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A Self-Organizing Agent-Based Sensor Network for Power Plant Condition Monitoring

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INTRODUCTION

The objective of this work is to develop algorithms and software systems that enable a sensor network for condition monitoring of power generation plants to be adaptive, resilient, and self-healing. This sensor network should dynamically discover the intrinsic communication topology of power generation systems, associate sensor data streams with operational objectives and reconstitute lost or degraded sensing and communication capabilities. The challenges and opportunities in developing the sensor network are listed in Table 1 below.

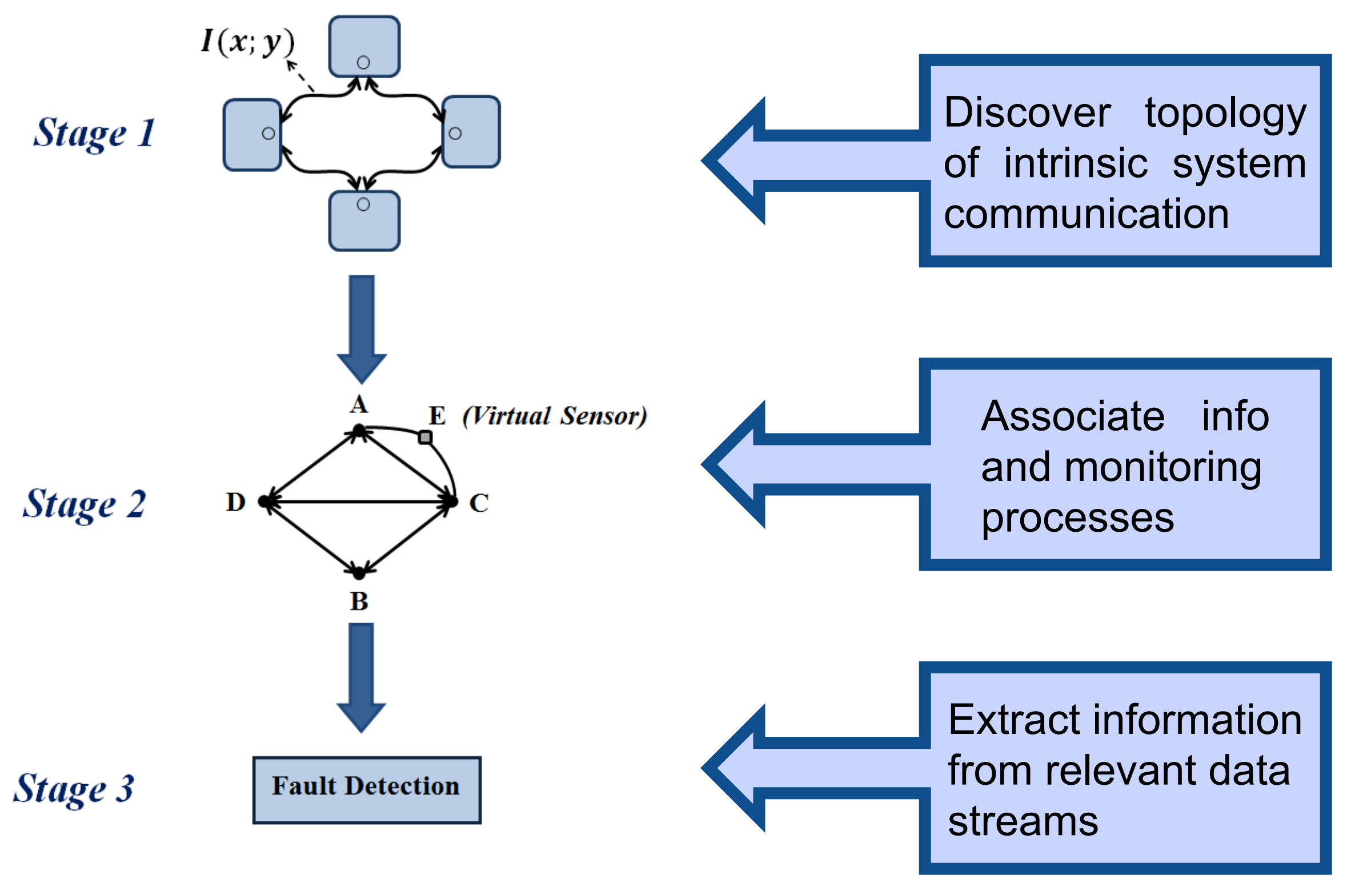
Table 1. Challenges and Opportunities

Challenges	Opportunities
➢ Scaling : ○ Complexity, ○ Data transmission (BW, QoS), ○ Computational footprint. ➢ Accommodate existing infrastructure ➢ Lack of a priori understanding of relevant systems ➢ Wide variation in operating conditions, ➢ System permeability	➢ Ubiquitous computational and (wireless) communication resources ➢ Power management technologies ○ No umbilical ○ Physically reconfigurable on-the-fly

These constraints and opportunities mandate a **distributed** and **agent-based** approach and strongly suggest the use of **biologically inspired** algorithms:

•**Distributed:** Scalability, accommodate new instrumentation and reorganizing existing infrastructure.
•**Agent-Based:** Flexible, provide a basis for bottom-up application, minimize communication requirements and distribute processing.
•**Biologically Inspired:** Capture emergent phenomena (provide basis for accommodating unanticipated contingencies).

TECHNICAL APPROACH



Discover topology of intrinsic system communication

Associate info and monitoring processes

Extract information from relevant data streams

Figure 1. Connecting Data to Operational Needs and Objectives

TOPOLOGY DISCOVERY

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 methods, e.g., swarm intelligence algorithms, are well suited to addressing this problem in an adaptive and distributed manner.

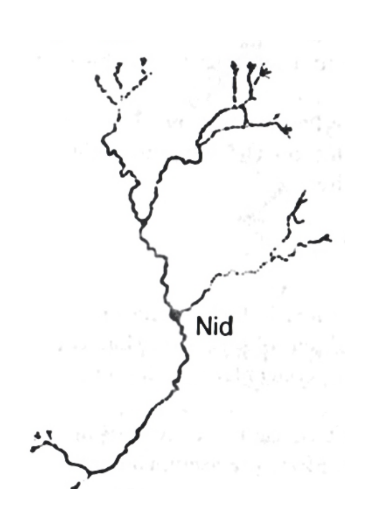
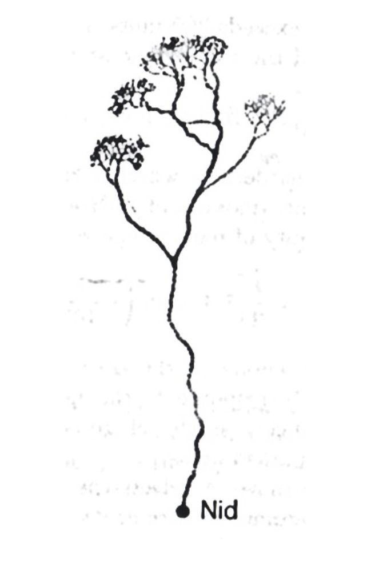
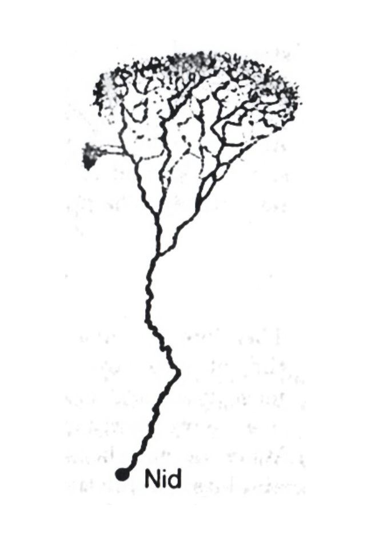
SWARM INTELLIGENCE

•Inspired by the collective behavior of animals in nature (insect colonies, bird flocks, and fish schools).
•Consists of a group of *agents interacting locally* with each other and with their environment.
•Agents follow simple rules governing local behaviors that, in turn, *emerge* global behaviors of value.

Self-organization	Stigmergy	Bounded Autonomy
• Positive Feedback *(Amplification)* • Negative Feedback *(Balancing)* • Amplification of Fluctuations • Many Interactions	Indirect communication between system elements via interaction with environment	Local behaviors are not specified in a deterministic manner, agents have limited autonomy.

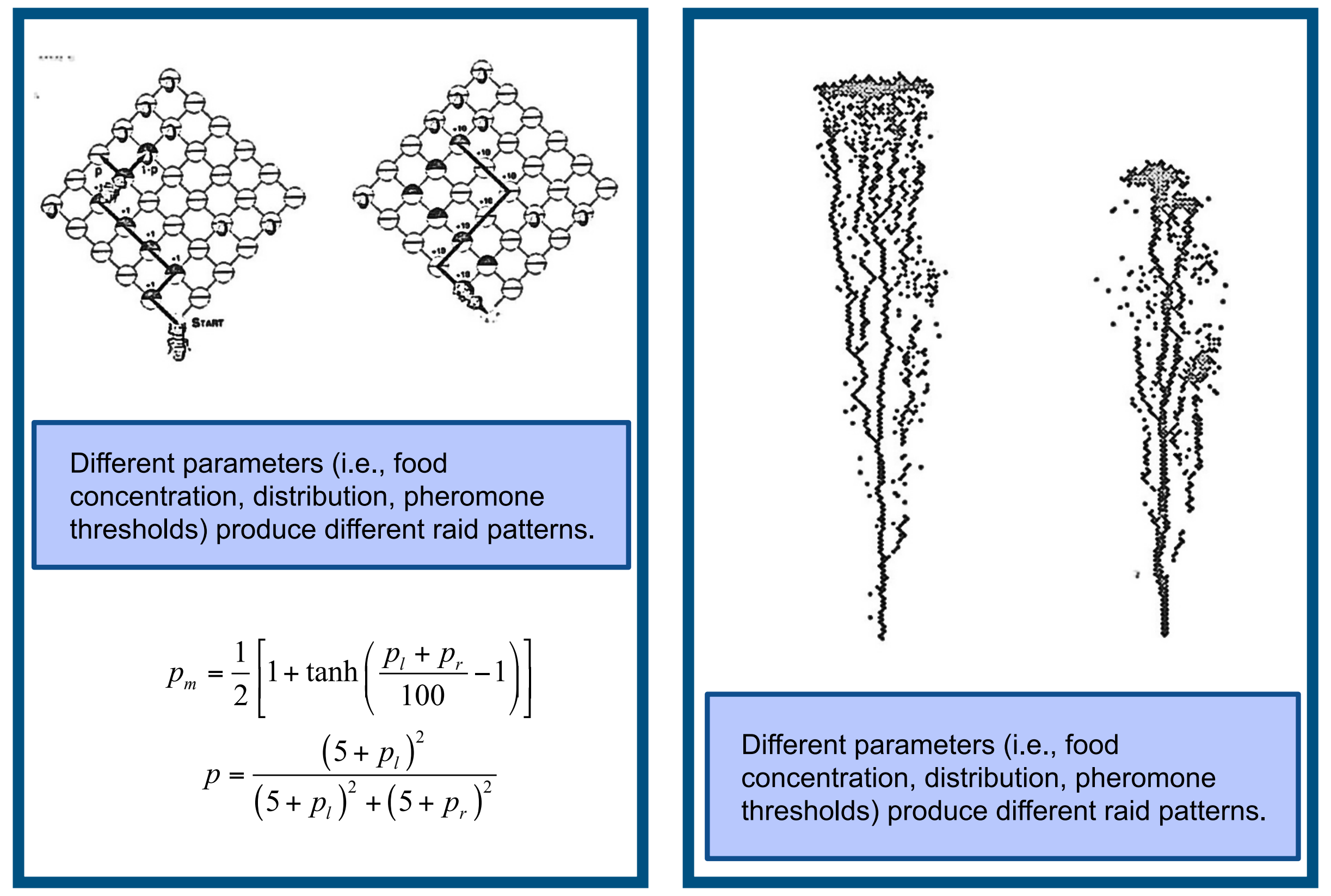
FORAGING BEHAVIOR

Foraging behaviors provide a basis for searching and optimization:
•Ant trails emerge "shortest path" solutions,
•Ants lay a pheromone trail as they move,
•Pheromone increase with traffic but dissipates over time,
•Pheromone marking reinforced on frequently used trails but fades on infrequently used trails => shorter paths visited more frequently.
•Reconfigurable "raid fronts" offer tunable exploration behaviors.

		
• **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

GENERAL FORAGING BEHAVIORS

Generalized Swarm Algorithms:



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

$$p_m = \frac{1}{2}\left[1 + \tanh\left(\frac{p_l + p_r}{100} - 1\right)\right]$$

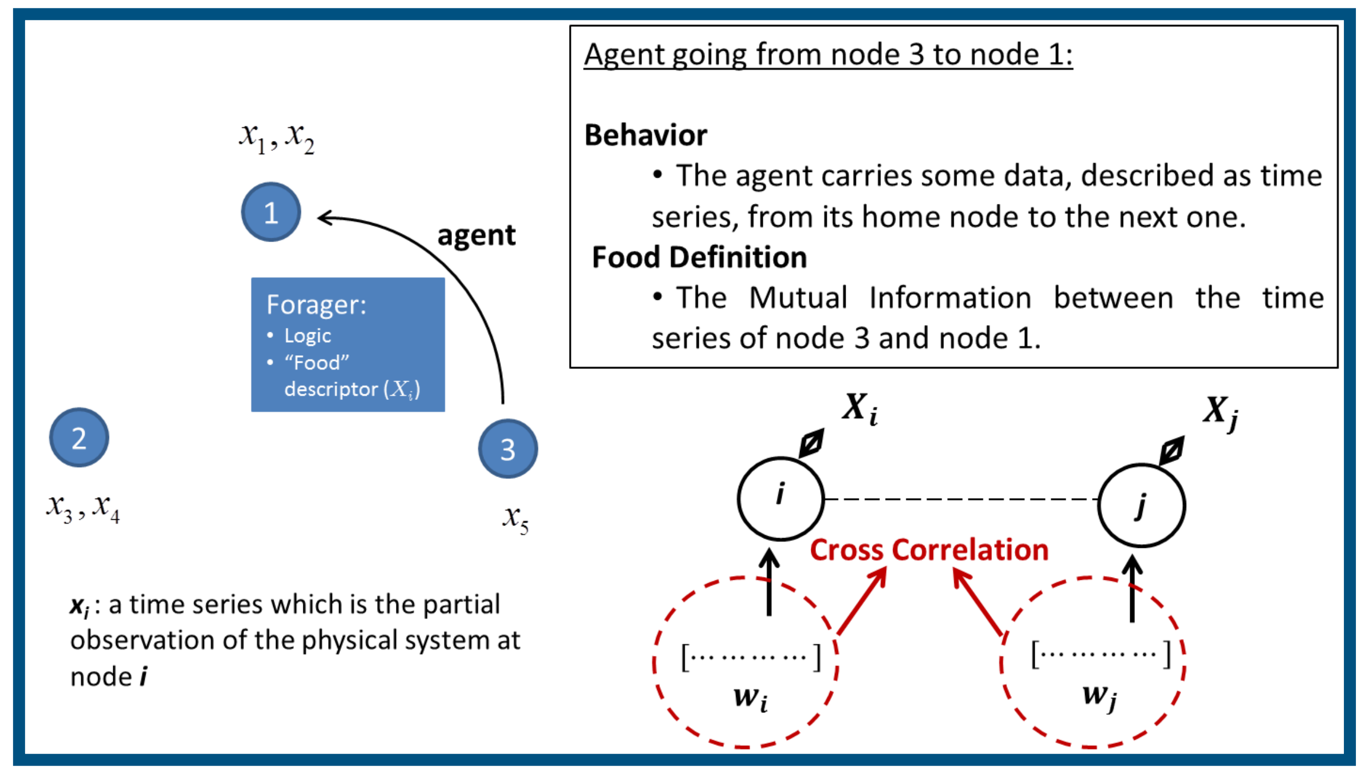
$$p = \frac{(5 + p_l)^2}{(5 + p_l)^2 + (5 + p_r)^2}$$

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

Figure 2. Adjusting the Parameters in Foraging

•General models of foraging provide more tunable behaviors,
•Probabilistic description of behaviors provides mechanism for specifying autonomy bounds probabilistically,,
•Multiple interacting swarms (super swarms) can manage disparate information streams.

NETWORK DISCOVERY



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.

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

Figure 3. Observation of Physical system from a Foraging Perspective

•Food defined as mutual information – agent carries information with it looking for data containing the "same information,"
•Moreover, want to preserve "dynamics" - historical content not preserved in information. Need to consider entropy rates or correntropy.
•Multiple "flavors" of information corresponding to different information sources can exist – approach can differentiate multiple flows of information.
•Key question: How should information be carried by agent?
  - Distribution? => Time history lost,
  - Sequence of data? => Preserves history but raises question of window size.

CORRENTROPY

Let X and Y be two RVs, define the estimated correntropy as:

$$\hat{V}(X,Y) = \frac{1}{N}\sum_{k=1}^{N} \kappa\left(x(k), y(k)\right)$$

Where $\left\{\left(x(k), y(k)\right)\right\}_{k=1}^{N}$ is the set of observations and κ is a non-negative definite function (e.g., mutual information) .
•Generalization of correlation to entropic measures,
•Can define a correntropy function to capture time shifted correlation.

Correlation:
•Restricted to capturing linear relationships between RVs,
•Provides useful proxy for investigating window size needed for agent-based estimation of correntropy (i.e. provides lower bound).

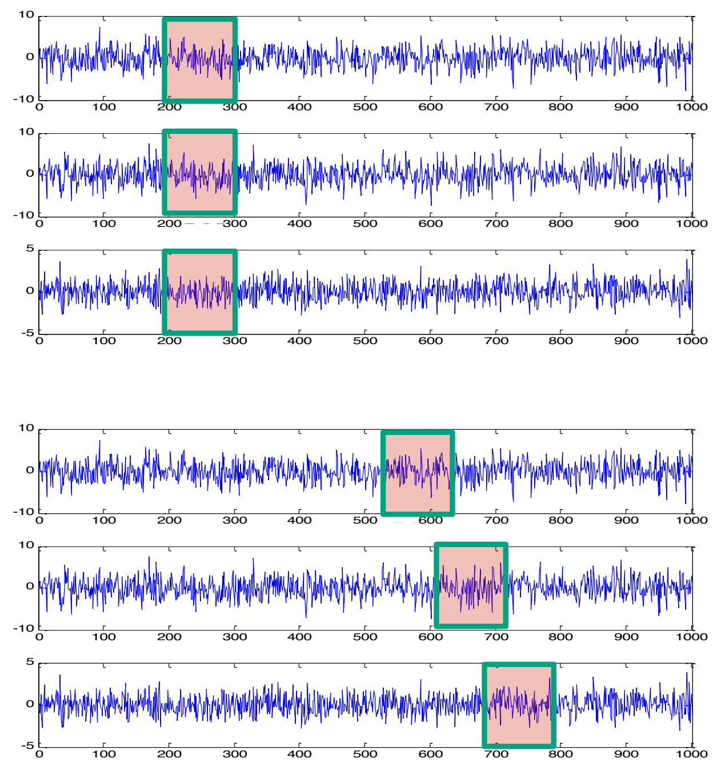
Exemplary liner system:

$$X_{k+1} = AX_k + D_p w_k$$

$$A = \begin{bmatrix} 0.7 & 0 & 0 \\ 0 & 0.3 & 0 \\ 0 & 0 & 0.4 \end{bmatrix} \quad D_p = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0.5 \\ 0 & 0.5 & 1 \end{bmatrix} \Rightarrow D_p D_p^T = \underbrace{\begin{bmatrix} 5 & 4 & 1 \\ 4 & 5.25 & 1 \\ 1 & 1 & 1.25 \end{bmatrix}}_{\text{Noise Correlation}}$$

•w_k ~ N(0,1)
•t_f = 1000
•Window size = [55, 200, 1000]

Results:



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

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

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

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

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

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

Figure 4. Examination of window size and lag on correlation estimation

CONCLUSIONS AND FUTURE WORK

•Proposed method to derive the intrinsic topology of the physical network by looking at the mutual information between system elements,
•Value of information measure provides basis for determining interconnection strengths,
•Examined approach using linear systems and correlation coefficients:
  - Best results for longer windows and aligned noise signals,
  - Even short windows detect existence of correlation,
  - Correlation (Correntropy) function needed to examine range of lags,
  - Window size chosen to be sensitive to system dynamics.

•Generalize to address nonlinear dynamics, inter-process/system coupling, non-Gaussian, and nonstationary processes using information measures..