Bio-inspired network protocols

Department of Mathematical Sciences
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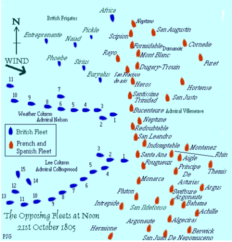
What is swarm intelligence?



Modeling and analysis objectives

- Construct a complete mathematical model of a basic ant-based routing protocol (BARP) and slime mold based sensor network protocols.
- Analyze the model to extract design principles.
- Compare with QualNet simulations.
- Refine/improve the model.

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Individual ant properties

- Lifespan: 1-2 years.

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  - Nearly blind.
  - Fast movers and carriers.
  - Can lay chemical trails of pheromones and detect trails.
  - Can consume food and regurgitate food through antennation.

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  - Can consume food and regurgitate food through antennation.
- Very simple programming.
  Searching for food (foraging), carrying food, recruiting others, alarm, attack.

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- Ants account for 15% - 20% of the terrestrial animal biomass on Earth. In tropical climates, estimates are closer to 25%. By this assessment, they are the most successful animals on Earth!

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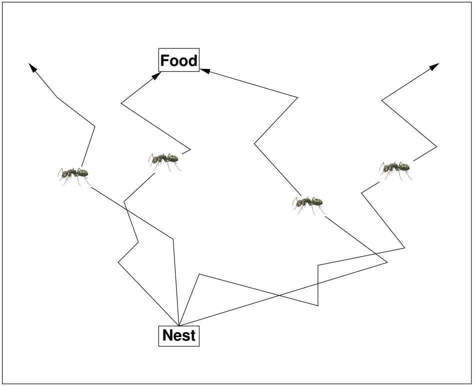
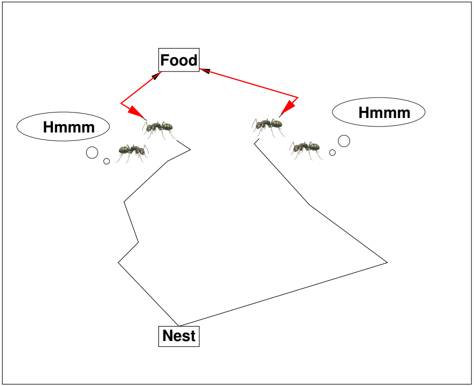
A heuristic for swarm optimization



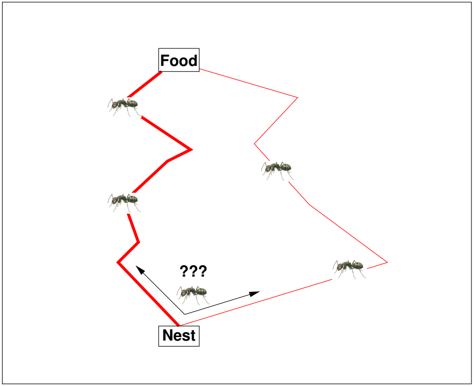
Random noisy exploration

A heuristic for swarm optimization



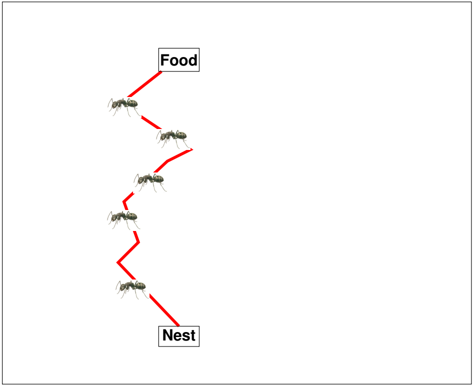
Stimergy (deposition of pheromone).

A heuristic for swarm optimization



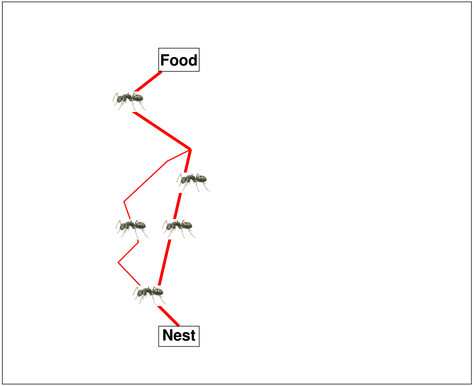
Evaporation.

A heuristic for swarm optimization

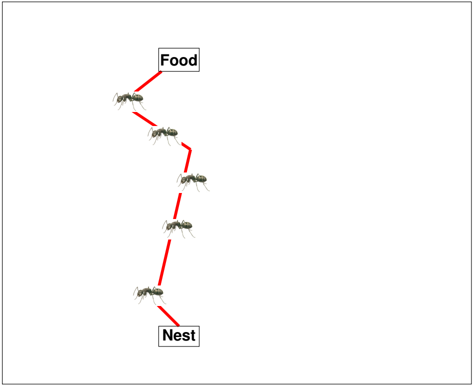


Nonlinear reinforcement.

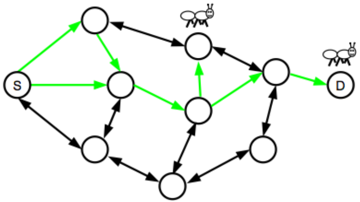
A heuristic for swarm optimization



A heuristic for swarm optimization

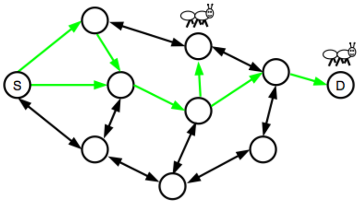


Forward ant propagation



$$p_{ij} = \frac{\left(\tau_{ij}\right)^{\alpha}\left(\eta_{ij}\right)^{\beta}\left(\psi_{ij}\right)^{\gamma}}{\sum_{h \in N_i}\left(\tau_{ih}\right)^{\alpha}\left(\eta_{ih}\right)^{\beta}\left(\psi_{ih}\right)^{\beta}},$$

Forward ant propagation



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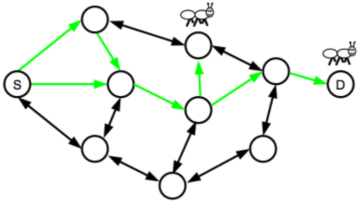
Forward ant propagation



$$p_{ij} = \frac{(\tau_{ij})^{\beta}}{\sum_{h \in N_i} (\tau_{ih})^{\beta}},$$

Ideal communication: $\vec{y}^{(n+1)} = P^{(n)}(\beta)\vec{y}^{(n)}, \quad P^{(n)} = [p_{ij}].$

Timescales

There are three critical timescales.

- h_1: time interval over which pheromone evaporates.
- h_2: time interval at which ants are released into the network.
- h_3: typical time required to make a single hop.

We assume $h_3 \ll h_1 \leq h_2$ and $m = h_2/h_1$.

$$\tau_{ij}^{(n+1)} = (1 - h_1\kappa_1)^m \tau_{ij}^{(n)} + h_2\kappa_2 \sum_{k=1}^{\infty} \frac{1}{k} \tilde{p}_{ij}^{sd}(k)$$

Nonlinear dynamics

$$\vec{y}^{(n+1)} = P(\beta)\vec{y}^{(n)},$$

$$\vec{\tau}^{(n+1)} = (1 - h_1\kappa_1)^{m_2}\tau_{ij}^{(n)} + h_2\kappa_2 \sum_{k=1}^{\infty} \frac{1}{k}\tilde{p}_{ij}^{sd}(k),$$

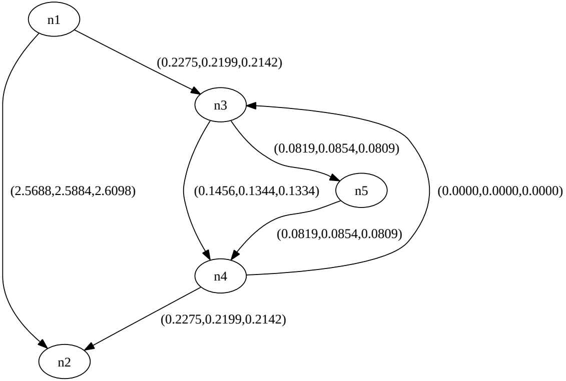
Goal: Identify stationary states of this system, and dynamic response to perturbations.

Nonlinear dynamics

$$\Lambda \tau_{ij} = \sum_{k=1}^{\infty} \frac{1}{k} \tilde{p}_{ij}^{sd}(k), \quad \Lambda = \kappa_1 / \kappa_2.$$

Goal: Identify stationary states of this system, and dynamic response to perturbations.

Model prediction versus Qualnet Simulations



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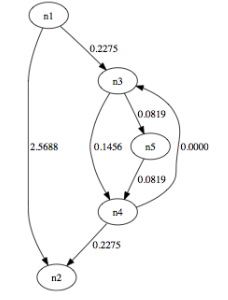
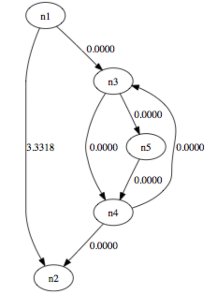
Experiments on a simple 5 node network

The structure of stable solutions varies based on the routing exponent β:

Example



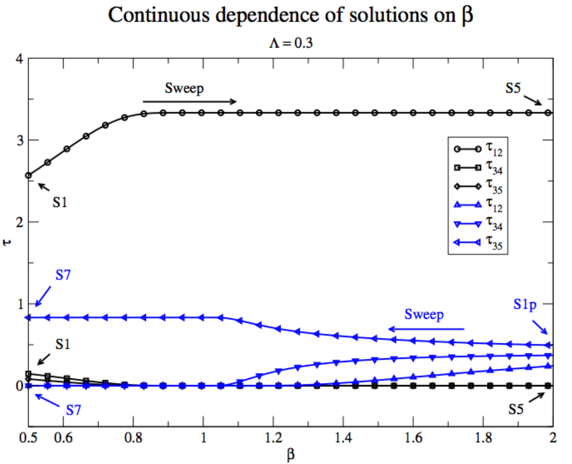
S1: $\beta = 0.5$, $\Lambda = 0.3$, multi-route solution



S5: $\beta = 2$, $\Lambda = 0.3$, single-route solution

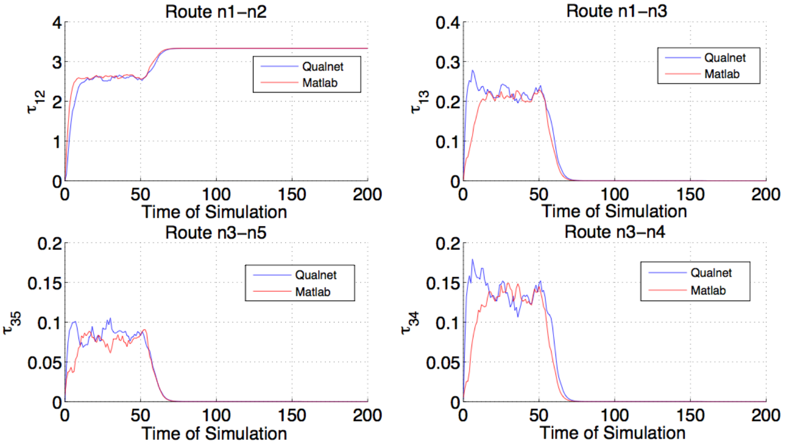
Trials with varying β

The multi-route solution is dynamically connected to the single-route solution



Varying β

After ramping up β from 0.5 to 2 by time step h_3, multiple route solutions will gradually shift to the stable single route solution:



Design principles for larger networks

Time of Simulation	199.99
N	200
β	$0.5 \rightarrow 2$
Λ	0.3
h1	1
h2	1
h3	0.01

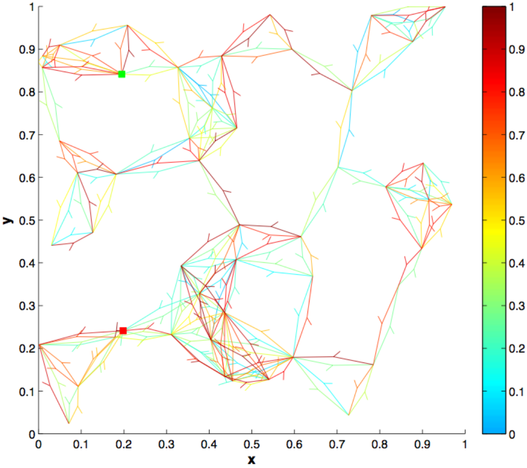
Large 50-node networks

Following are some parameters we used Matlab and Qualnet parameters:

Simulation time	200
N	200
β	0.5$\rightarrow$ 2
Λ	0.3
h1	1
h2	1
h3	0.01

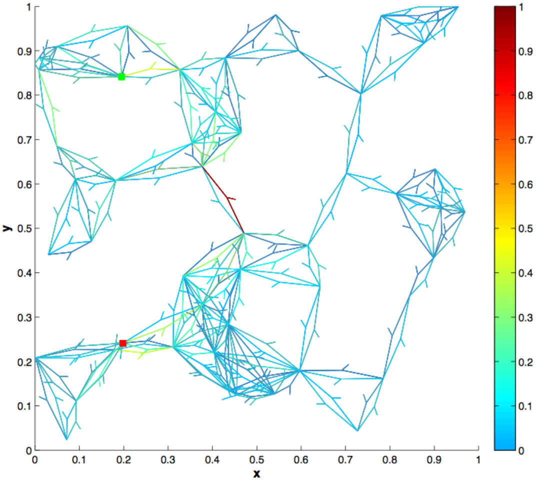
Random initial conditions.

Exploiting the dynamics



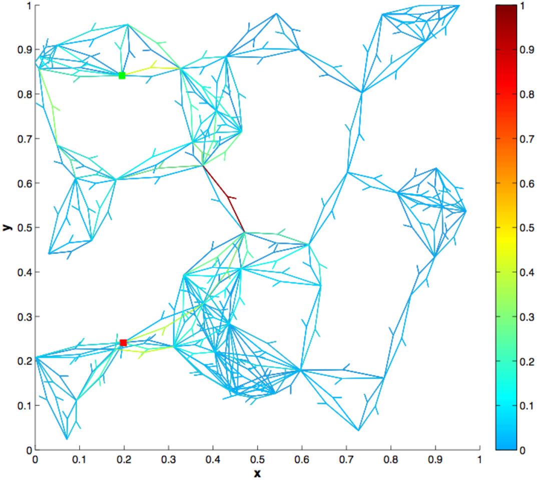
$$T = 0 \ (\beta = 0.5)$$

Exploiting the dynamics



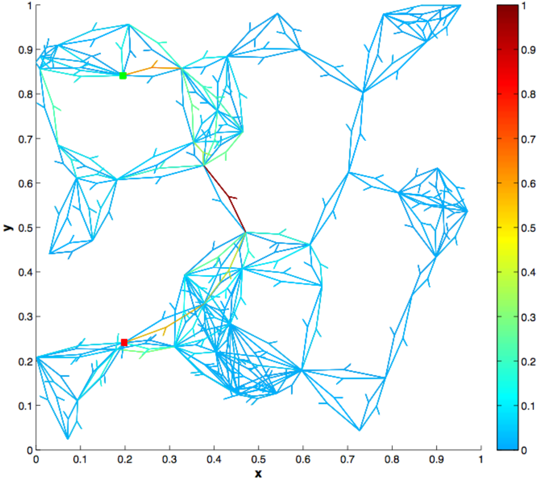
$T = 30 \ (\beta = 0.5)$

Exploiting the dynamics



$$T = 50 \ (\beta = 0.5 \rightarrow 2)$$

Exploiting the dynamics



$$T = 65 \; (\beta = 0.5 \rightarrow 2)$$

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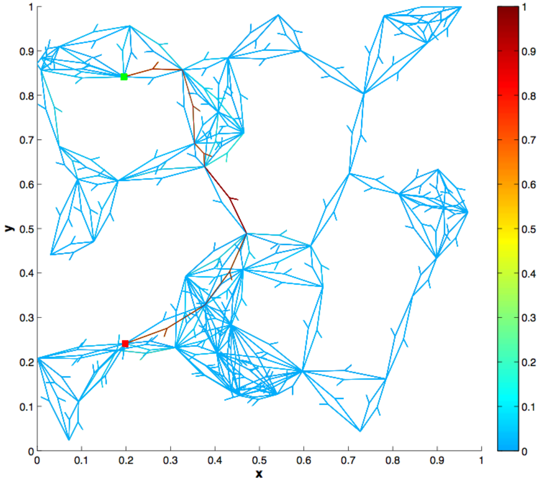
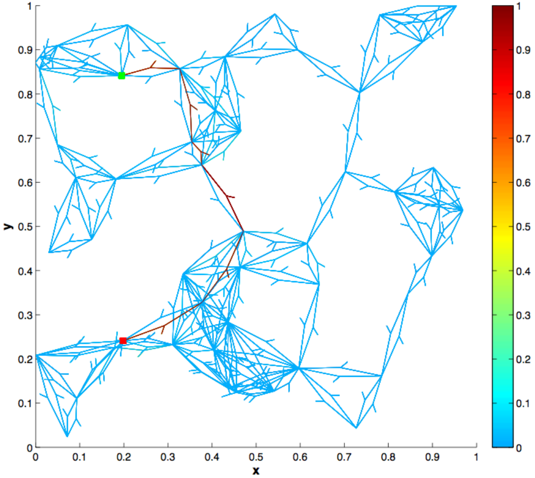
Exploiting the dynamics



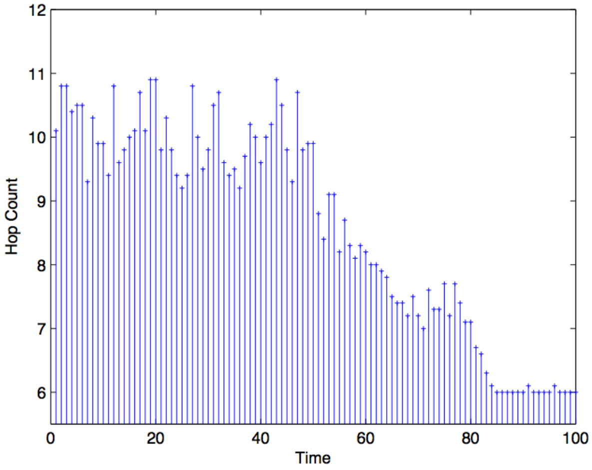
$T = 80$ ($\beta = 0.5 \to 2$)

Exploiting the dynamics

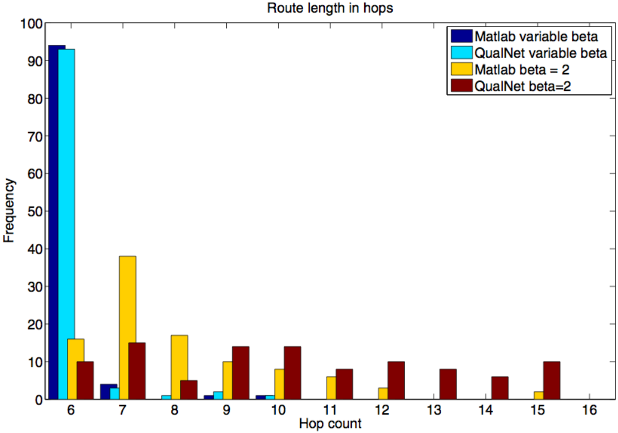


T = 100 ($\beta = 2$)

Hop count versus time

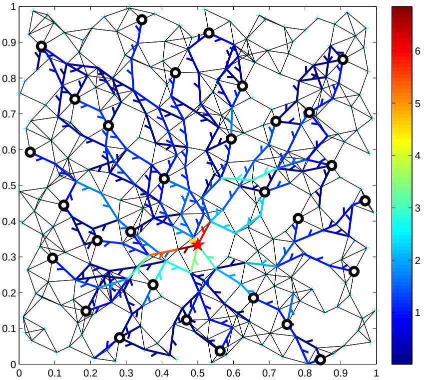


Statistical comparison



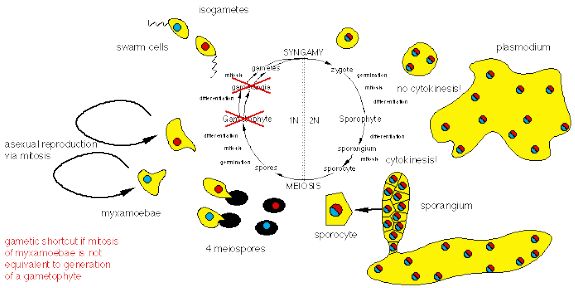
Problem: Sensor networks

Given an ad-hoc network of data sources, relay nodes (data sources without data) and a data sink, how do we move the data from the sources to the sink?



What is *Physarum polycephalum*?

Life Cycle of *Physarum polycephalum*



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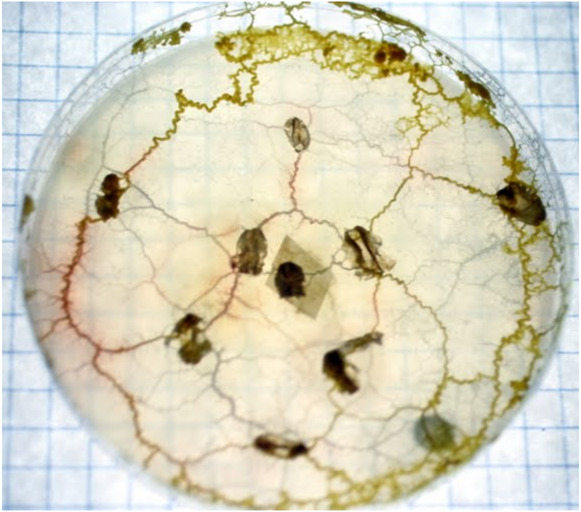
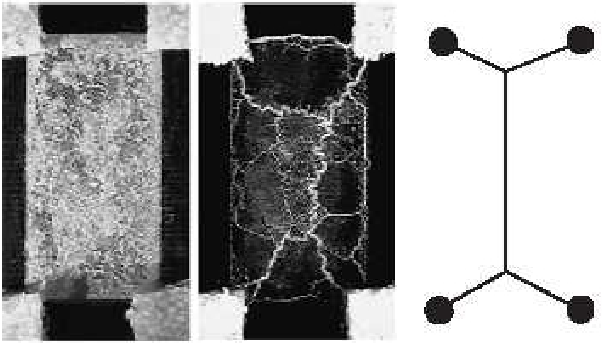


Mold solves hard problems

Steiner problems...



Slime mold solves the problems without central control.

T. Nakagaki, A Tero. et al. Nature 407 (2000), Proc. Roy. Soc. 271 (2004), J. Theo. Bio. 244 (2007)

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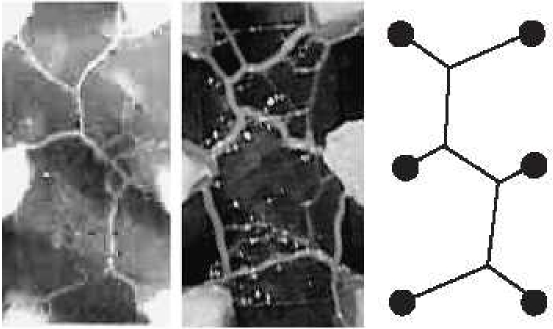

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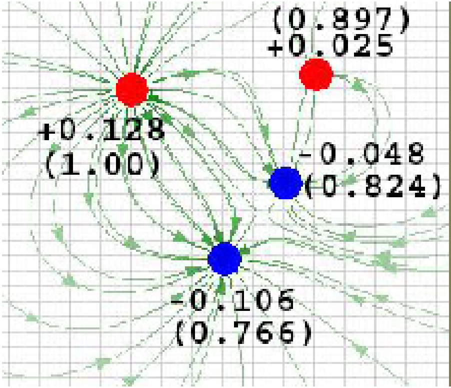
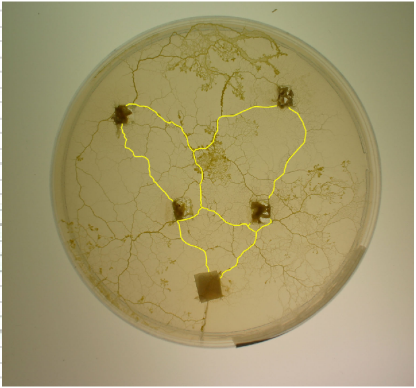
Mold and singular potentials



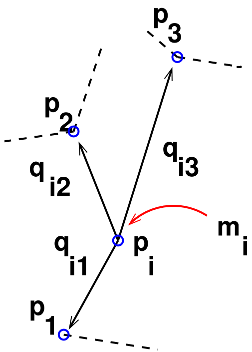


Attack the problem with an electrostatic model.
Application: Sensor/Actor networks.

The Tero model for slime mold

Model the sensor network as a system of pipes.

$$
\begin{aligned}
q_{ij} &= \frac{D_{ij}}{L_{ij}}(p_i - p_j), \\
\sum_{j \in N_i} q_{ij} &= m_i, \\
\frac{dD_{ij}}{dt} &= f\left(|q_{ij}|\right) - rD_{ij},
\end{aligned}
$$

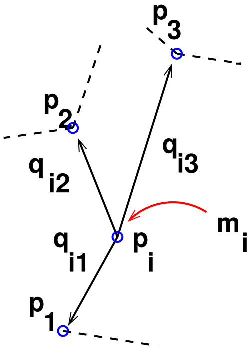


where

$$
f(x) = rD_{\max}\frac{a|x|^{\mu}}{1 + a|x|^{\mu}}.
$$

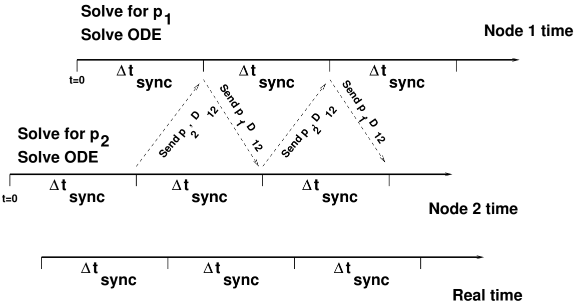
Note that we need to globally solve the pressure equation.
$m \to p \to q$.

The pressure equation



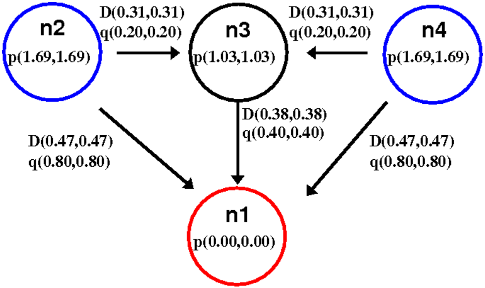
$$\sum_{j \in N_i} \frac{D_{ij}}{L_{ij}}(p_i - p_j) = m_i$$

Synchronized wireless Jacobi iterations



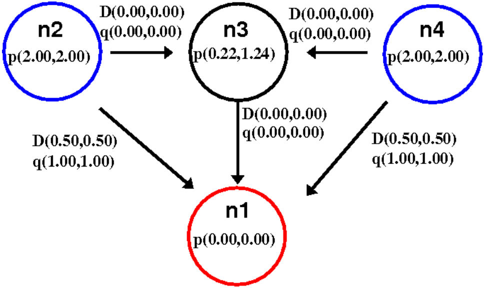
$$p_i \leftarrow \frac{m_i + \sum_{j \in N_i} \frac{D_{ij}}{L_{ij}} p_j}{\sum_{j \in N_i} \frac{D_{ij}}{L_{ij}}}$$

A very small network



$$\mu = 1/2$$

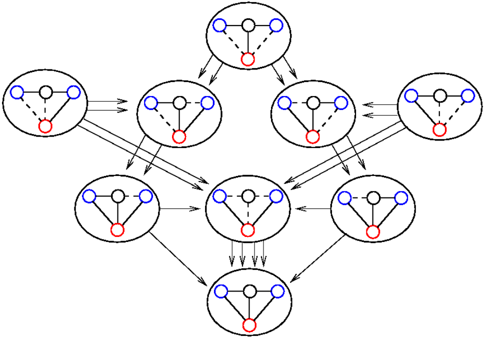
A very small network



$$\mu = 2$$

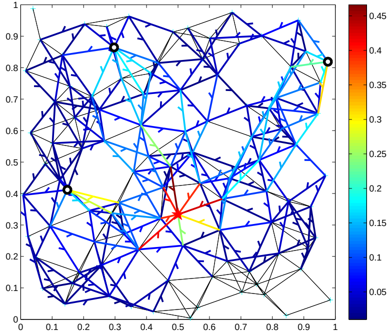
A very small network

Linear stability of stationary states in the network.



$\mu = 1/2$

Sample problems



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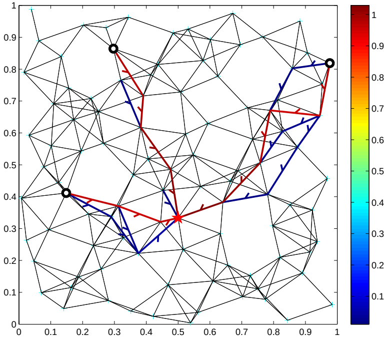

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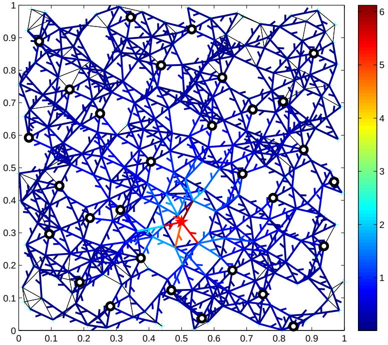

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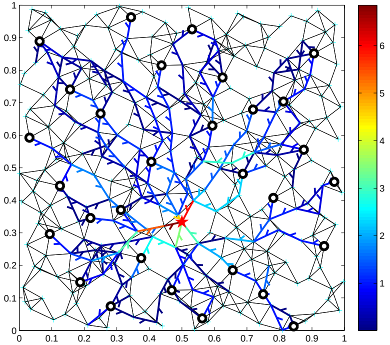

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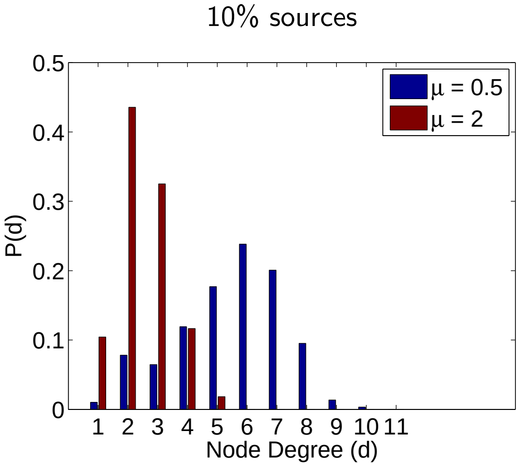
Robustness - degree distribution



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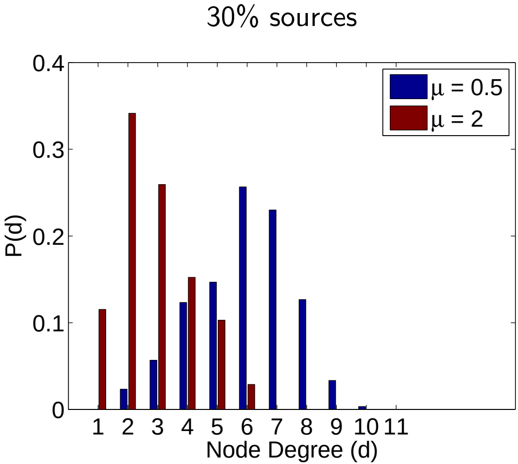

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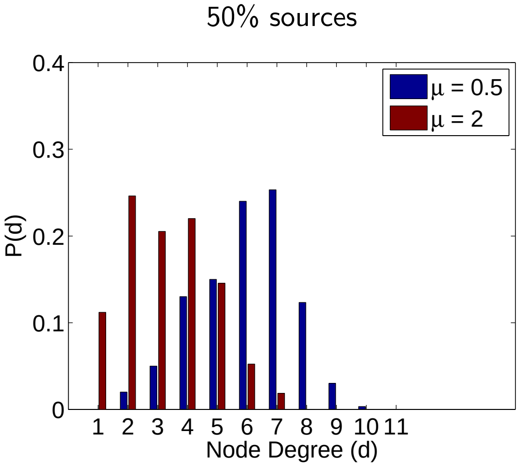

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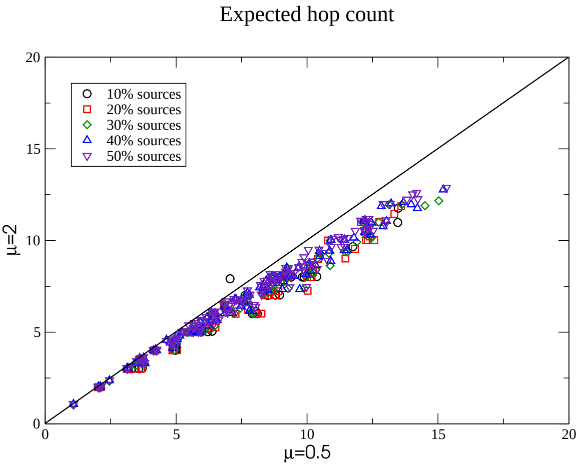
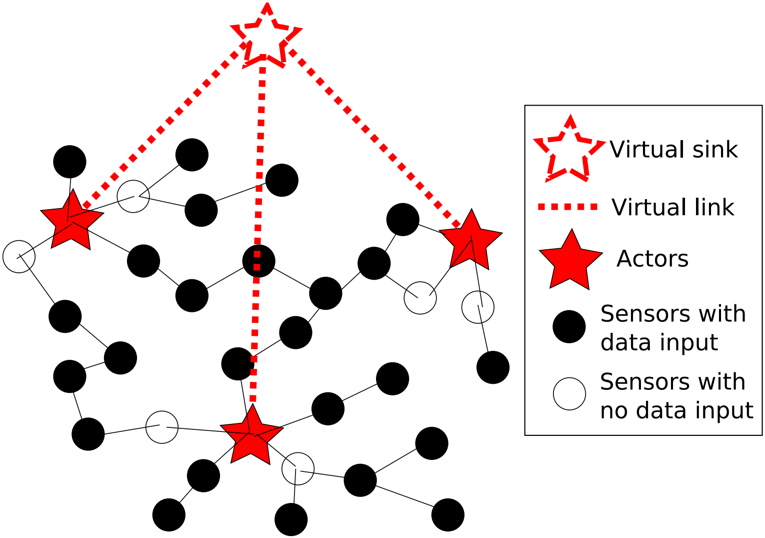
Fault tolerance

	10%		30%		50%	
μ	0.5	2	0.5	2	0.5	2
1-fault	1	.9851	.9856	.9761	.9799	.9530
2-fault	.9998	.9700	.9709	.9616	.9595	.9070

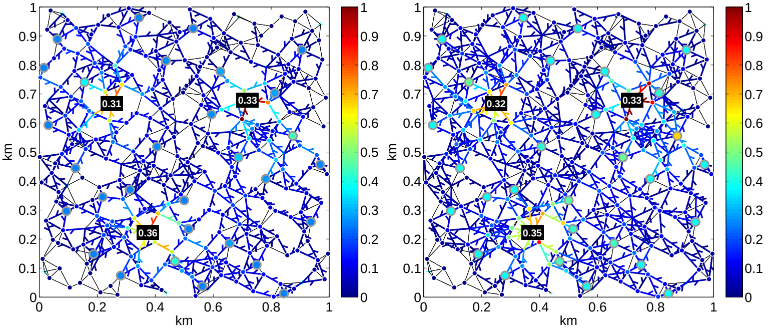
Impact on performance



Extension to sensor actor networks

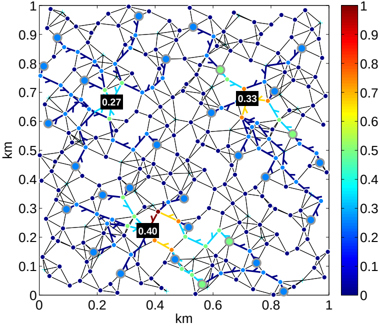


Sensor actor networks with $\mu = 0.5$

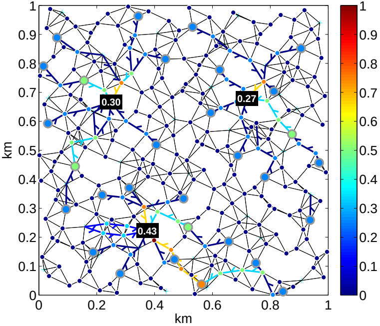


Matlab Qualnet

Sensor actor networks with $\mu = 2$



Matlab



Qualnet

Summary

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- Our model for ant-based and slime-based protocols captures actual protocol behavior well.
- Using pressure rather than pheromone poses special problems on ad-hoc networks that can be addressed with the asynchronous Jacobi algorithm.
- Nonlinear dynamics helps us understand phase transitions when we vary the routing or flux exponent.
- Design principles from small networks transfer to large networks.