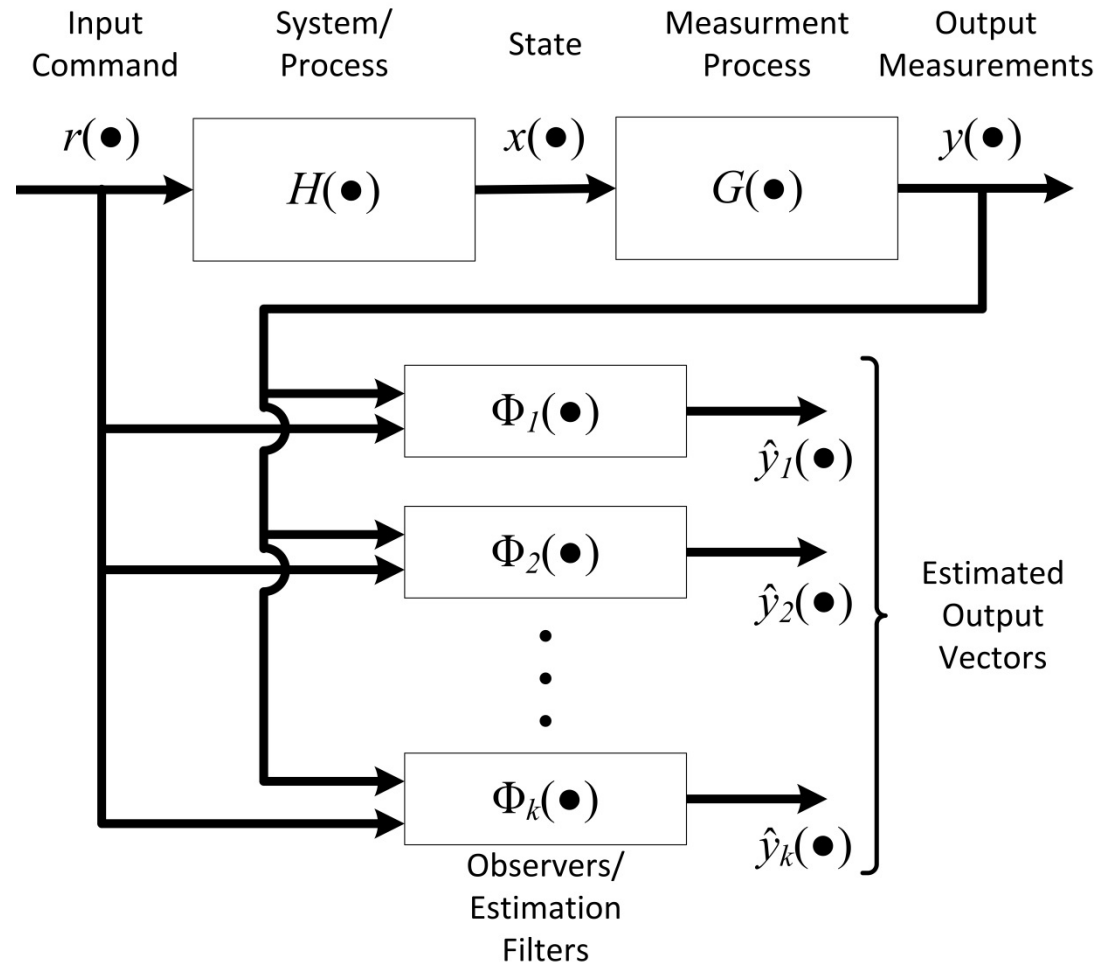
Key Concept

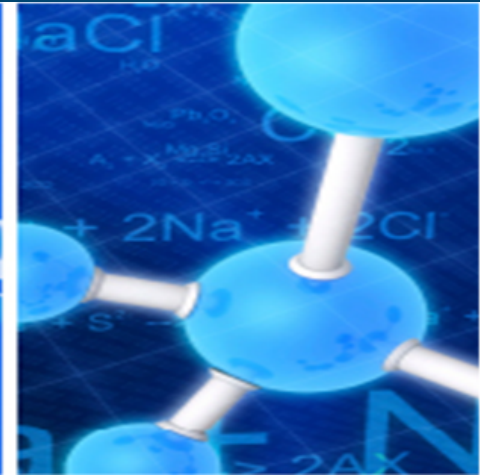
- **Basic idea is to compare observed behavior to models of behavior**
 - Can use deviation of measured behavior from expected (modeled) behavior as fault indicator.
 - A collection of models can be used to diagnose known faults.
 - Higher order error statistics can be used to improve performance.
- **Key design driver is trade-off between fidelity and efficiency.**

Technical Approach

Use of Observer/Filter Banks

- **“Modeling” approach is based on classical state estimation methods;**
 - Deterministic systems => Luenberger Observer,
 - Non-deterministic systems => Linear or Nonlinear Filters.
- **Operate a bank of observers/filters each corresponding to different operating conditions.**

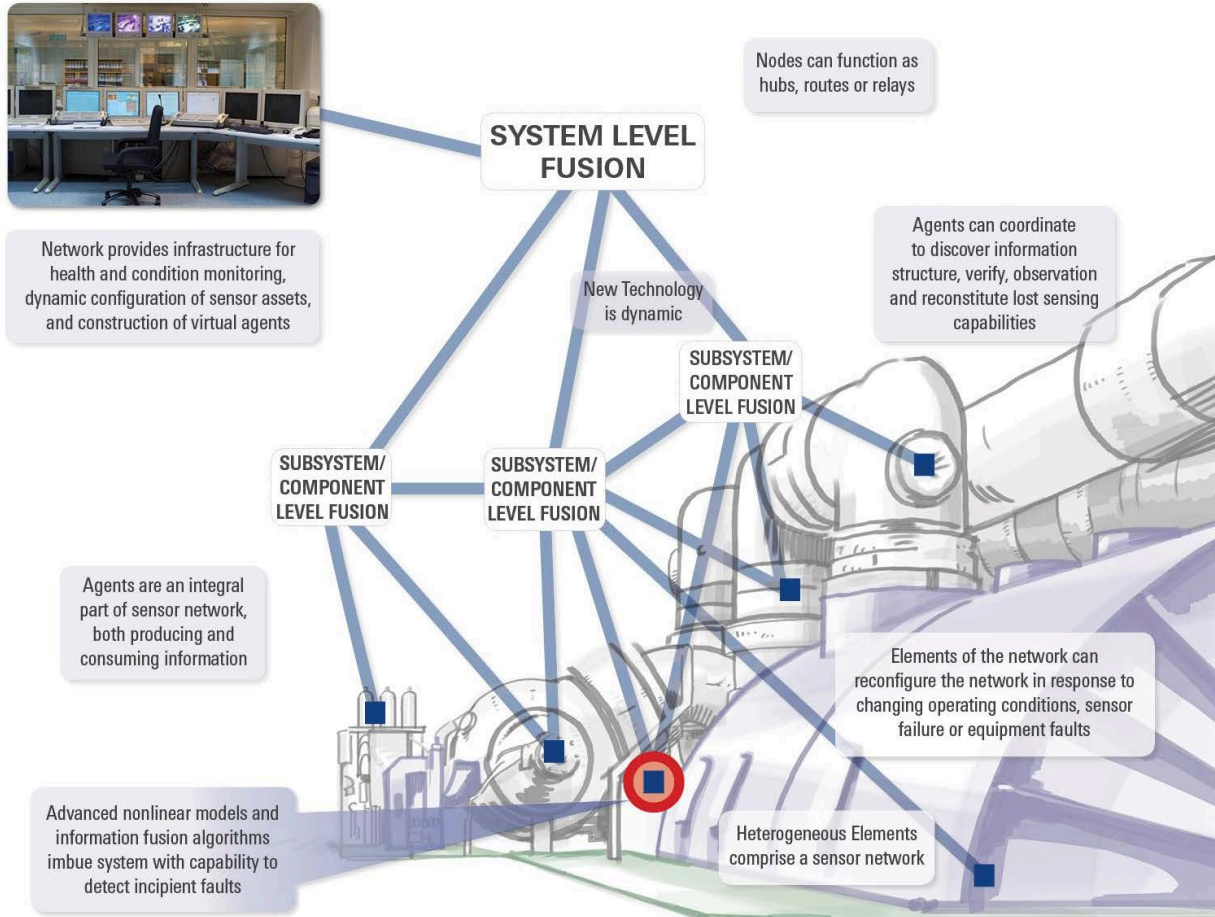




System Integration

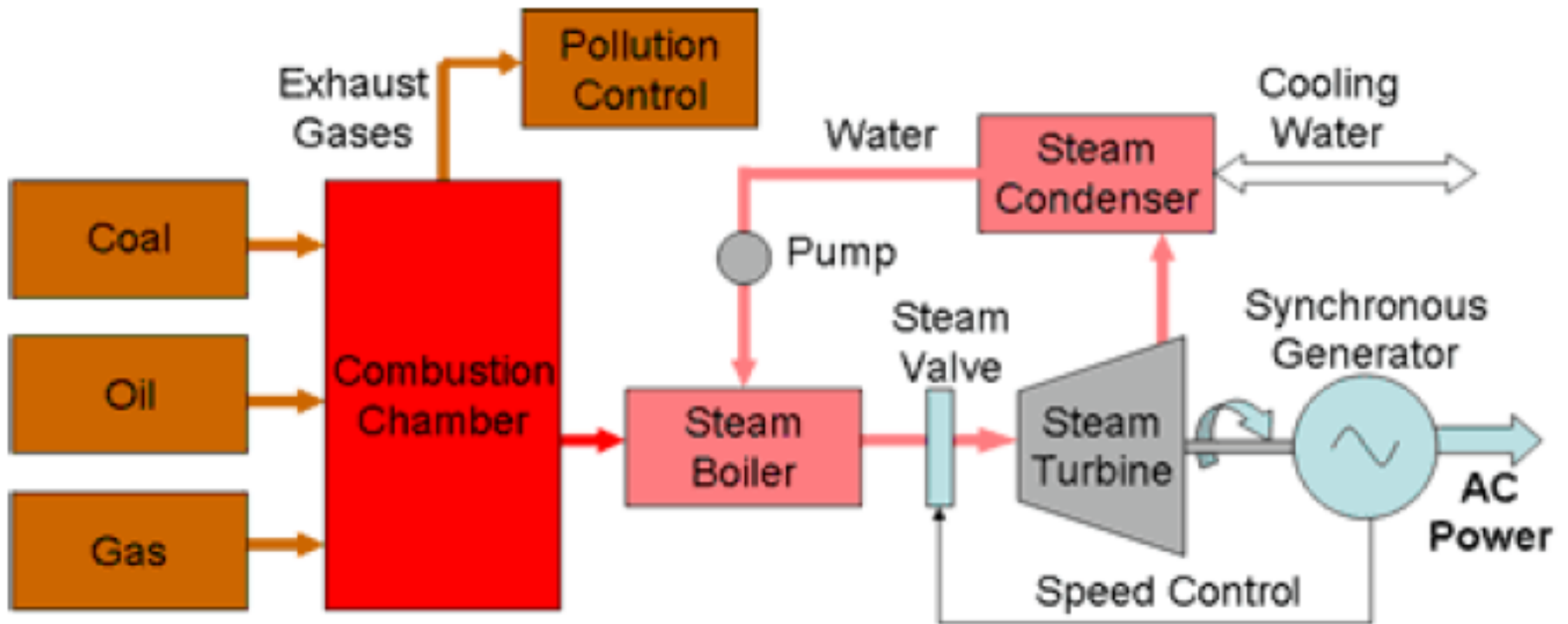
Target System

Self-organizing, information centric sensor network



Simulation Development

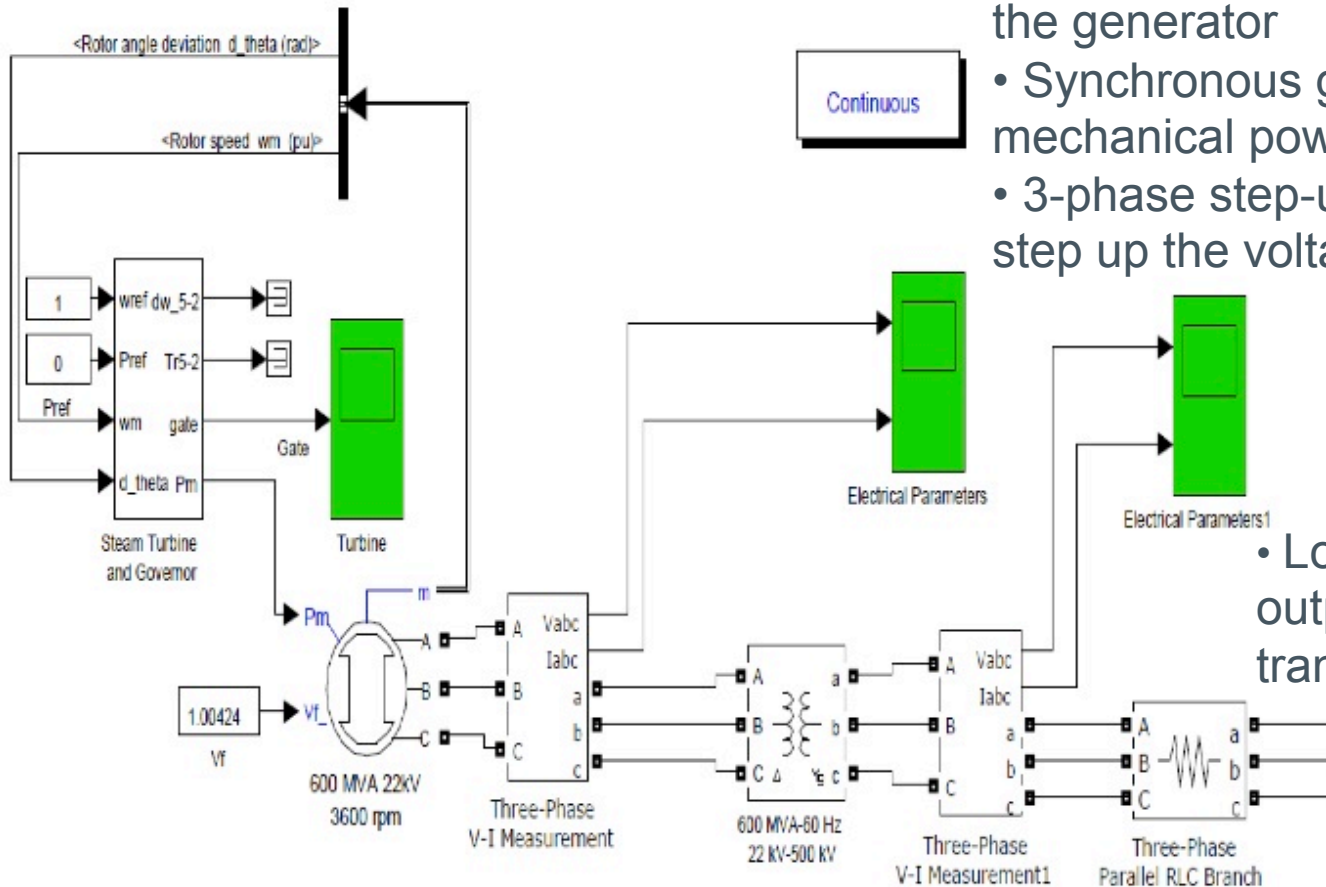
System Schematic



Simulation Development

Preliminary Model

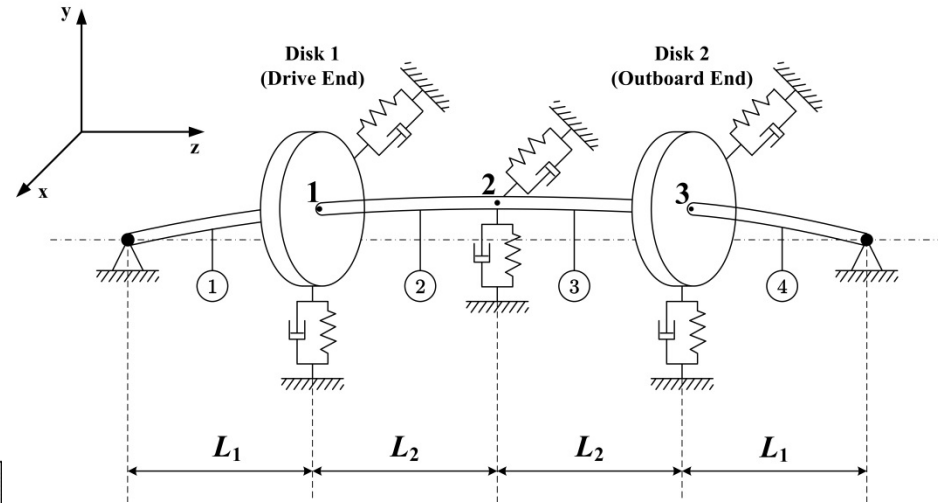
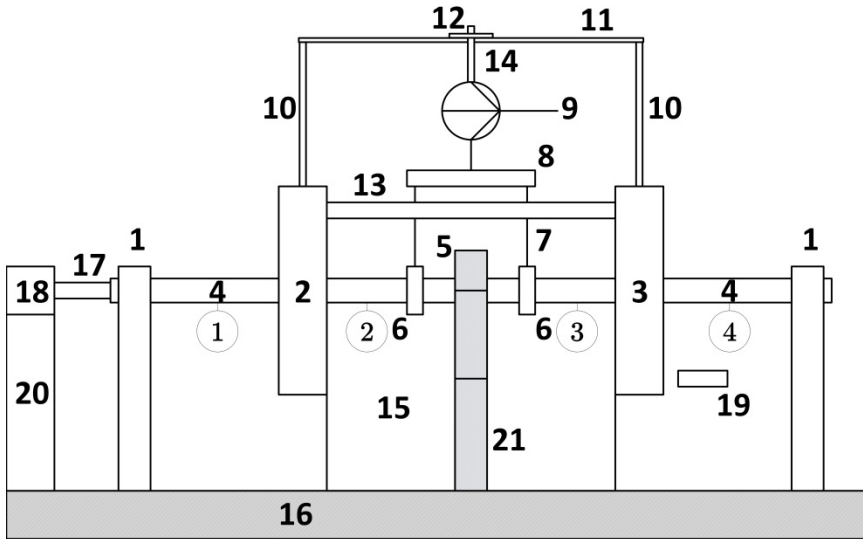
- Steam turbine provides rotary power to the generator
- Synchronous generator converts the mechanical power into electrical power
- 3-phase step-up transformer is used to step up the voltage for transmission



- Load is connected at the output of the 3-phase transformer

Journal Bearing Test Rig

Physical test rig and 24 state nonlinear model



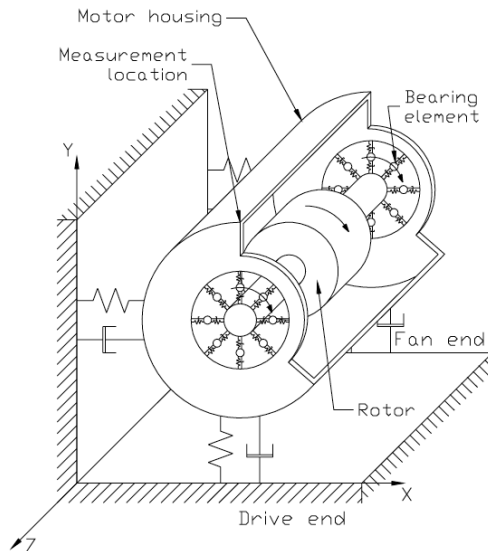
Legend:

- | | |
|-----------------------------|-------------------------|
| 1 – End Bearing | 12 – Knob |
| 2 – Drive End Balancer | 13 – Lid |
| 3 – Out Board Balancer | 14 – Threaded Rod |
| 4 – Shaft | 15 – Oil Tank |
| 5 – Journal Bearing | 16 – Table Support |
| 6 – Load Support | 17 – Quill Shaft |
| 7 – Rods | 18 – DC Motor |
| 8 – Beams | 19 – Key Phasor |
| 9 – Load Measurement Device | 20 – Motor Support Base |
| 10 – Columns | 21 – Aluminum Base |
| 11 – Beam | |

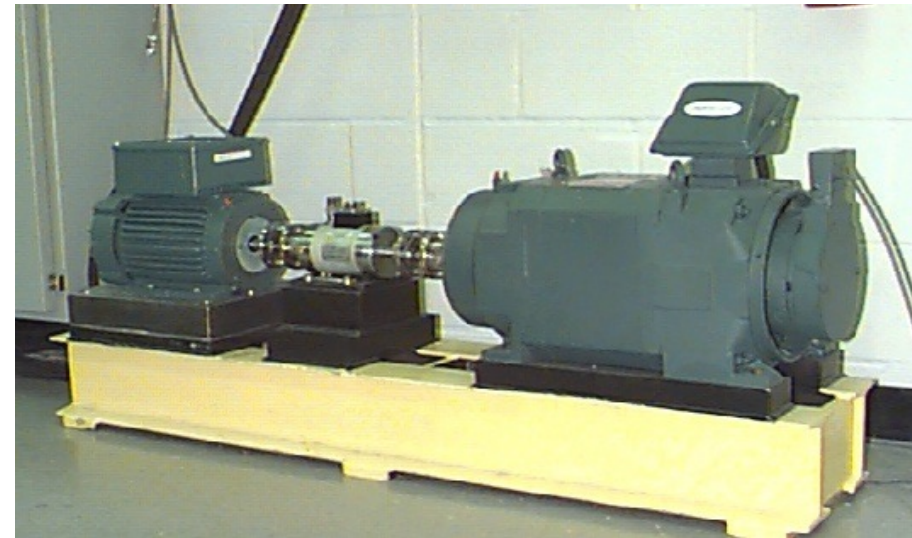
- Refurbished bearing test rig with controllable shaft preload, shaft speed, and disk unbalance.
- Key phasor and Bentley-Nevada proximity probes located at journal bearing.
- 24 state simulation implemented with nonlinear bearing models.

Rolling Element Test Rig

Instrumented bearings and motor



- Housing has 4 DOF - linear springs and dampers
- 8 DOF lumped mass rotor model includes gyroscopic effects. Cylindrical disk is accommodated by redistributing some disk mass to the bearing mass stations
- Each bearing element is a 1 DOF mass with nonlinear Hertzian stiffness and linear damping. 9 elements at drive end, 8 elements at fan end
- Defects are modeled as a change in the radius of the raceway



- 2hp induction motor (left)
- Torque transducer is center
- Dynamometer (right) applies torsional load
- Vibration measured with 5g accelerometer placed on motor housing, 12 o'clock position above drive end bearing
- Data recorded with a DAT (digital tape recorder) at 12k samples/sec.

Bearing Condition Simulator

Matlab-based simulation and diagnostic software

The screenshot displays the MATLAB environment with several windows open:

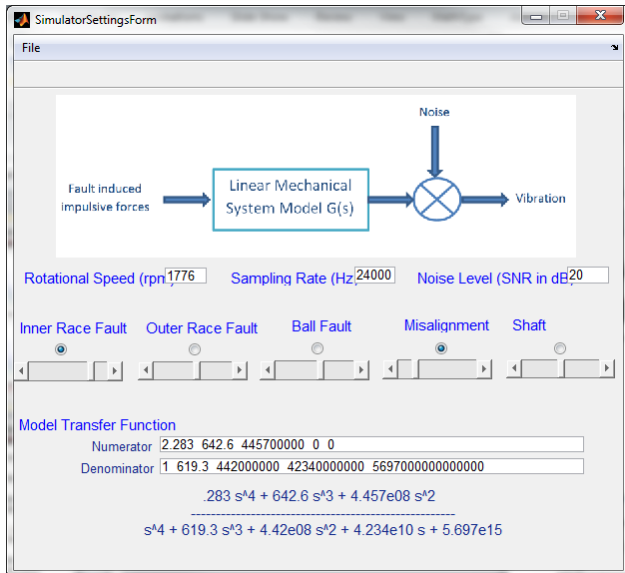
- Editor:** Shows a MATLAB script for the simulator. Key parameters include:
 - Rotational Speed (rpm): 1776
 - Sampling Rate (Hz): 24000
 - Noise Level (SNR in dB): 20
- SimulatorSettingsForm:** A block diagram showing "Fault induced impulsive forces" entering a "Linear Mechanical System Model G(s)", which then outputs "Vibration" with added "Noise".
 - Model Transfer Function:

$$\frac{2.283 \times 10^3 s^4 + 642.6 s^3 + 4.457 \times 10^8 s^2}{1.6193 \times 10^3 s^4 + 619.3 s^3 + 4.42 \times 10^8 s^2 + 4.234 \times 10^{10} s + 5.697 \times 10^{15}}$$
- Analysis Settings:**
 - Sampling Frequency (Hz): 12000
 - Speed Estimate Range: from 1700 to 1800
 - Frequency Band for the Envelope Spectrum: from 2200 to 4200
 - Fault Trigger Levels in dB:

	IR	OR	Ball
Incipient	8	8	8
Moderat	15	15	15
Severe	25	25	25
- Bearing Condition Monitoring Software:**
 - Data Source:** Simulator
 - Bearing:** Bearing T...
 - Rotational speed:** Estimate
 - Speed (rpm):** 2300
 - Select Bearing:** 6203R
 - Pitch:** 39
 - Ball Diameter:** 8
 - # of balls:** 8
 - Time Domain:**
 - RMS: 0.4
 - Kurtosis: 9.2
 - Defect Frequencies:**
 - IR: 184.8 Hz
 - OR: 121.9 Hz
 - Ball: 89.5 Hz
 - Defect Freq. Mag / Carpet Level:**
 - IR: 24.1 dB
 - OR: 4.7 dB
 - Ball: 5.1 dB
 - Diagnosis Results:**
 - Inner Race: Moderate Defect
 - Outer Race: Normal
 - Rollers: Normal
 - Misalignment:

Bearing Fault Simulator

Two modes of operation



(a) Simulation Context Menu

	IR	OR	Ball
Incipient	8	8	8
Moderat	15	15	15
Severe	25	25	25

(b) Analysis Context Menu

- Bearing condition monitoring software provides 2 capabilities:
 - Defect simulation of vibratory behavior,
 - Analysis of existing data files, including data from externally generated sources.
- Intended for real time monitoring and can be implemented easily with existing bearing test rigs or other instrumented machinery.

Possible Next Steps

- Demonstration using Alstom's 1000MWe fossil steam power plant dynamic simulator



- define the scope of fault simulation scenarios for a boiler island and steam plant
- specify a list of dynamic simulation cases with predefined faults:
 - typical sensor faults, actuator faults, process faults;
 - well-developed and incipient fault levels
- specify the noise pattern and levels for the preselected variables
- specify a list of process variables for data recording from simulation – to be distributed for university analysis
- investigate applications to advanced controls and diagnostic monitoring for fossil steam power plants

Acknowledgements

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