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

Self-Organizing Logic

Agenda

Topics and Themes

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

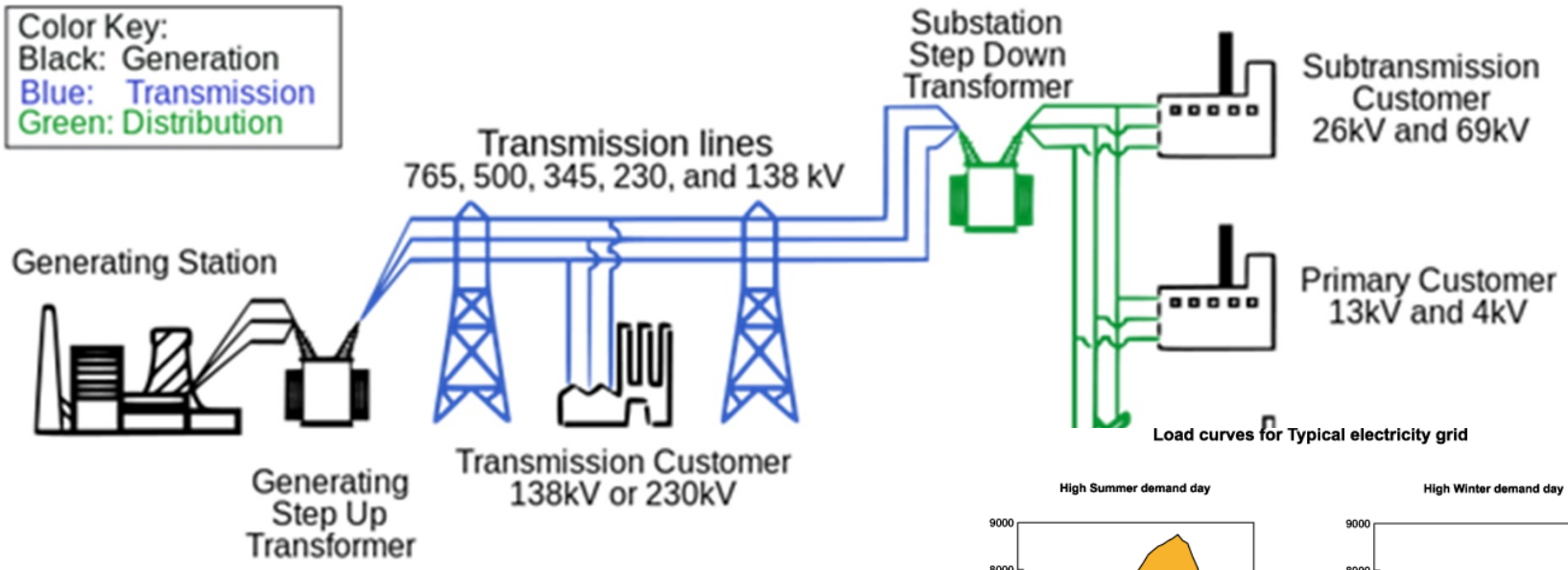
Agenda

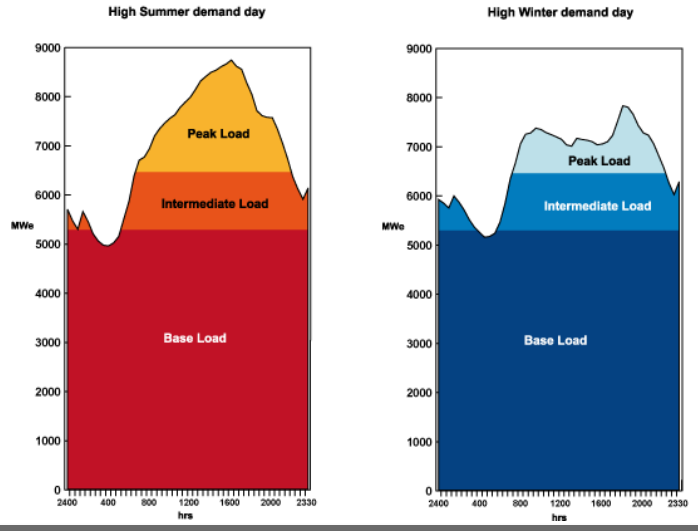
Topics and Themes

- Element Objectives
- Challenges and Opportunities
- Technical Approach
- Design Study Results
  - Swarm Intelligence
    - *Foraging*
      - Biologically-inspired optimization
      - General foraging behaviors
    - *Other eusocial behaviors (sorting, recruitment,….)*
- Proposed Framework
  - Apply to Real Steam Plant Data

Base System

Electric Power System

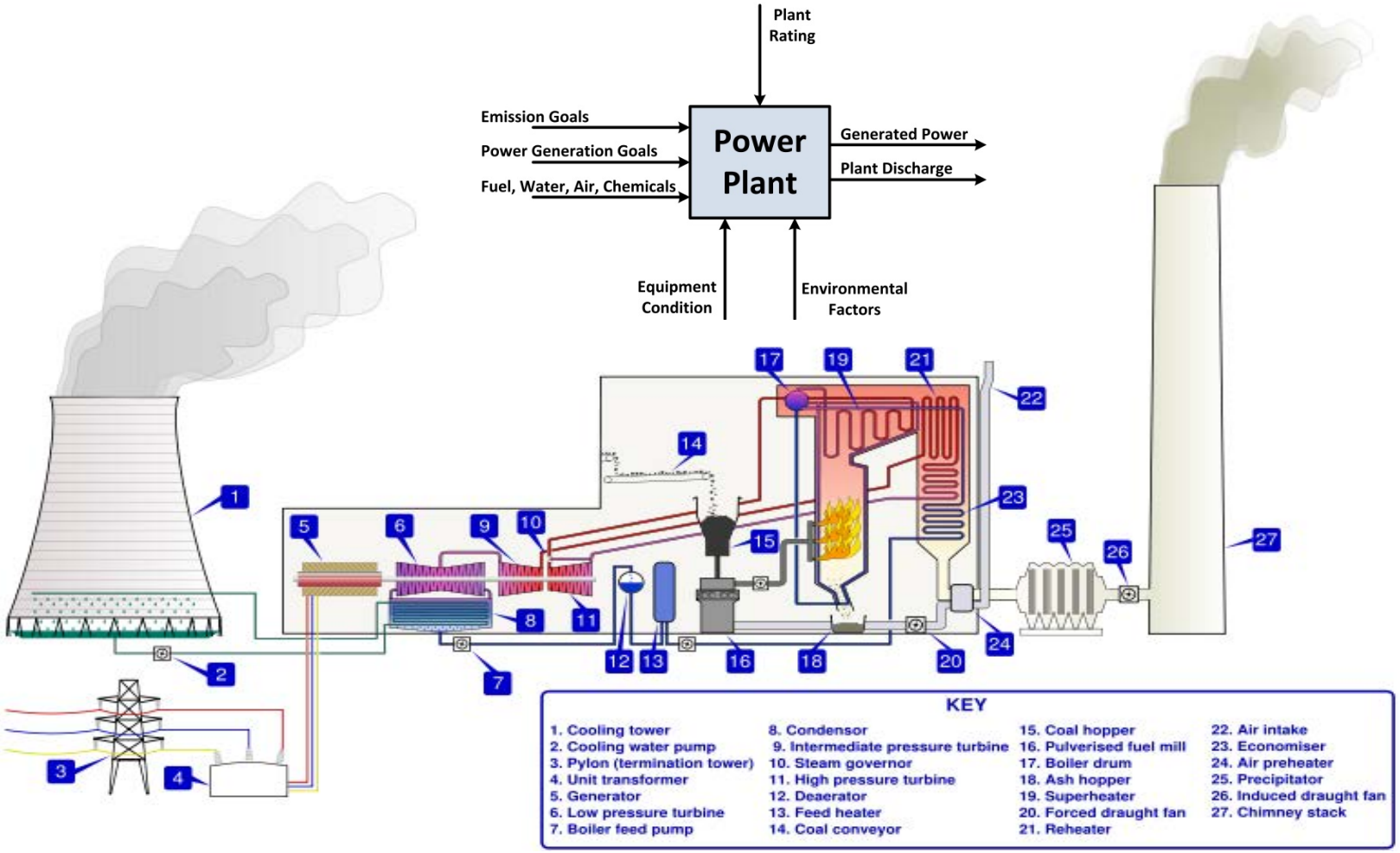




The operation of a power generation plant must be understood within the context of its environment. Most notably, that it is driving an electric power system with time varying loads and configurations that directly affect the operation of power generation equipment.

Base System

Coal-fired Power Generation Plant



Coal-fired Power Plant

Key functions

- Coal & ash handling
  - Handles treatment and storage of coal
  - Handles and dispose of ash
- Steam generating
  - Creates steam for the greater percentage of power station in-efficiency
- Energy conversion
  - Converts steam energy to rotational mechanical energy
  - Converts rotational mechanical energy into electrical energy.
- Feed water & cooling
  - Condenses steam used in boiler chamber back to water for re-use

Measurement and Sensors

Phenomena and available instrumentation

- Pressure measurement
  - Mechanical instruments (dial gauges)
  - Electronic pressure transducers
- Flow measurement
  - Flowrate measurement
    - Flowrate / pressure differential devices
    - Liquid filled manometers
  - Electronic differential pressure instrument
  - Magnetic induction flow measurement
  - Volumetric flow meters
    - Turbine type (widely used for centrifugal pump)
    - Gear wheel type
    - Rotary piston type
  - Flow indicators

Measurement and Sensors (Cont.)

Phenomena and available instrumentation

- Power Measurement
  - Torque measurement
  - Torque measurement with eddy current sensors
  - Electrical power measurement (Current and Voltage measurement)
- Speed measurement
  - Mechanical tachometers
  - Impulse transmitters
  - Eddy current generators
  - Slip meters

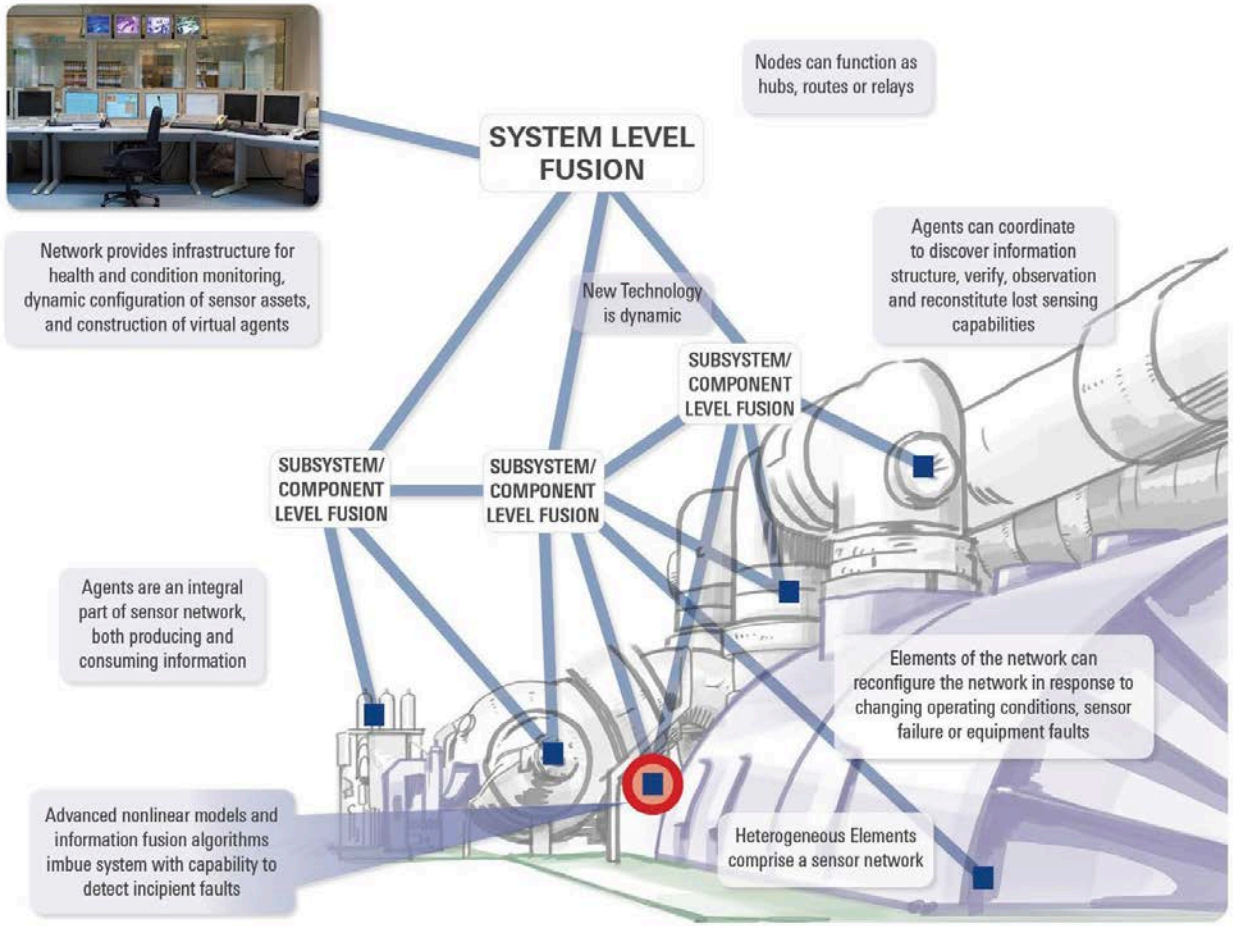
Measurement and Sensors (Cont.)

Phenomena and available instrumentation

- Temperature measurement
  - Mechanical contact thermometers
  - Electrical contact thermometers
    - Resistance thermometers
    - Thermocouples
- Vibration measurement
  - Accelerometers

Target System

Self-organizing, information centric sensor network



Project Goals

Realizing the potential of next generation instrumentation systems

1. Enable robust and flexible health and condition monitoring systems through the development of an *intelligent agent-based information theoretic architecture* for advanced power plant applications.
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 the power plant.
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

- 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 some of these “messages”;
  - Messages may be corrupted,
  - Not all messages can be observed directly.
- Proper understanding of observations requires an understanding of both the processing and the network topology!

Information Theory

Data and Information are not the same!

- Information is the amount of surprise contained in the 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*:

$$H(X) = -\sum_{x \in \mathcal{X}} p(x) \log_d p(x),$$

where $X \in \mathcal{X}$ is a discrete R.V., $\mathcal{X}$ is a finite set known as the alphabet, and $p(x) = \Pr\{X = x\}$

The Multivariate Case

- For a pair of discrete R.V.'s (X,Y) with joint and conditional distributions $p(x,y)$ and $p(x|y)$, the joint and conditional entropies are, respectively:

$$H(X,Y) = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(x,y)\log_2 p(x,y)$$

$$H(X|Y) = -\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(x,y)\log_2 p(x|y)$$

- The relationship between these R.V.'s is captured by *Mutual Information*:

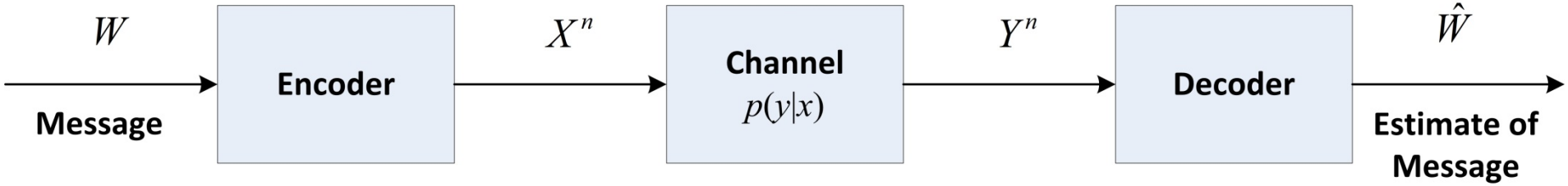
$$I(X;Y) = \sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(x,y)\log_2 \frac{p(x,y)}{p(x)p(y)}$$

- These quantities are related via the chain rule:

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

Information Channels

Modeling Information Flow



- Let $\mathcal{X}$ and $\mathcal{Y}$ be the *input alphabet* and *output alphabet*, respectively, and let S be the set of channel states. An information channel is a system of probability functions:

$$p_n(\beta_1, \ldots, \beta_n | \alpha_1, \ldots, \alpha_n : s)$$

  where $\alpha_1, \ldots, \alpha_n \in \mathcal{X}$, $\beta_1, \ldots, \beta_n \in \mathcal{Y}$, and $s \in S$ for $n = 1, 2, \ldots$.

- Mutual information between the input and output provides a measure of *channel transmittance*:

$$T(\mathcal{X}; \mathcal{Y}) = H(\mathcal{X}) - H(\mathcal{X}|\mathcal{Y})$$

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

Systems and Information

- The properties of information, e.g., its *branching property*, provide a fundamental basis for decomposing systems.
- The generalization of information theory to N-dimensions provides a statistical analysis tool for understanding systems in terms of the information geometry of its variables;
  - Permits measurement and analysis of rates of constraints (i.e., historical conditioning),
  - System decomposition follows from decomposition of constraints on information and associated rates.

Information Rates

Capturing History

- Information captures relationships between present values of variables.
- Constraints due to past values are captured via entropy rates;
  - The entropy of X conditioned on all prior values,
  - Computationally challenging in this form.
- Alternative formulation follows from recognition that the total uncertainty of $\langle X_1, X_2, \ldots, X_n \rangle$ is approximately the entropy rate times the length of the sequence:

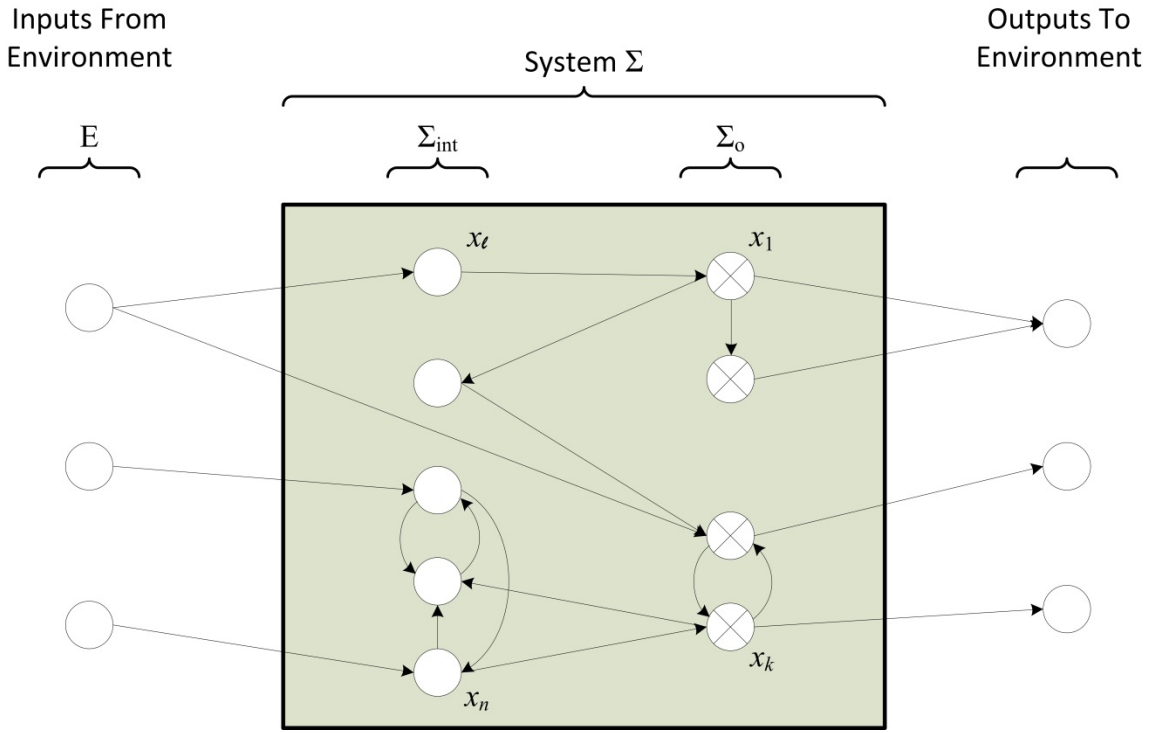
$$\bar{H}(X) = \lim_{n \to \infty} \frac{1}{n} H(X_1, X_2, \ldots, X_n)$$

Information Structure

- Can determine the communications topology provided by available observation processes;
  - fusing information from multiple sensors,
  - Reconstituting lost or degraded sensing,
  - Detect system changes reflected in changing communication topology.
- Identify “correlative” structure of sensor data;
  - Provides means of identifying relevant (possibly abstract) subsystems,
  - Basis for mesoscopic models and “summary” variables.

System Structure

Information-theoretic View of Systems



- System Σ is defined as a set of ordered variables $\Sigma = \{X_i | 1 \square i \square n\}$ where the set of internal variables is denoted Σ_{int} and directly observable variables by Σ_{out}

System Decomposition

- Systems are characterized by their associated variables hence information theoretic measures can be applied, e.g.,

$$H(\Sigma) = -\sum_{s \in \mathcal{S}} p(s) \log_2 p(s),$$

- Information chain rules provide a calculus for partitioning systems,

$$\bar{I}(\Sigma_i; \Sigma_j) = \bar{H}(\Sigma_i) + \bar{H}(\Sigma_j) - \bar{H}(\Sigma_i, \Sigma_j)$$

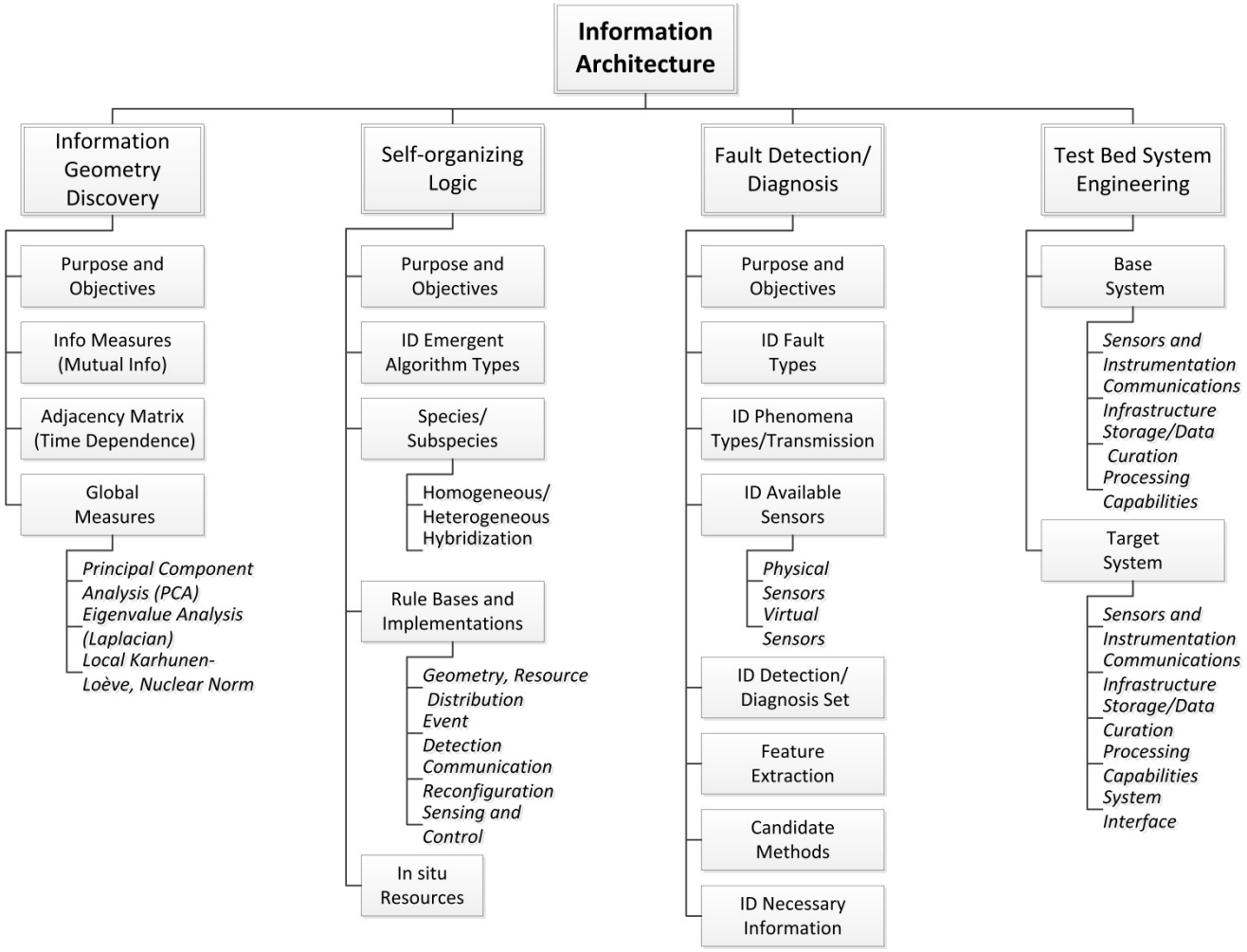
- More sophisticated “Laws of Information” can be constructed.

Expected Results

- Effective (accurate, computationally tractable with sufficient precision) means of computing entropy measures for the processes/components/systems of interest.
- Distributed and self-organizing method for using entropy measures to identify intrinsic 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 the severity and prognosis of system performance degradation.

Functional Breakdown Structure

Project organization per thesis breakout



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Self-Organizing Logic

Element Objectives

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

Challenges and Opportunities

Challenges

- 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

Opportunities

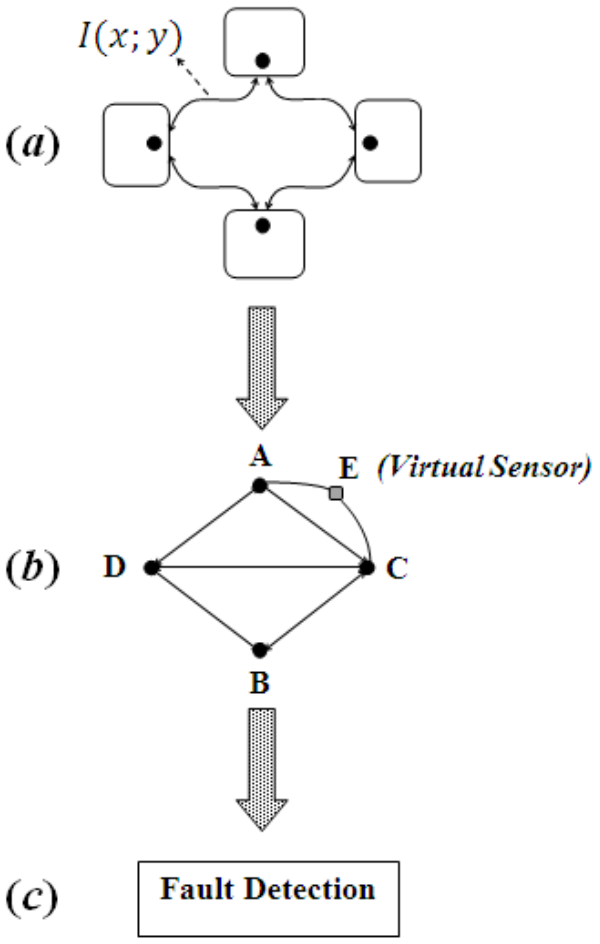
- Ubiquitous computational and (wireless) communication resources
- Power management technologies engendering a new class of instrumentation”
  - No umbilical
  - Physically reconfigurable on-the-fly

Technical Approach

- The aforementioned constraints and opportunities mandate a **distributed**, and **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.

Sensor Network

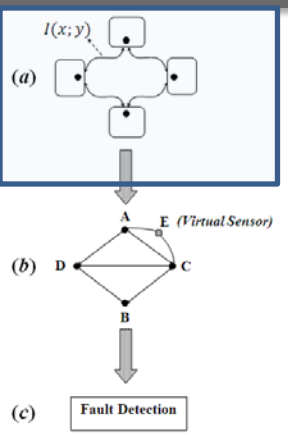
Connecting data to operational needs and objectives



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

Topology Discovery

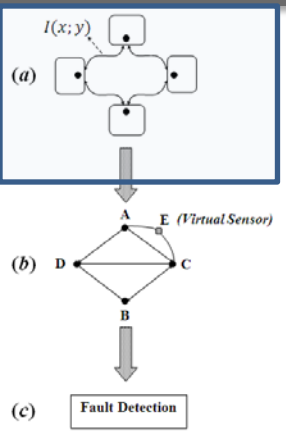
Overview of Swarm Intelligence



- The first step in implementing the sensor network is to determine the system's **intrinsic topology**. The intrinsic communication between elements of the system manifests in the **mutual information** between the sensing performed at disparate locations of the network and thus can be used to extract the system's intrinsic topology.
- Biologically inspired approaches are strong candidates for developing the distributed agent based system for the sensor network.

- In particular, **Swarm Intelligence** is investigated for these purposes:
  - Swarm intelligence is inspired by the collective behavior of animals in nature. Some natural examples include insect colonies, bird flocks, and fish schools.
  - A swarm intelligence system consists of a group of *agents interacting locally* with each other and with their environment. The agents follow simple rules governing their local behaviors that, in turn *emerge* global behaviors in a bottom-up fashion.

Principles of Swarm Intelligence



1. Self-organization

- Positive Feedback (Amplification)
- Negative Feedback (Balancing)
- Amplification of Fluctuations (Random Walks, Error)
- Multiple Interactions

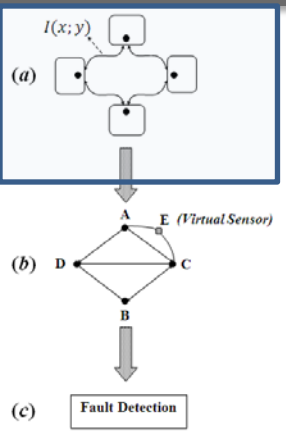
2. Stigmergy

Indirect communications between system elements via interaction with environment, i.e. individual behavior modifies the environment which in turn modifies the behavior of other individuals

3. Bounded Autonomy

Local behaviors are not specified in a deterministic manner, rather bounds on allowable behaviors are given, typically probabilistically.

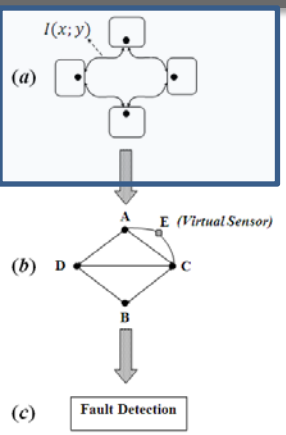
Candidate Approaches



- Some of the algorithms inspired by the emergent behavior of social insect colonies and other animal societies:
  - **Foraging Behaviors**
    - *Ant System (AS)*
    - *Ant Colony Optimization (ACO)*
    - *Basic models of foraging activities*
  - **Ant Clustering Behaviors**
    - *Cemetery organization*
    - *Larval sorting*

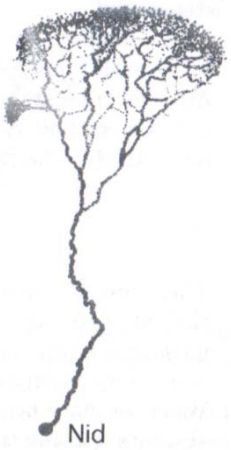
Foraging Behavior

Foraging Patterns of Three Army Ant Species with Different Diets



- **Eciton hamatum**
- **Diet:** dispersed social insect colonies
- **Food distribution**: rare but large

- **Eciton rapax**
- **Diet:** intermediate diet
- **Food distribution:** intermediate food source

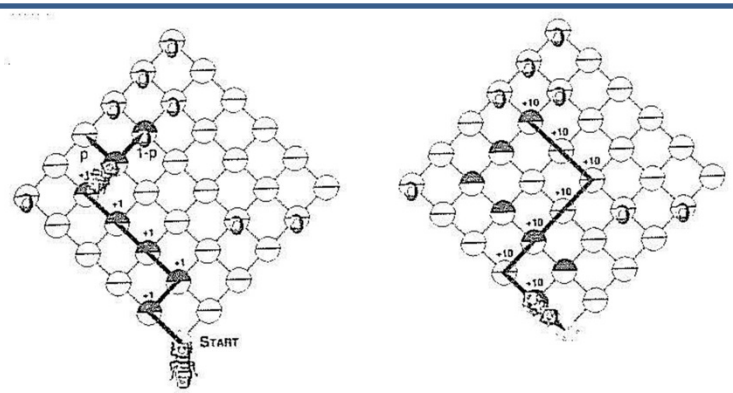


- **Eciton burchelli**
- **Diet:** scattered arthropods
- **Food distribution:** can easily be found but each time in small quantities

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**. Further, the behaviors can be adapted to the specifics of the problem at hand.

Army Ant Foraging Behavior Modeling

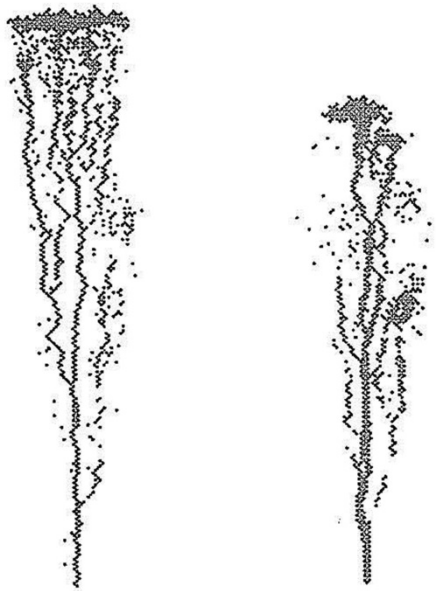
Foraging for foraging's sake



More general model of ant foraging including sojourn probabilities, pheromone thresholds, provides richer source of behaviors:

$$p_{moving} = \frac{1}{2}\left[1 + \tanh\left(\frac{\rho_l + \rho_r}{100} - 1\right)\right]$$

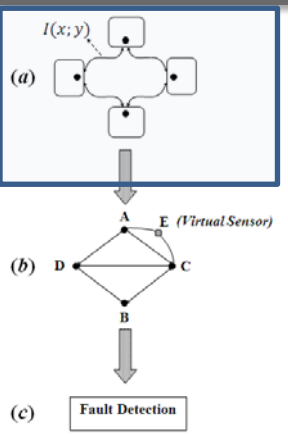
$$p_{moving\ to\ left} = \frac{(5+\rho_l)^2}{(5+\rho_l)^2 + (5+\rho_r)^2}$$



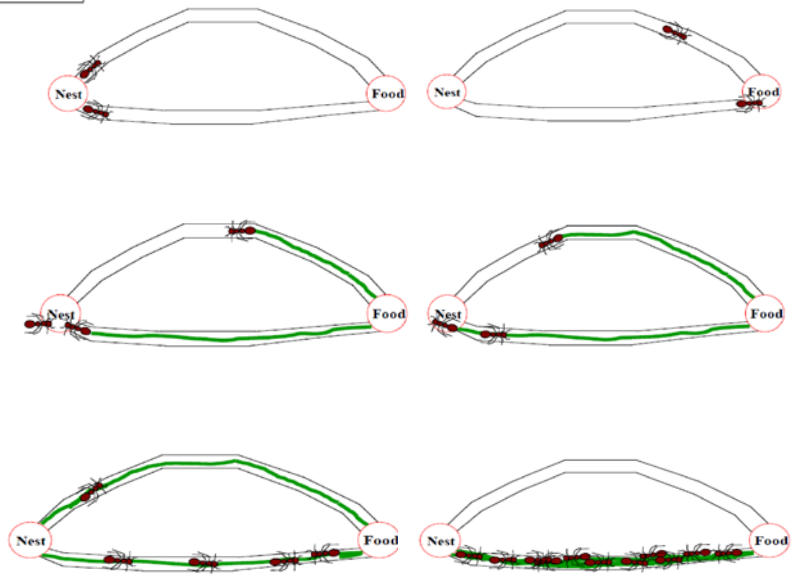
Different parameters (i.e., food concentration, distribution, pheromone thresholds) produce different raid patterns.

Optimization in Foraging Behavior

An introduction to Ant Colony Optimization (ACO)



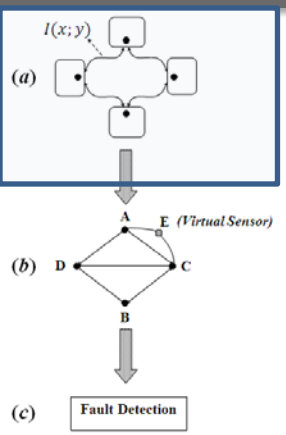
- Introduced by Marco Dorigo (1992)
- Ants lay a pheromone trail as they move. Pheromone levels increase with traffic but decrease with dissipation over time. The pheromone marking is thus reinforced on frequently used trails are and fades on infrequently used trails.



- Two ants start with equal probabilities of taking either path. shorter path => shorter transit time => more pheromone => the next ant takes the shorter path
- The combination of reinforcing pheromone trail leads to the shortest path to the food source. With random search procedures, the ants tend to also explore the alterative food sources.

ACO/AS Simulation

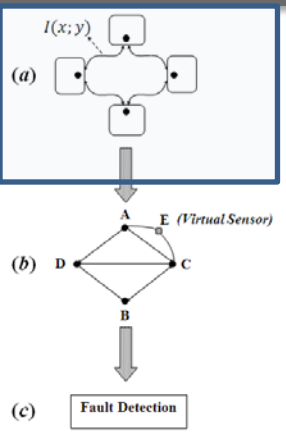
Network detection as optimization problem

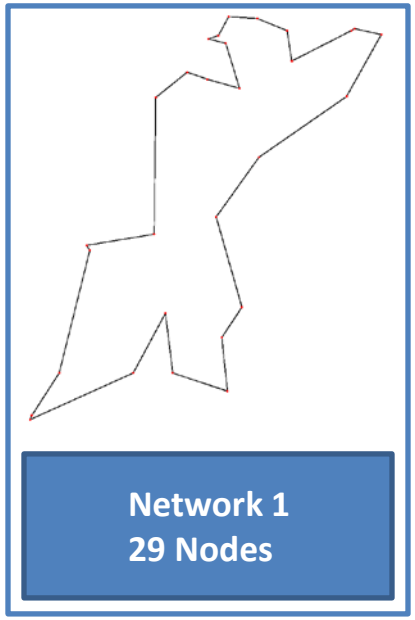


- Applied AS and ACO to problem of finding shortest paths on a network
  - System elements and sensors => nodes
  - Find shortest information distance => greatest mutual information
- Three networks considered:
  - Different number of nodes,
  - Different configurations.
- Implemented in Matlab©
- Examined performance and tuning options

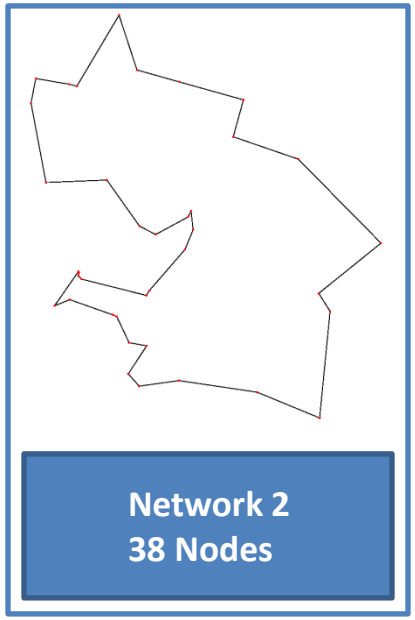
Networks

The three considered networks

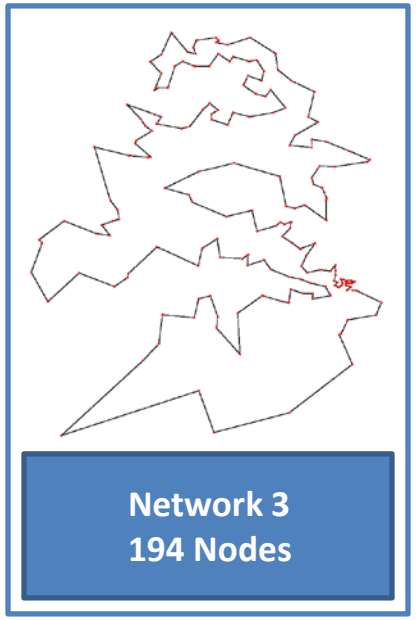




Network 1
29 Nodes



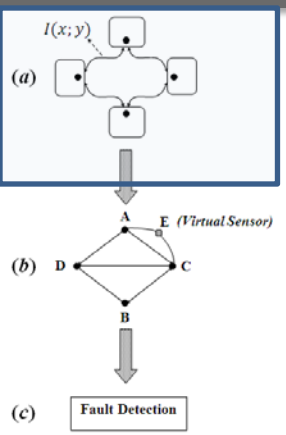
Network 2
38 Nodes



Network 3
194 Nodes

Ant System

Actionable Information



1. Place ants randomly on nodes.

   Number of Ants = Number of Nodes

2. Choose the next node *j* with probability:

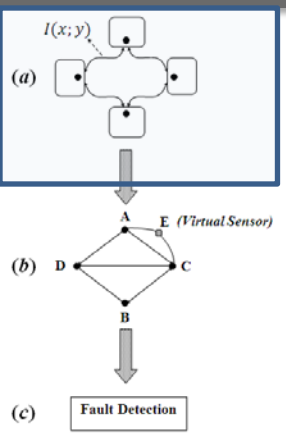
$$p_{ij}^{k} = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{l \in J_i^k}[\tau_{il}(t)]^{\alpha}.[\eta_{il}]^{\beta}}$$

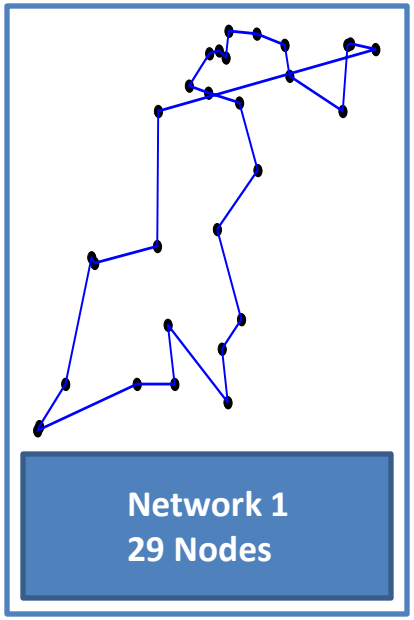
3. Update the pheromone trail:

$$\tau_{ij}(t) \leftarrow (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(\mathrm{t}) + e.\Delta\tau_{ij}^{e}(t)$$

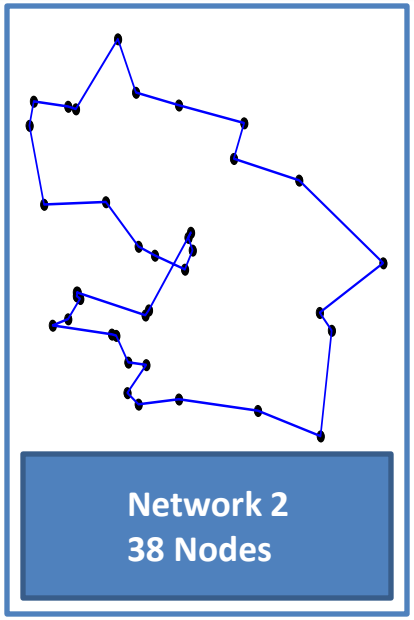
Results

Comparing the algorithm accuracy for each network

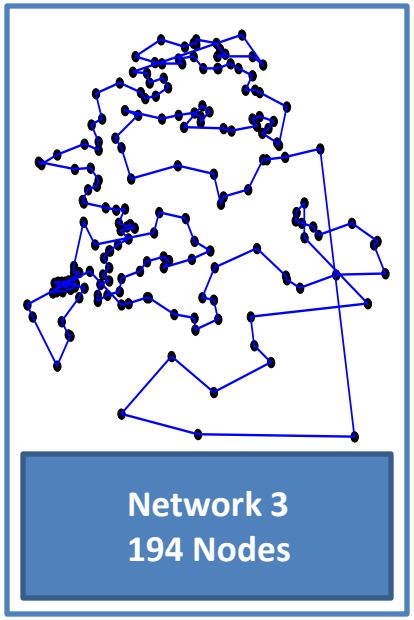




Network 1
29 Nodes



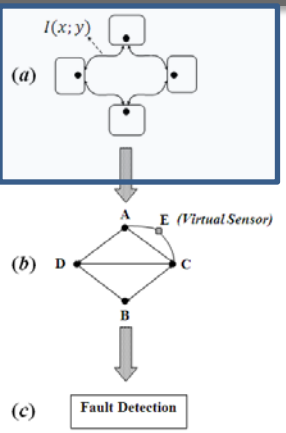
Network 2
38 Nodes



Network 3
194 Nodes

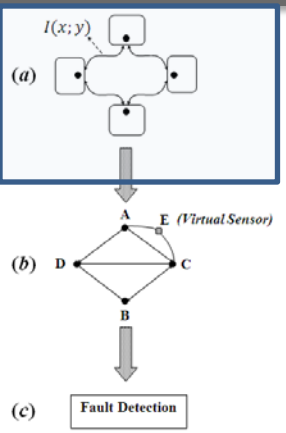
Network	Iterations	Accuracy
Network1	25	% 89.12
Network 2	25	% 98.35
Network 3	25	% 77.34

Observations



- The AS algorithm performance does not scale well with increasing node count.
- Displays poor sensitivity to adjustable parameters (i.e. not easily tuned).

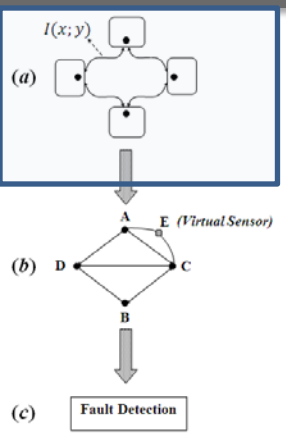
Ant Colony System

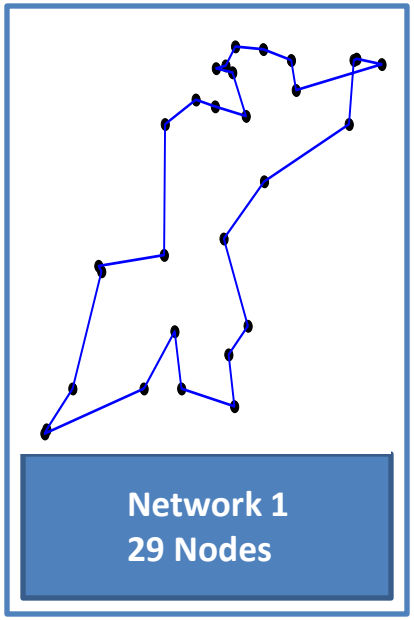


- Ant Colony System is similar to Ant System, which is based on the foraging behavior of ants.
- There are four main differences between these two algorithms:
  I. Exploration
  II. Transition Rule
  III. Global Trail Update
  IV. Local Trail Update

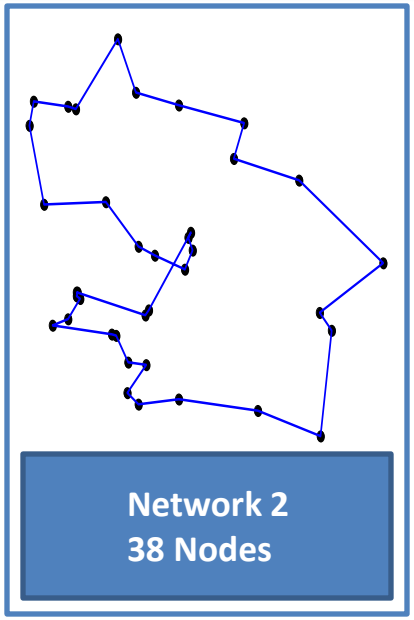
Results

Comparing the algorithm accuracy for each network

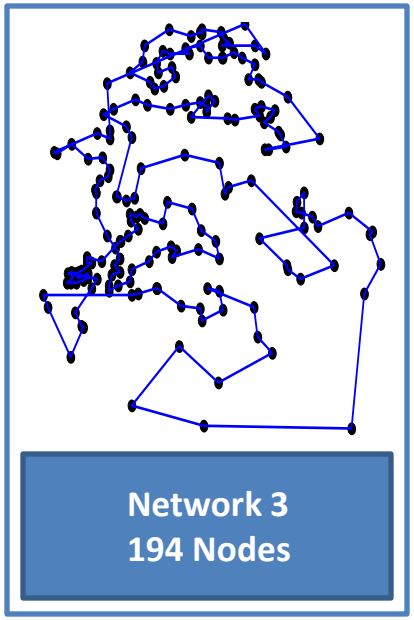




Network 1
29 Nodes



Network 2
38 Nodes



Network 3
194 Nodes

Network	Number of Agents	Number of Iterations	Accuracy
Network1	50	25	% 98.5
	100	50	% 95.8
Network 2	50	25	% 100
	100	20	% 100
Network 3	200	50	% 82.8
	300	25	% 81.9

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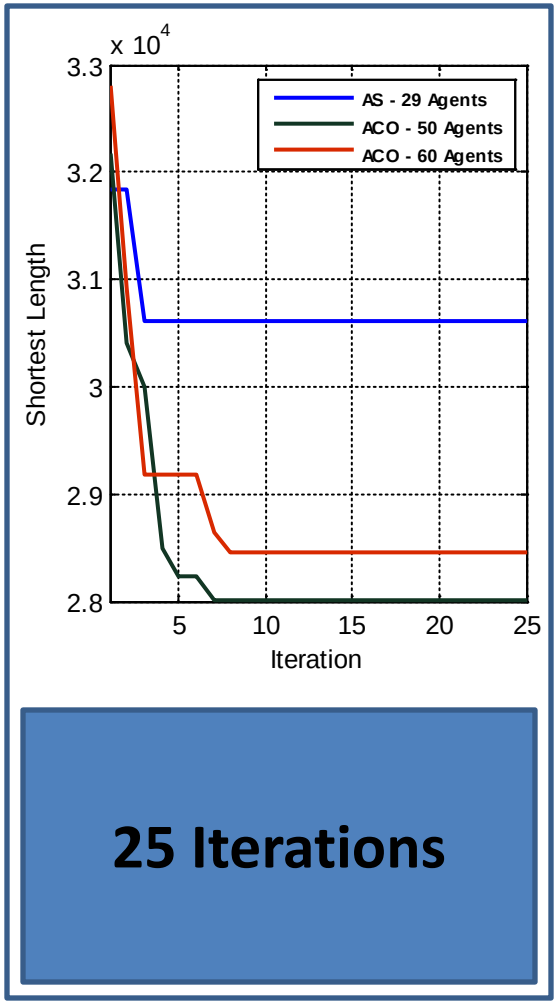
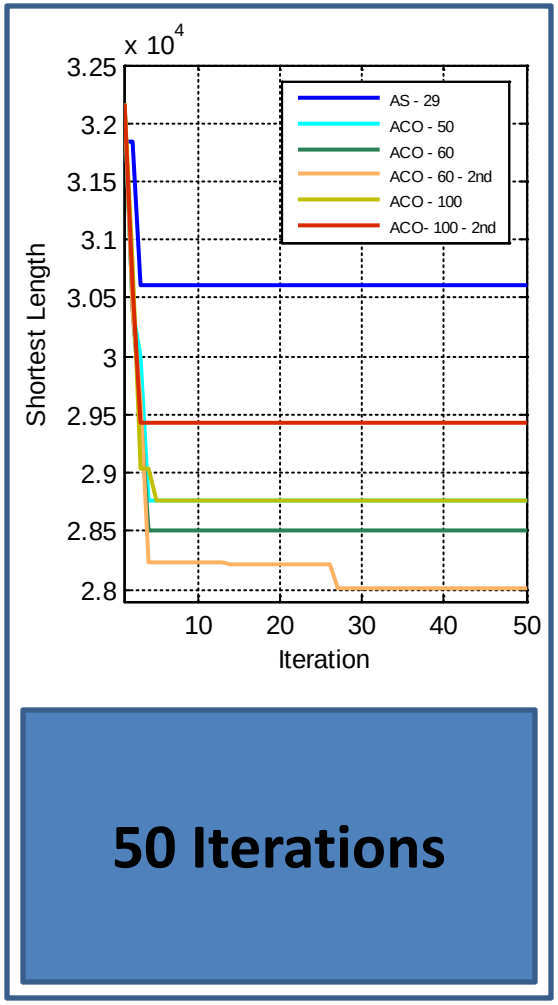
AS and ACS Comparison

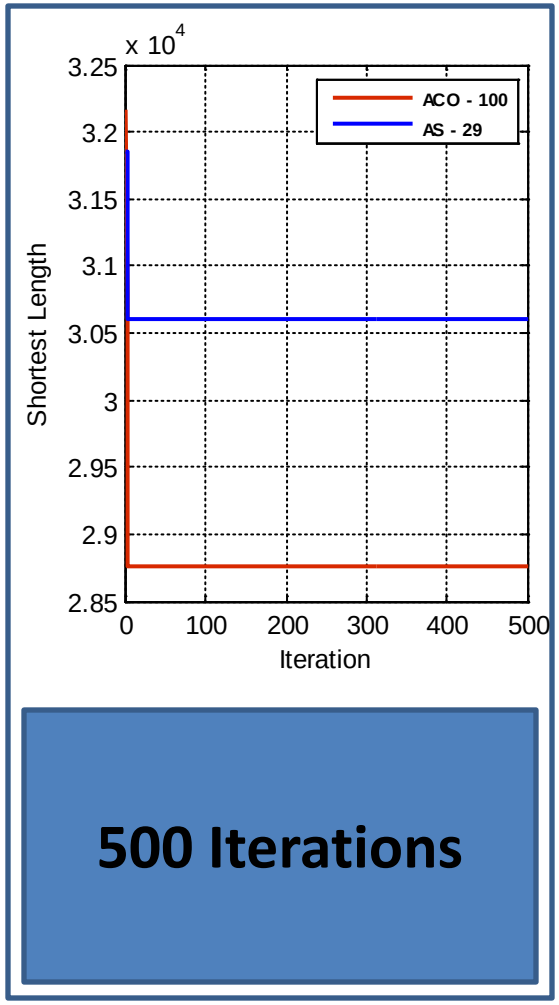
Network 1 with Different number of Agents



25 Iterations



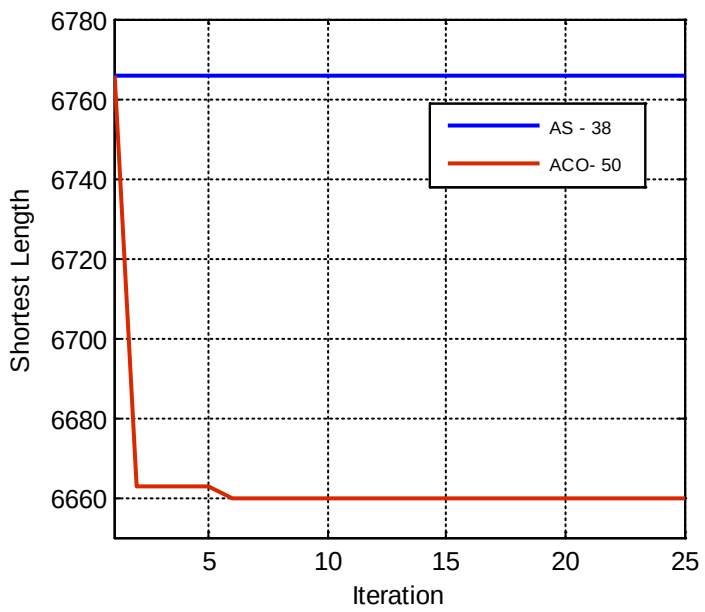
50 Iterations



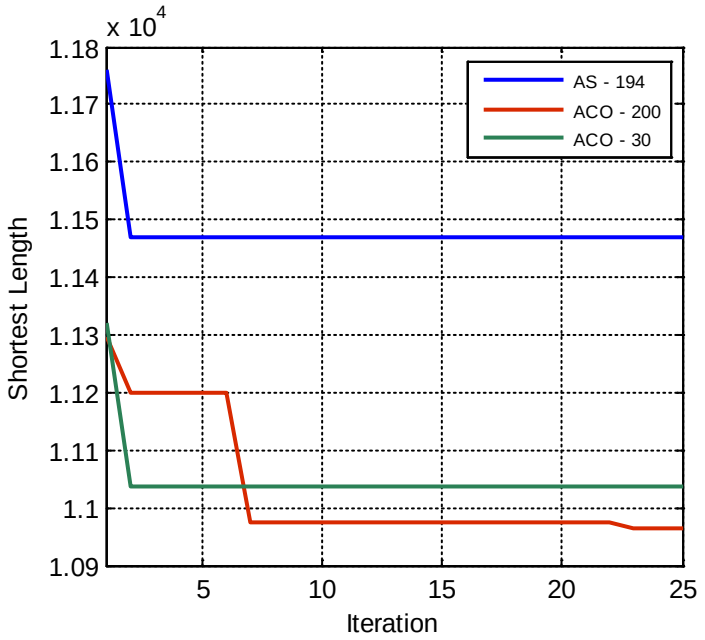
500 Iterations

AS and ACS Comparison

Networks 2 and 3 with Different number of Agents



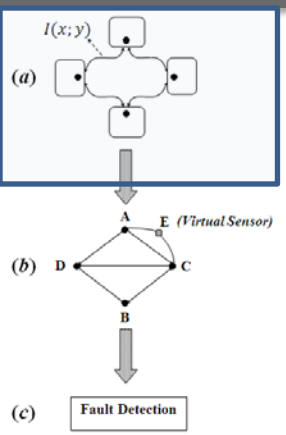
- **Network 2**
- **25 Iterations**



- **Network 3**
- **25 Iterations**

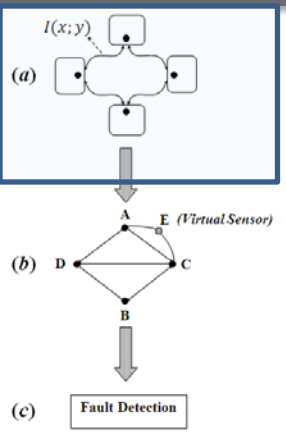
Recapitulation

ACO and AS Comparison



- The ACS algorithm works better than the AS algorithm.
- Changing the characteristics of the algorithm such as parameter values will not affect the results.
- The selection of the starting points at each iteration and pheromone trail update play an important role in this algorithm. Choosing the appropriate strategy will improve the results.
- These methods are designed for optimization and are limited in the behaviors that they can demonstrate and hence the flexibility that they offer.

Steam Plant Simulation

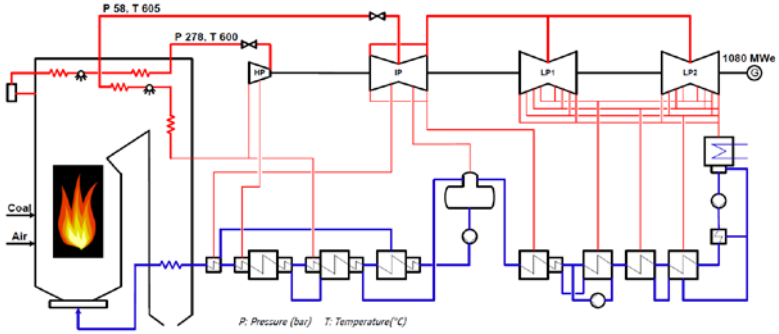


The Reference Unit:

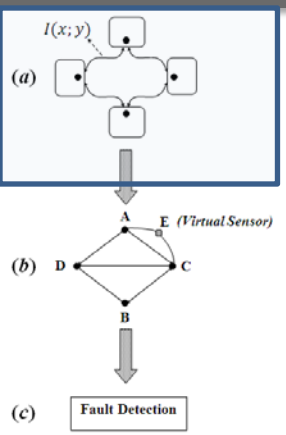
- Alstom's ultra-supercritical pulverized coal-fired plant design
- Gross electrical output of 1080MWe.
- The steam generator will produce steam flow to a turbine generator with boiler outlet conditions of main steam flow of 600°C @ 278 bar g and RH outlet steam flow of 605°C @ 58 bar g.
- The plant net heat rate is 9045 kJ/kWh.

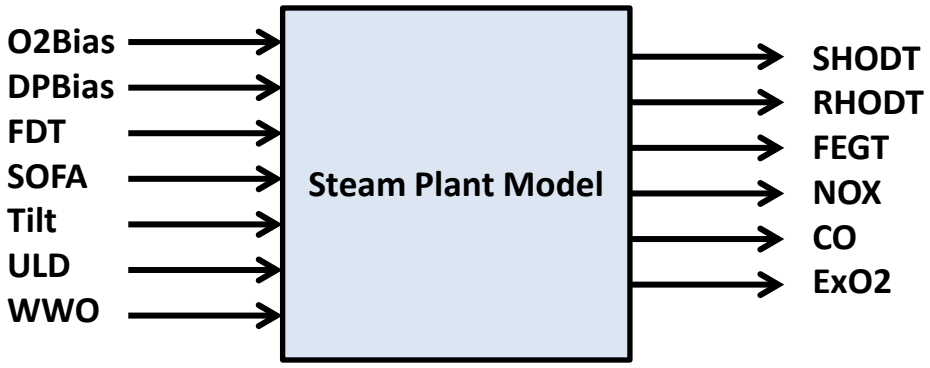
Model Subsystems:

- steam generator (boiler)
- steam turbines
- feedwater preheating system



Model Structure



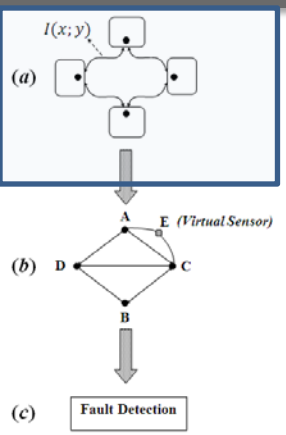


Inputs	
O2Bias	O_2 Setpoint Bias
DPBias	Furnace Differential Pressure Setpoint Bias
FDT	Final desuperheater Temperature
SOFA	Separated overfire air damper bias
Tilt	Main Wind Box Tilt
ULD	Unit Load Demand
WWO	Waterwall Outlet

Outputs	
SHODT	Superheater Outlet Temperature Deviation
RHODT	Reheater Outlet Temperature Deviation
FEGT	Final Exhaust Gas Temperature
NOX	Stack NOx
CO	Stack CO (constraint)
ExO2	Excess O_2 (constraint)

Raw Data

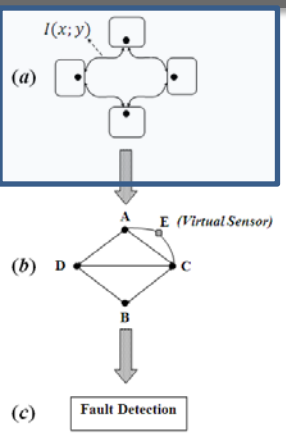
Step Testing Data

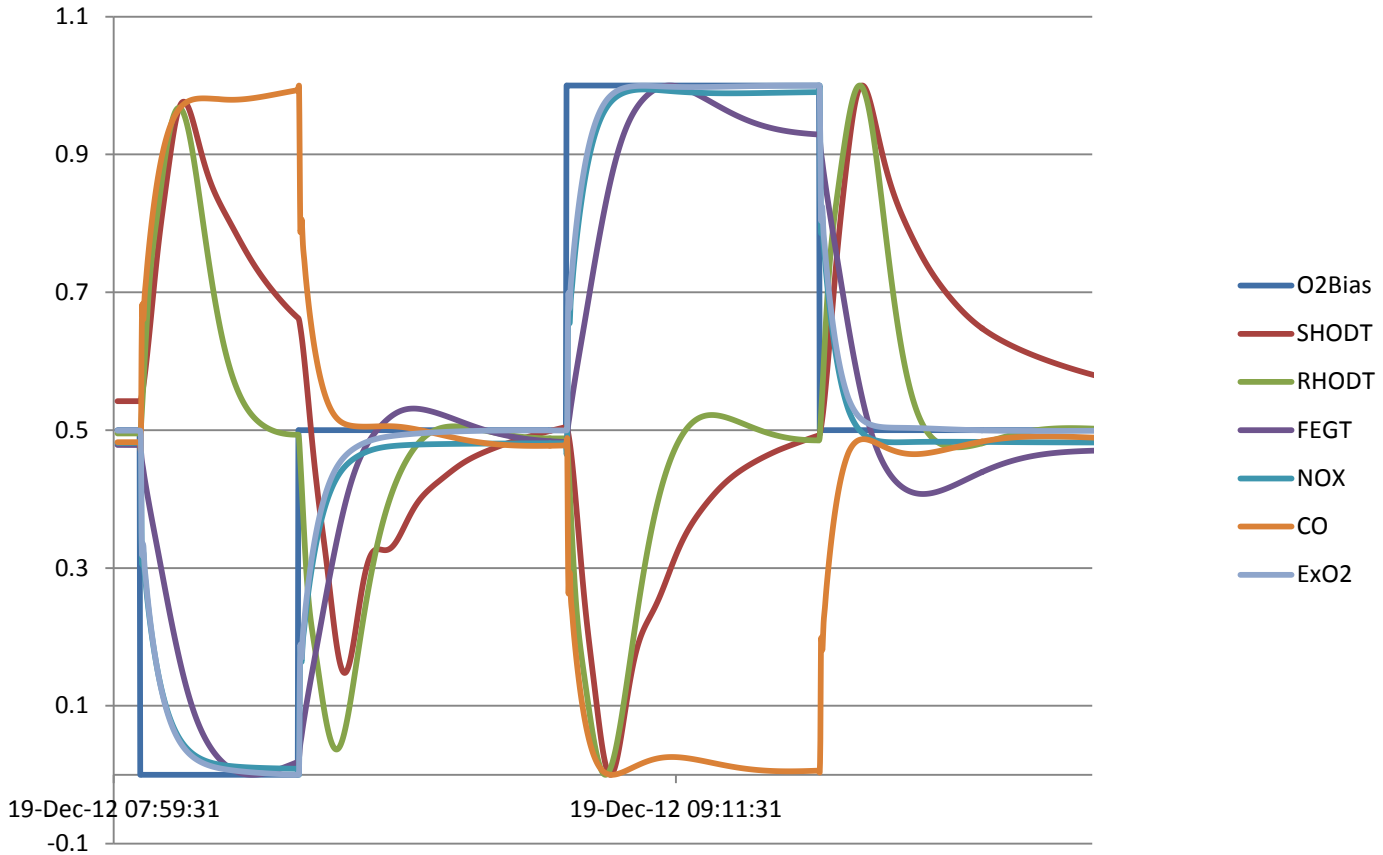


- **Step testing data:**
  - To identify the input/output model between each pair for dynamic model identification, a step test sequence is performed to stimulate the process.
  - The dynamic simulation is run to steady state at one operating point.
  - For each settled MV, the values of all CVs are recorded.
- **Coal flow, MW generation, air flow and other specifications are also recorded during the step testing.**

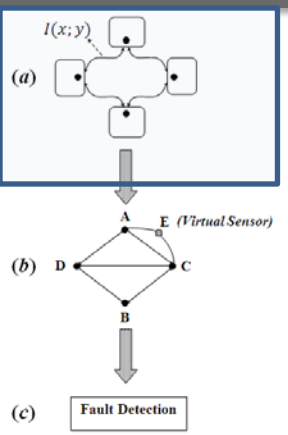
Step Test for O2Bias

Normalized



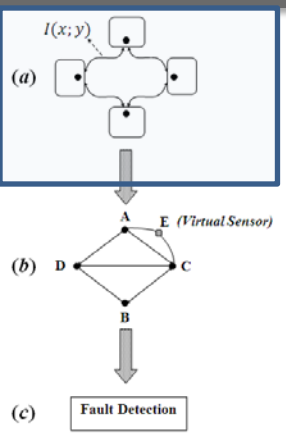


Preparing Data for Modeling

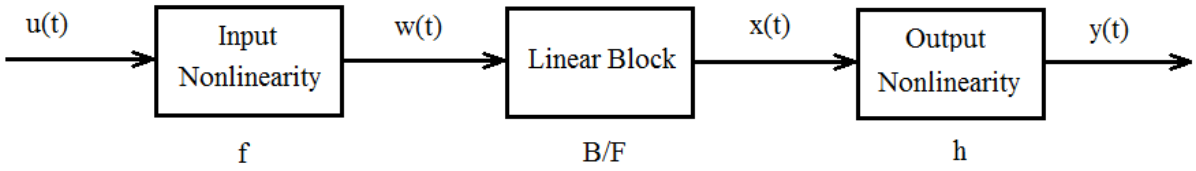


- **Normalize data between [0.1].**
  - Normalization does not impact correlation coefficient calculations.
- **Construct IDDATA object for used with Matlab's System Identification Toolbox.**
- **Construct model:**
  - Merge all data sets into a single data set and compute a MIMO model.
    - *Results were not promising. The single model could not capture the nonlinearity between all of the input/output pairs.*
  - A SISO model is computed for each input/output pair. At the end we will have 6x7 SISO models for our steam plant simulation.

SISO Modeling Results



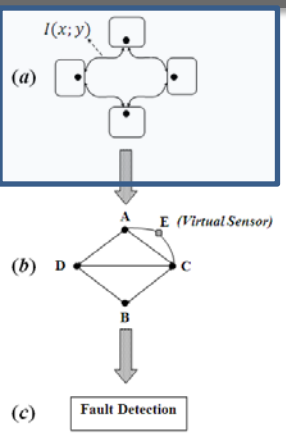
- **Hammerstein-Wiener Model**
  - Block Diagram :



- w(t) = f(u(t)): nonlinear function transforming input data u(t).
- x(t) = (B/F)w(t): linear transfer function.
- y(t) = h(x(t)): nonlinear function that maps the output of the linear block to the system output.

DPBias Modeling Results

Models with their fit percentage

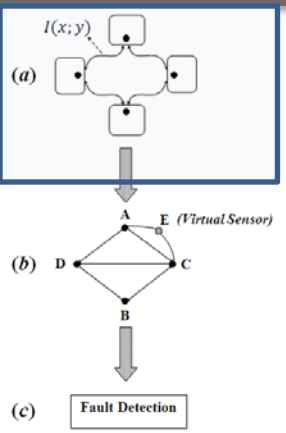


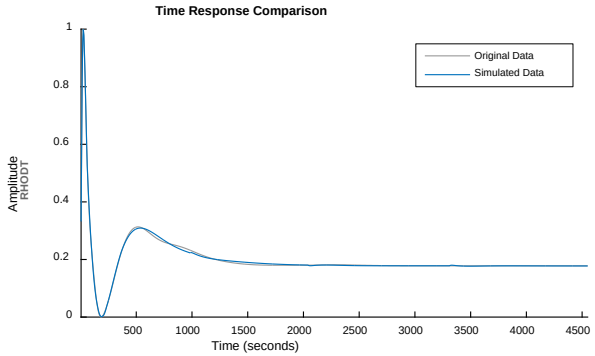
DPBias

- M_1 → **RHODT** (%95.4)
- M_2 → **SHODT** (%84.38)
- M_3 → **FEGT** (%82.5)
- M_4 → **NOX** (%98.77)
- M_5 → **CO** (%95.42)
- M_6 → **ExO2** (%83.51)

DPBias-RHODT Model

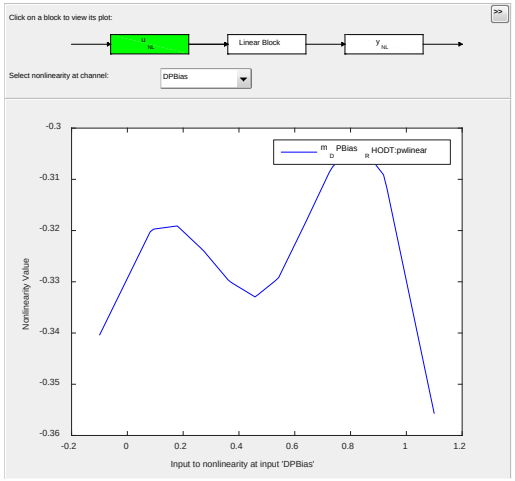
System Identification



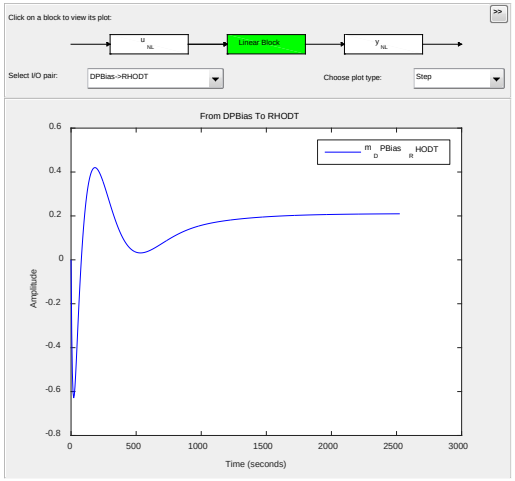


Model Accuracy: %95.4

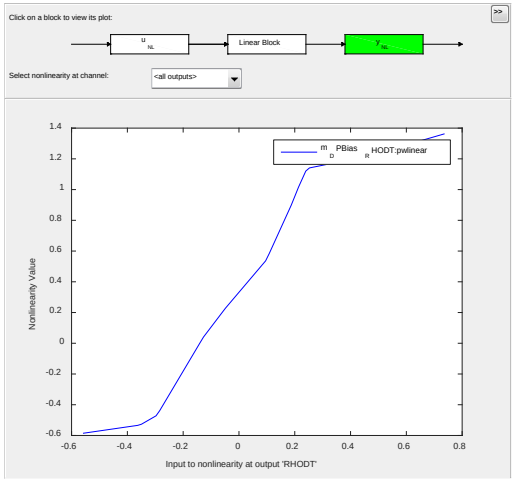
Input Nonlinearity



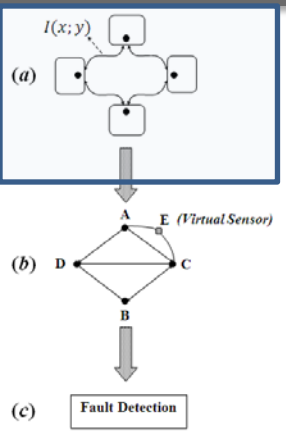
Linear Block Step Response



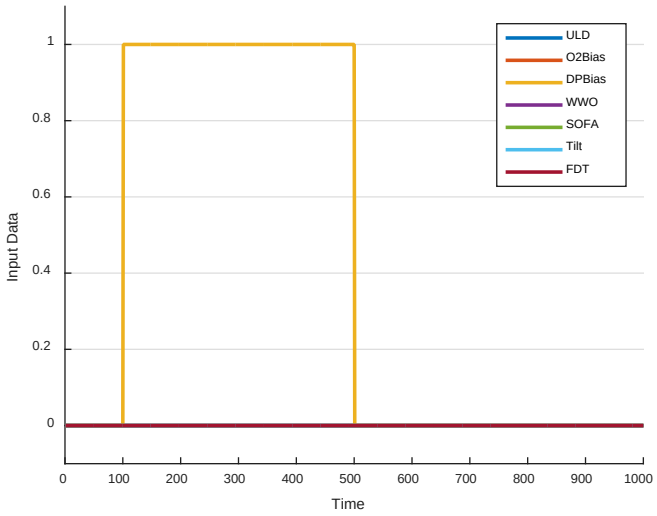
Output Nonlinearity

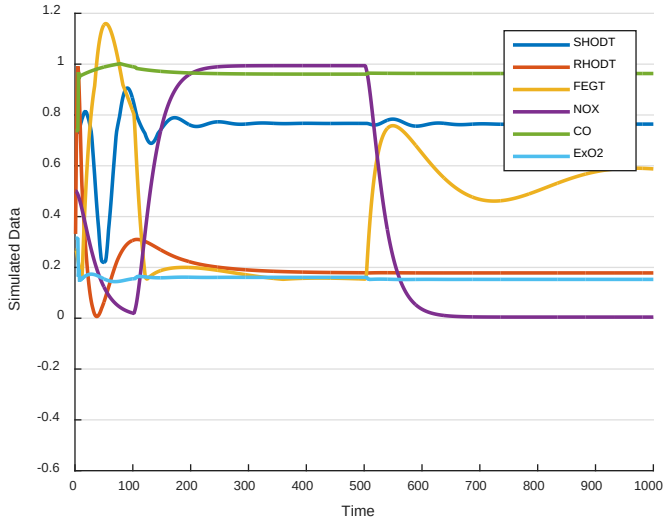


Constructing New Data



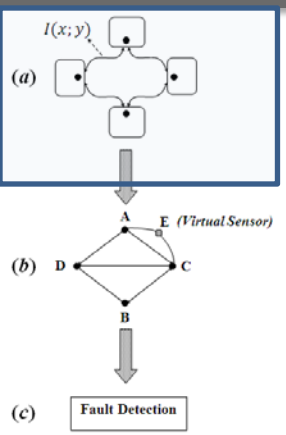
- **Using calculated SISO models, construct new data with custom input signals.**
- **Enables introduction of faults into the system for testing performance of fault detection framework.**

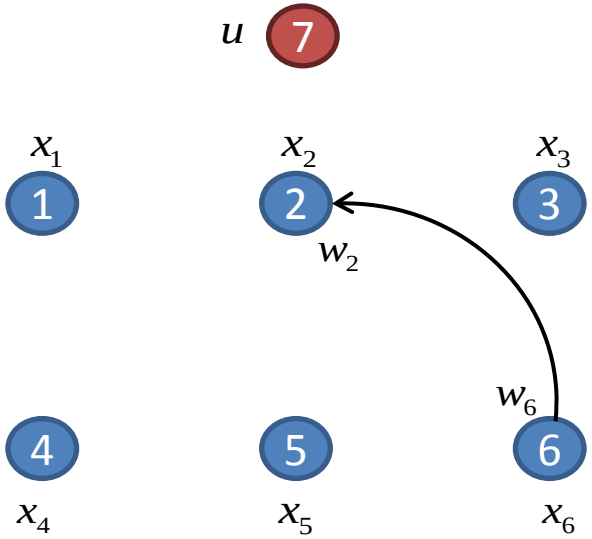




Network Discovery

The observation of physical system from a foraging perspective





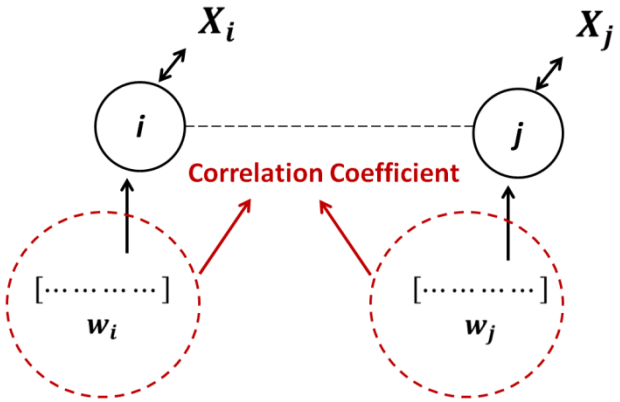
Agent going from node 6 to node 2:

Behavior:

The agent carries the data, w_6 ,from its home node to the next node.

Food Definition:

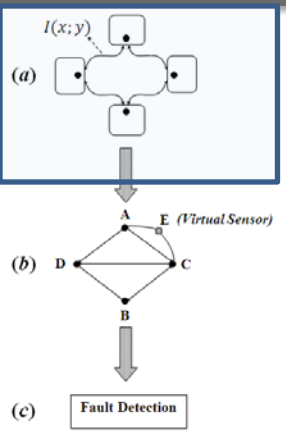
The Correlation Coefficient between the time series w_6 and w_2.



x_i : a time series which is the observations at node *I*

w_i : a time series which is the partial observations of x_i at node *i*

Proposed Algorithm Based on Foraging Behavior of Ants



- A set of agents are randomly placed on the nodes such that each node has at least one agents.
- Agents select the next node based on the current correlation coefficient for that time frame. They favor the nodes with higher correlation coefficient.
- As the agents travel, pheromone is deposited on the edges as a function of correlation coefficient between the source and destination node.
- Based on the pheromone values at the end of the last iteration, a topology is extracted.

Proposed Algorithm Based on Foraging Behavior of Ants

- For agent $\boldsymbol{k}$ at node $\boldsymbol{i}$, the next node $\boldsymbol{j}$ is chosen based on the following rule:

$$g(w_i, w_u) = \left| correlation_coefficient(w_i, w_u) \right|$$

$$j = \begin{cases} \arg \max_{u \in J_i^k} \{ g(w_i, w_u) \} & if \ q \le q_0 \\ J & if \ q > q_0 \end{cases}$$

  - q : a random variable uniformly distributed over
  - q_0: a tunable parameter over
  - J_i^k : set of all the nodes in the system except for the current node
  - $J \in J_i^k$: node that is randomly selected according to this probability:

$$p_{ij}^k(t) = \frac{[g(w_i, w_J)(t)]}{\sum_{l \in J_i^k} [g(w_i, w_J)(t)]}$$

- The agent $\boldsymbol{i}$ goes to node $\boldsymbol{j}$ and updates the pheromone trail of the pair $(\boldsymbol{i}, \boldsymbol{j})$ according to the following rule:

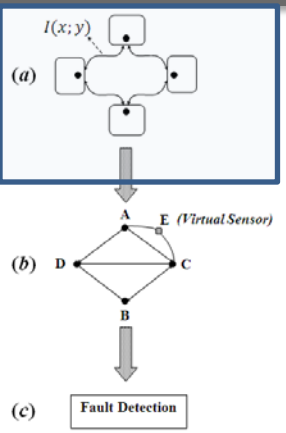
$$\tau_{ij}(t) \leftarrow (1-\rho) \cdot \tau_{ij}(t) + f(w_i, w_j)$$

where:

$$f(w_i, w_j) = \left| correlation_coefficient(w_i, w_j) \right|$$

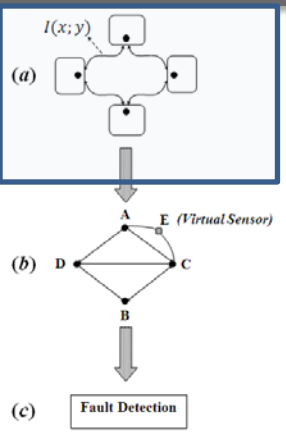
  - Note that the exact value of correlation coefficient is deposited on the edge which is different from the previous version.

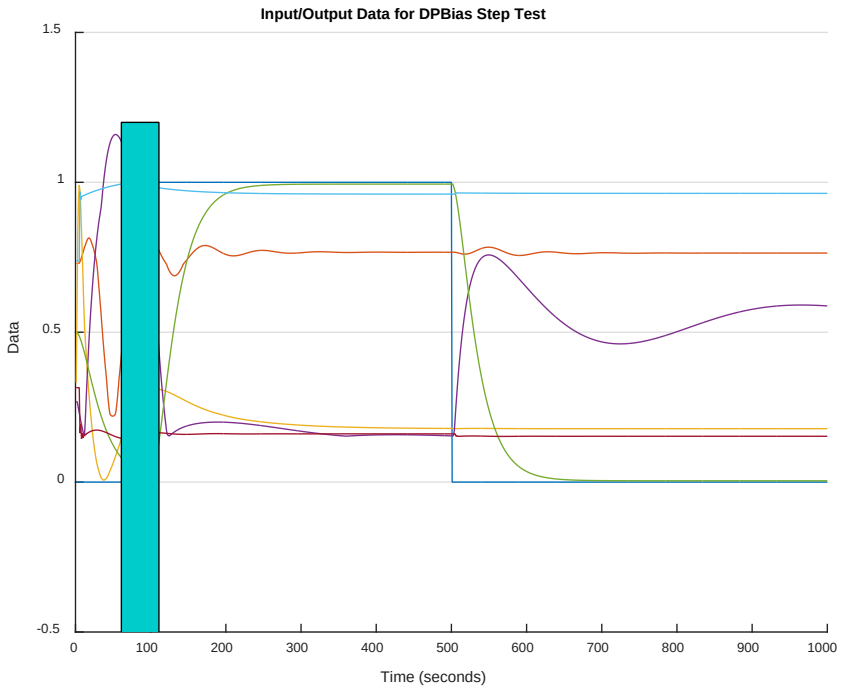
Initialization



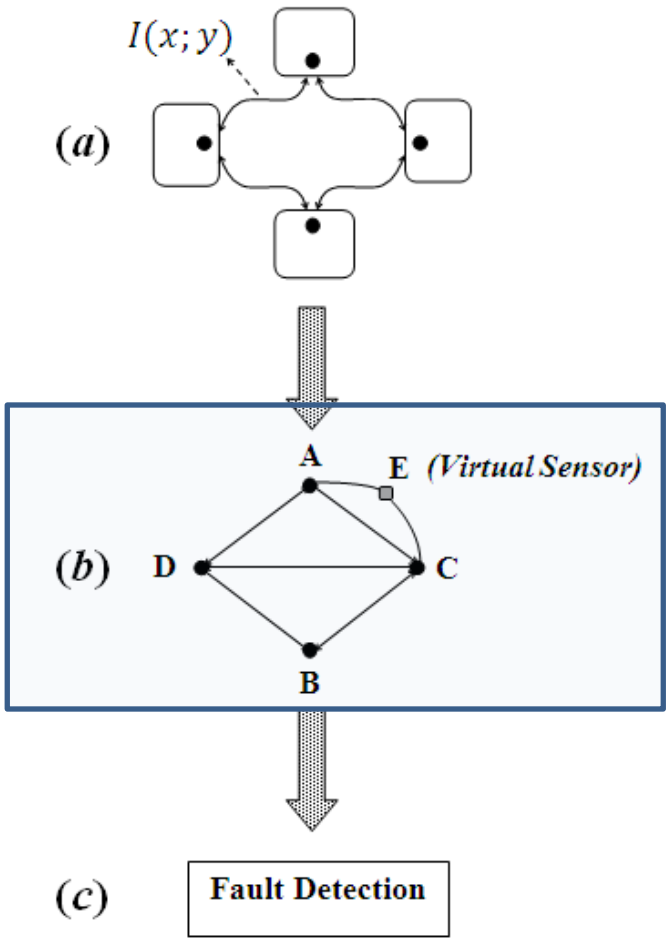
- **Number of Nodes= 7**
- **Number of Agents= 7x100**
  - 7 distinct swarms, each containing 100 agents, deployed to the network at different times during the simulation. Each swarm deposits a distinct pheromone and only follow their own pheromone on the edges.
    - *Time Period=50s*
- **Initial Value on pheromone Trail=0**
- **pheromone decay coefficient=0.1**
- **Initial position of the agents= random, but at least one agent at each node**

Simulation Snapshot



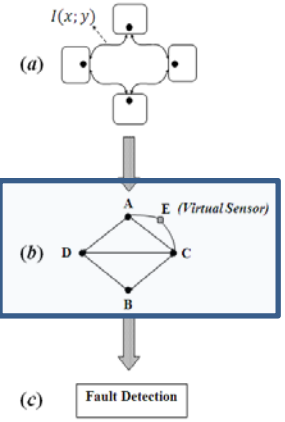


Information/Objective Mapping



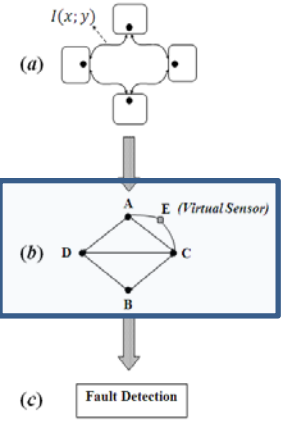
- Having the knowledge on intrinsic topology, we can properly align our observation processes, including **virtual sensors**, with the intrinsic communication topology.
- Virtual sensors can be used to:
  1. Sense things that we cannot directly instrument.
  2. Validate or verify other measurements.
  3. Reconstitute lost sensing and communication.

Graph Similarity Measures



- Graph similarity techniques can be used to detect the changes in the extracted topology.
- These changes can be the result of a fault in the system or the changes in system's dynamics.
- In a class of similarity methods in which an element (e.g., a node or edge) in graph G_A and an element in graph G_B are considered similar if their respective neighborhoods within G_A and G_B are similar.

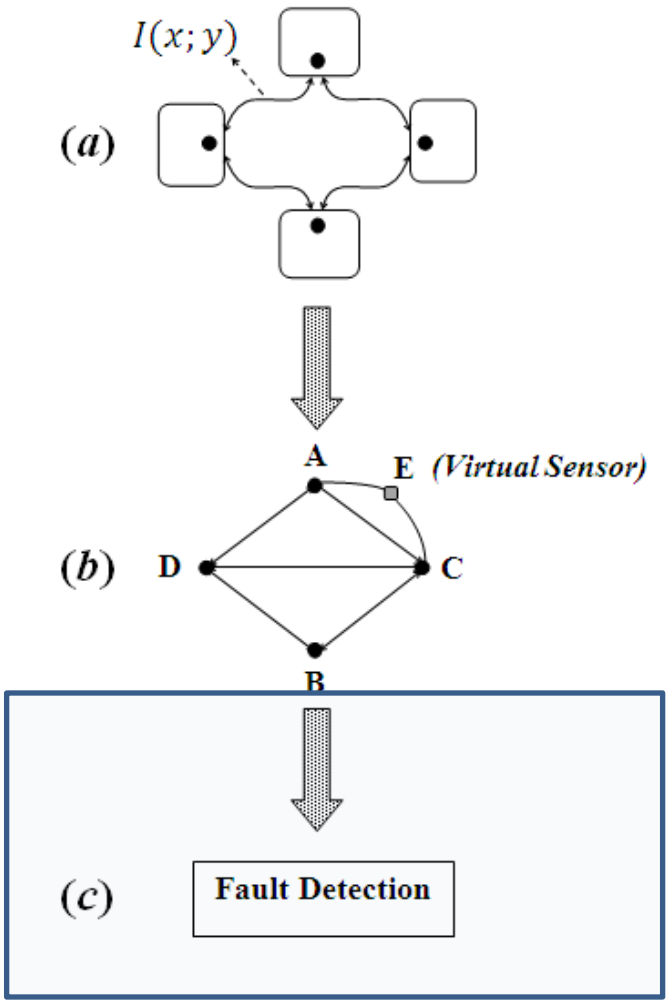
Pattern Mining



- In pattern mining, dynamic graphs have been analyzed from two main research tracks:
  - The study of the properties that describe the topology of the graph,
  - The extraction of specific sub-graphs to describe the graph evolution.

Fault Detection and Diagnosis

Processing the information/objective mapping for Fault Detection



- Map the information streams to operational objectives and needs for fault detection.

Conclusions

- **In this presentation, we discussed foraging behavior and raid patterns of army ants.**
- **Examined and run simulation for two optimization algorithms based on social behavior of ants.**
- **Proposed a new algorithm for condition monitoring of a steam plant based on foraging behavior of ants and applied it to real data.**
- **For the path forward, we will explore graph similarity and pattern mining techniques to select the appropriate approach for our project.**

Thank you…

BACKUP SLIDES

DIFFERENCES BETWEEN ACS AND AS ALGORITHMS

1- Exploration

- A **Candidate List** is formed for each city which is the list of **preferred cities** to be visited from that given city and consists of ***cl*** **closest** cities.
  - From any given city, first the candidate list for that city is examined for possible next city.
  - If all the candidate list cities are visited, the next city will be the closest of the yet unvisited cities.

2- Transition Rule

- An ant *k* on city *i* chooses the next city *j* to move based on the following rule:

$$j = \begin{cases} \arg max_{u \in J_i^k} \{[\tau_{iu}(t)].[\eta_{iu}]^{\beta}\} & if\ q \leq q_0 \\ J & if\ q > q_0 \end{cases}$$

  - q: a random variable uniformly distributed over [0,1]
  - q_0: tunable parameter over [0,1]
  - $J \in J_i^k$: city that is randomly selected according to this probability:

$$p_{iJ}^k(t) = \frac{[\tau_{iJ}(t)].[\eta_{iJ}]^{\beta}}{\sum_{l \in J_i^k}[\tau_{il}(t)].[\eta_{il}]^{\beta}}$$

3- Global Trail Update

- The global trail updating is only applied to the edges belonging to the best tour since the beginning of the trial:

$$\tau_{iu}(t) \leftarrow (1-\rho).\tau_{iu}(t) + \rho.\Delta\tau_{iu}(t)$$

  - (i,j): the edges belonging to the best tour T^+
  - ρ: a parameter governing the pheromone decay
  - $\Delta\tau_{iu}(t) = {}^{1}/_{L^+}$

4- Local Trail Update

- The local pheromone update is performed after each transition by the following formula:

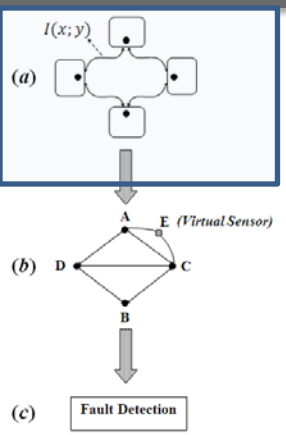
$$\tau_{iu}(t) \leftarrow (1-\rho).\tau_{iu}(t) + \rho.\tau_0$$

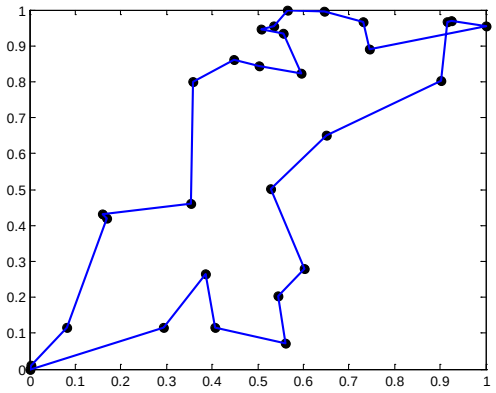
  - $\tau_0 = (n.L_{nn})^{-1}$: the initial value of pheromone trail
  - n: number of cities
  - L_{nn}: length of a tour produced by the nearest neighbor heuristic

DETAILED RESULTS FOR ACS

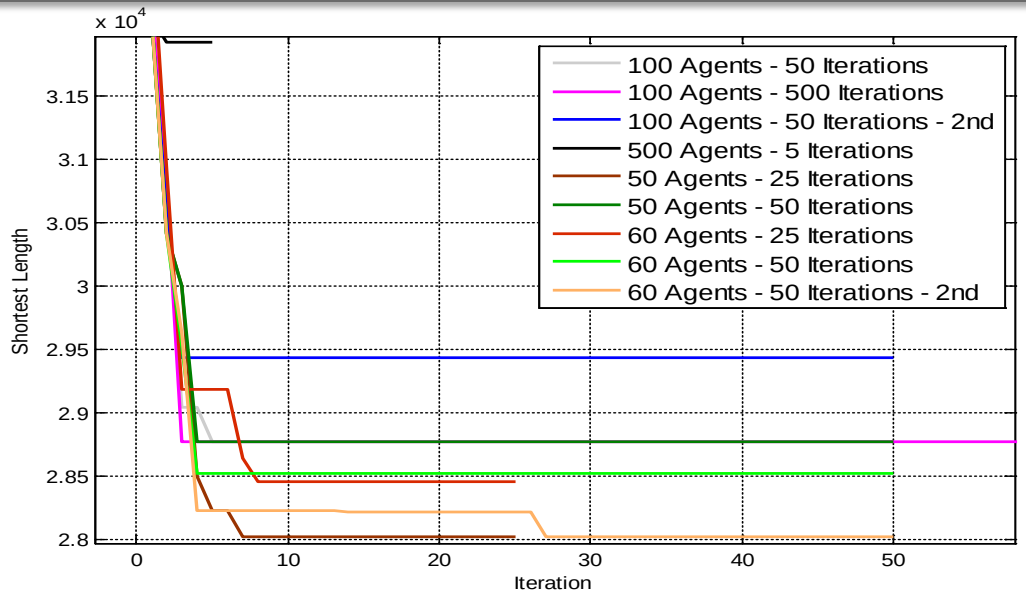
Network 1 Simulation Results

Comparing the algorithm accuracy for network 1





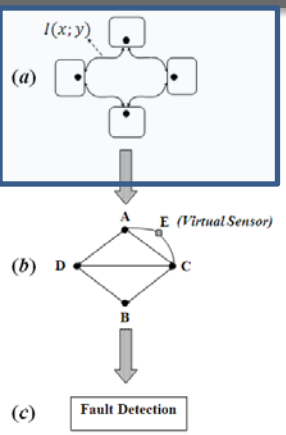
Network 1 with 29 Nodes

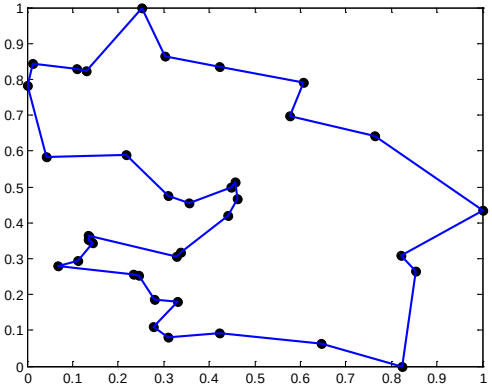


Number of Agents	Number of Iterations	Accuracy
50	**25**	**% 98.5**
50	50	% 95.8
60	**25**	**% 96.9**
60	**50**	**% 96.7**
100	50	% 95.8
100	500	% 95.8
500	5	% 84.3

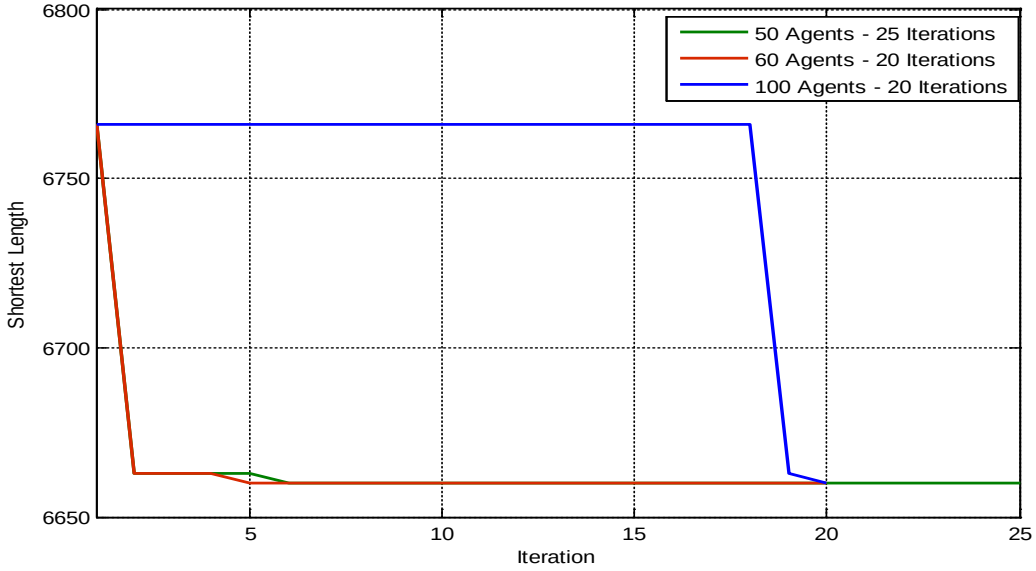
Network 2 Simulation Results

Comparing the algorithm accuracy for network 2





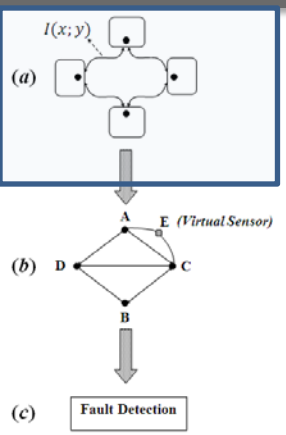
Network 2 with 38 Nodes

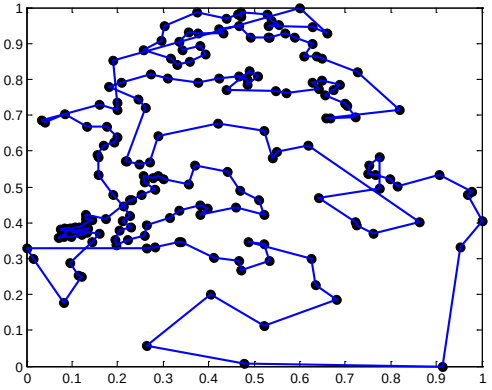


Number of Agents	Number of Iterations	Accuracy
50	25	**% 100**
60	20	**% 100**
100	20	**% 100**

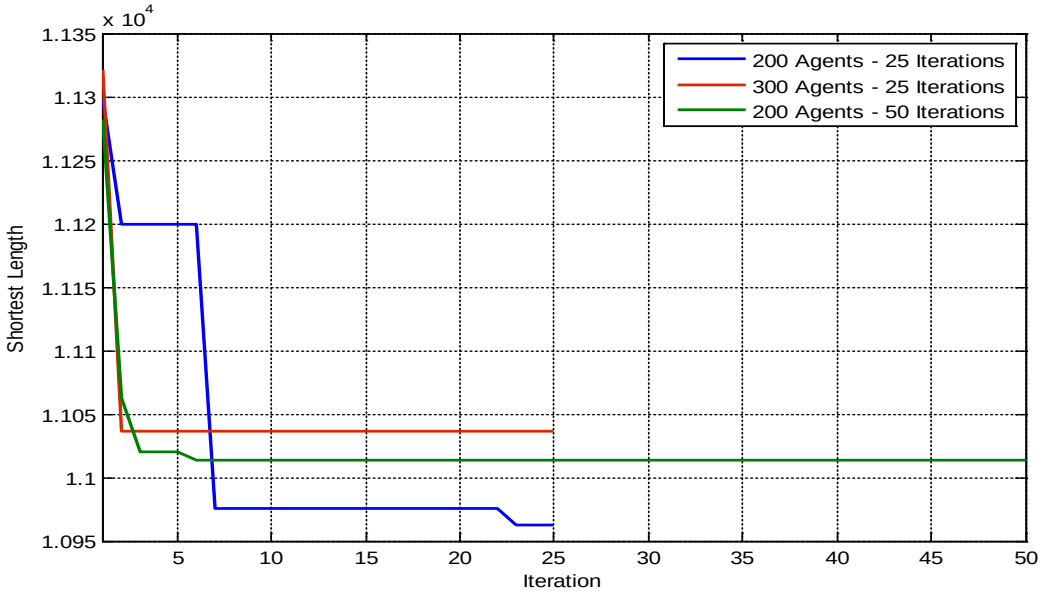
Network 3 Simulation Results

Comparing the algorithm accuracy for network 3





Network 3 with 194 Nodes



Number of Agents	Number of Iterations	Accuracy
200	**25**	**% 82.8**
300	25	% 81.9
200	50	% 82.2

CORRELATION COEFFICIENT AND NORMALIZATION

Correlation Coefficient

Normalization Impact

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sqrt{E[(X-\mu_X)^2]}\sqrt{E[(Y-\mu_Y)^2]}}$$

$$X^{new} = \frac{X - \min(X)}{\max(X) - \min(X)}, \quad \sigma_X{}^{new} = \frac{1}{\max(X) - \min(X)}\sigma_X$$

$$Y^{new} = \frac{Y - \min(Y)}{\max(Y) - \min(Y)}, \quad \sigma_Y{}^{new} = \frac{1}{\max(Y) - \min(Y)}\sigma_Y$$

$$\mathrm{cov}(X,Y)^{new} = \left(\frac{1}{\max(X) - \min(X)}\right)\left(\frac{1}{\max(Y) - \min(Y)}\right)\mathrm{cov}(X,Y)$$

$$\rightarrow \rho_{X,Y}{}^{new} = \rho_{X,Y}$$