

# Spatial Models for Ad Hoc Wireless and Sensor Networks

## Optimizing for Energy Efficiency

Stochastic Networks Conference 2004

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# Motivation - Ad hoc and Sensor Nets

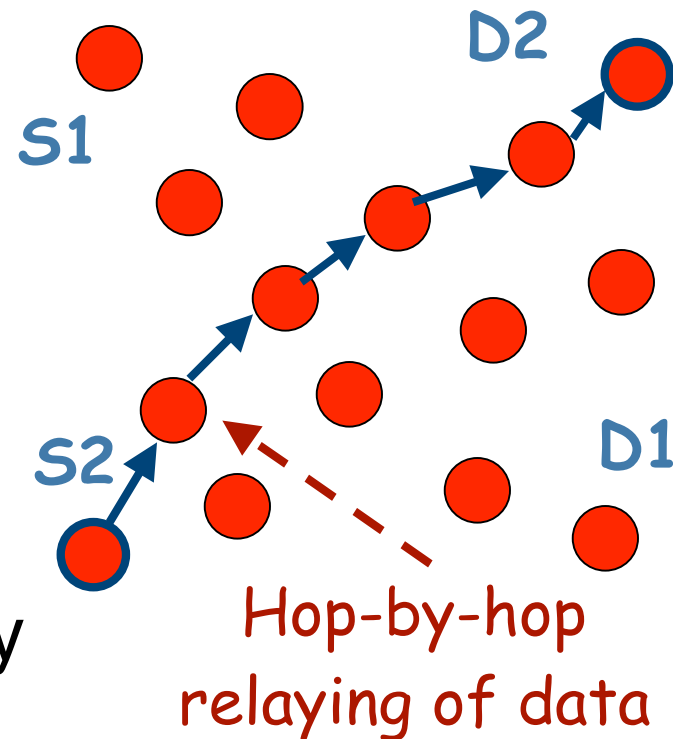
- Distributed peer-to-peer networking and/or sensing applications enabled by local wireless communication links

- **Energy burdens**

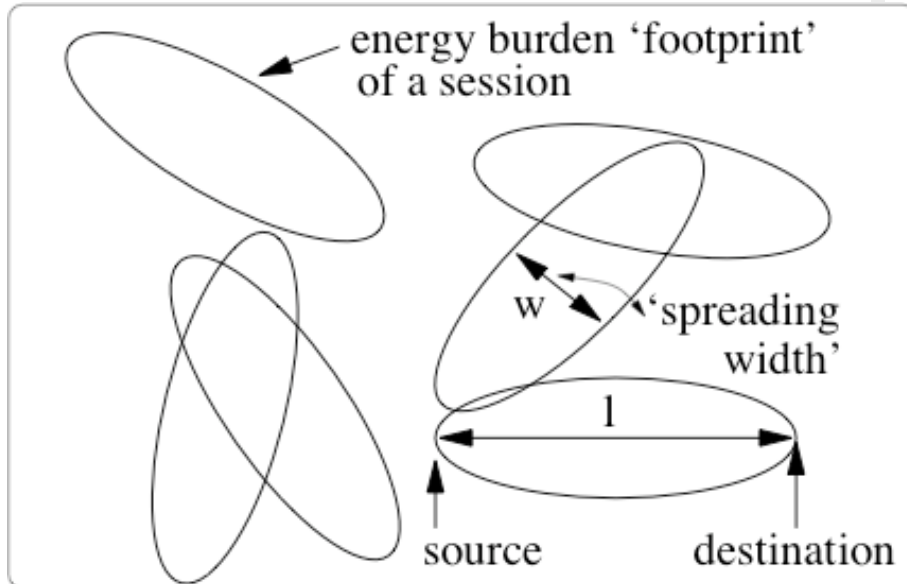
- Computation
- **Communication**

- Typically limited

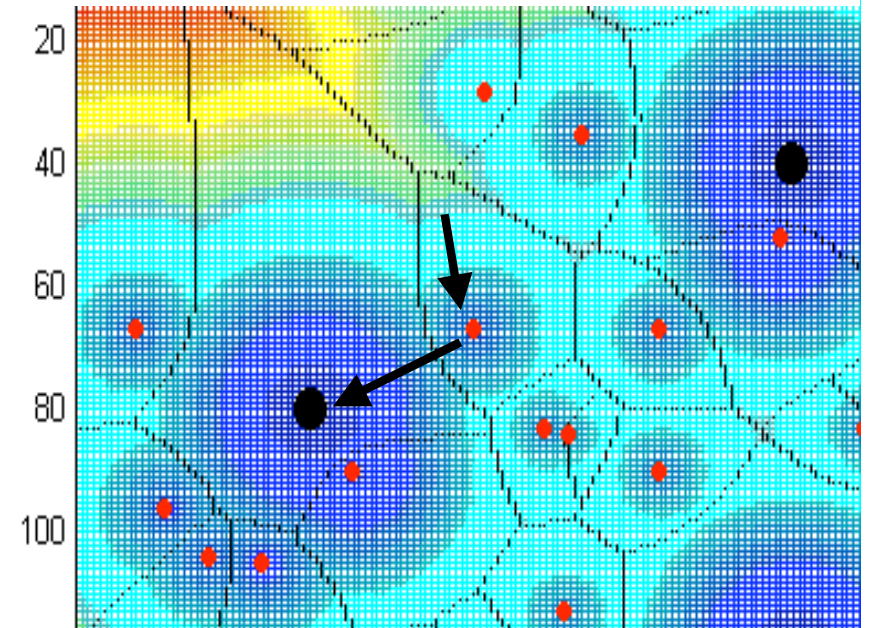
- Battery reserves
- Replenishing capability



# This Talk: Optimal 'shapes' for energy sensitive routing & hierarchies



- Balancing energy burdens by spreading traffic loads versus increased energy costs to realize spreading



- Decrease energy burdens via data/header compression versus energy cost to reach compression nodes.

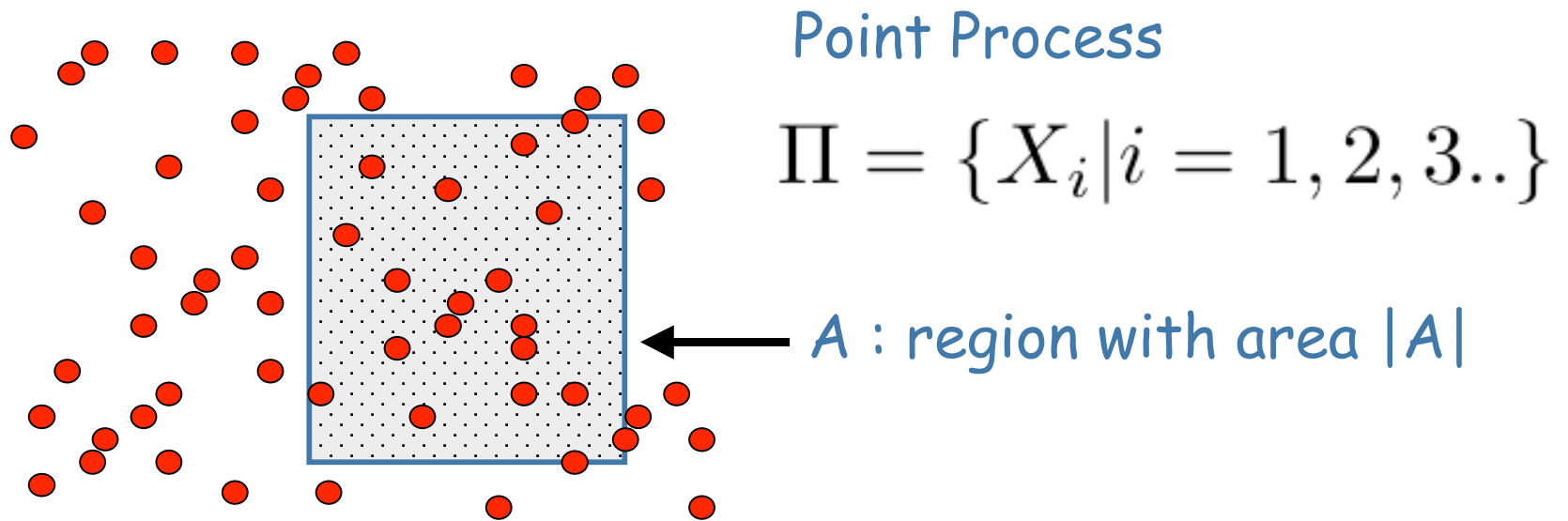
**Two tradeoffs to be explored**

# Talk Outline

- Some background on stochastic geometry
  - See e.g., Moeller, Kendall, Stoyan & Mecke
  - Telecom Models: Baccelli, Zuyev, and collaborators
- Part 1: Routing for energy balancing in ad hoc wireless networks
- Part 2: Routing hierarchies for wireless sensor networks using compression and sink nodes

# Poisson Point Process with intensity $\lambda$

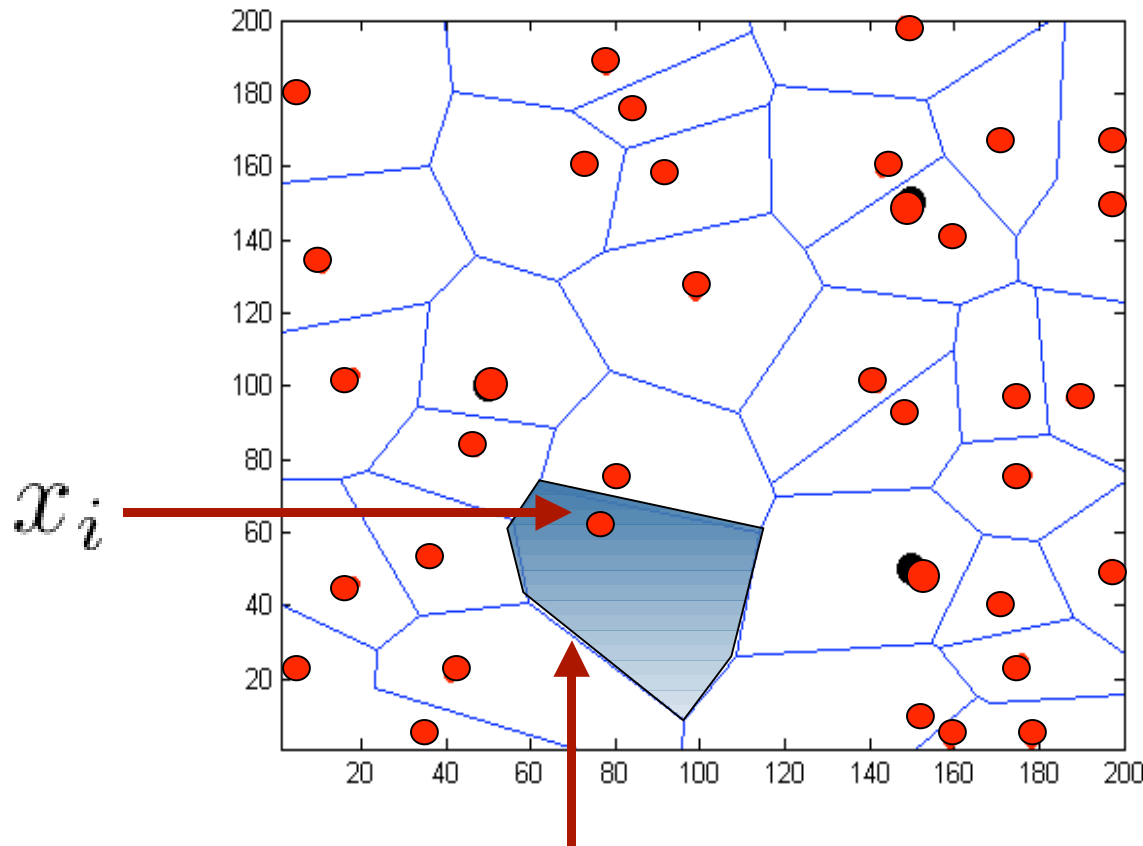
- Modeling spatial traffic loads and/or locations of network/sensor nodes



$$N(A) = \sum_{X_i \in \Pi} \mathbf{1}(X_i \in A) \sim \text{Poisson}(\lambda|A|)$$

# Voronoi Tesselation induced by $\Pi=\pi$

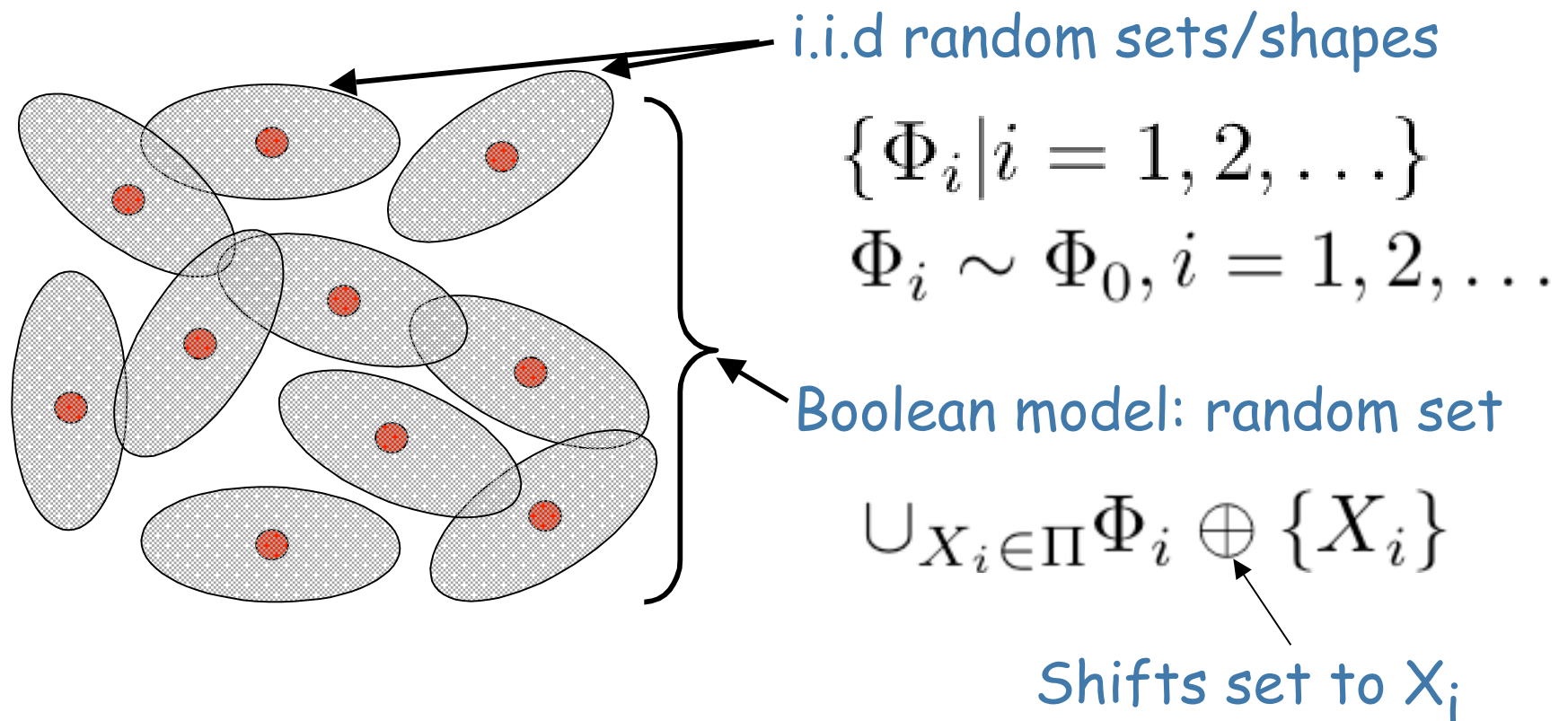
- Modeling spatial network/routing hierarchies



$$V_{x_i}(\pi) = \{z \in \mathbf{R}^2 \mid |z - x_i| < |z - x_j|, \forall x_j \in \pi\}$$

# Boolean Model

- Modeling random sets: e.g., coverage of wireless service/sensors



# Shot-Noise Process

- Modeling spatial fields: e.g., traffic overlaps spatial energy burdens induced by routing

‘Random’ functions :

$$h(\cdot, \Phi_i) : \mathbf{R}^2 \rightarrow \mathbf{R}$$

support set

Shot-Noise process:

$$E(x) = \sum_{X_i \in \Pi} h(x - X_i, \Phi_i)$$

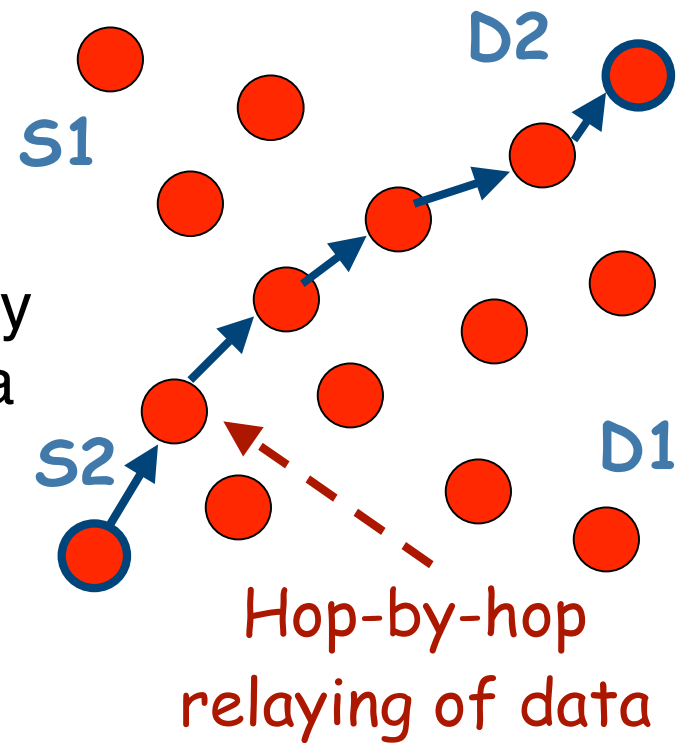
shifts  $h(\cdot, \cdot)$  to  $X_i$

Example:

$$E(x) = \sum_{X_i \in \Pi} \mathbf{1}(x \in \Phi_i \oplus X_i) \sim \text{Poisson}(\lambda E[|\Phi_0|])$$

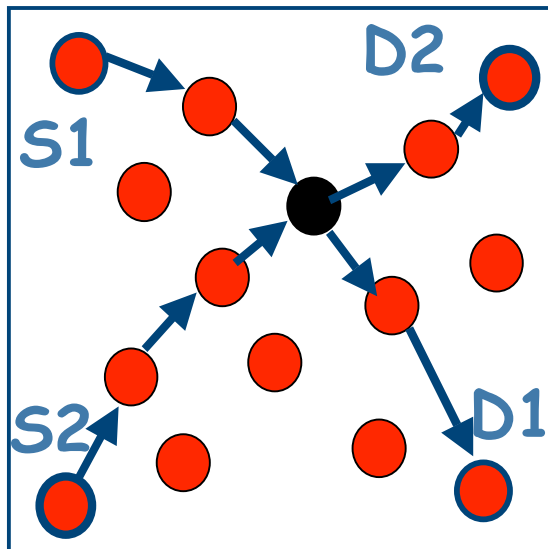
# Part 1: Routing for energy balancing in ad hoc wireless networks

- Simple routing/energy model
  - Hop-by-hop routing along `neighboring' nodes
  - Same transmit/receive energy expenditure per hop/unit data
  - Energy expenditure proportional to data flow rate and # of hops.

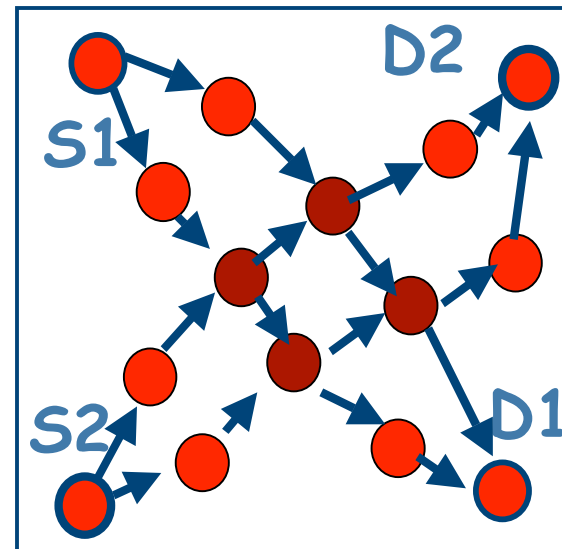


# Energy Balancing - Multipath Routing

Shortest Path Routing



Multipath Routing



Unbalanced energy burdens ` Balanced' energy burdens

- Poor `balancing' of energy burdens results in
  - Energy hotspots with eventual total depletion of node's energy reserves.
  - Possibly use of inefficient longer routes to circumvent depleted areas (future work)

# Related work

- Dynamic shortest path routing based on depletion levels
  - Overheads (updating state) and robustness
- `Optimal' dynamic multipath routing to extend network lifetime [Chang and Tassiulas]
  - Overheads and scalability
- Randomized packet routing to spread loads across fixed region in a grid [Servetto and Barrenechea]
  - Randomization energy efficient ?
  - How much should one spread?
- ***This talk:*** attempt to systematically evaluate spatial energy burdens under *proactive multipath routing*



# Modeling Ad hoc Network

- Realization for node's locations:

$$\pi = \{x_i | i = 1, 2, \dots\}$$

- **Voronoi tessellation:**

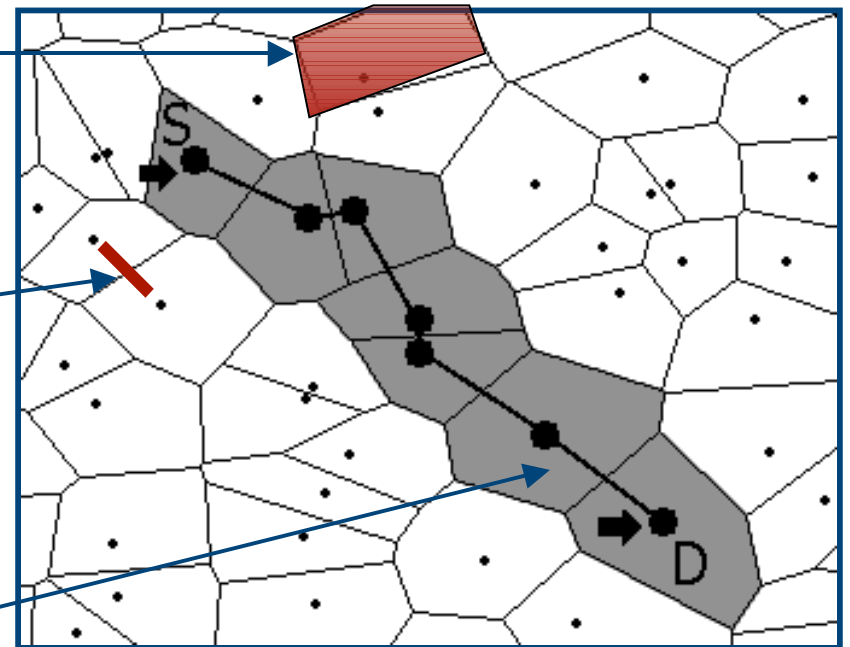
- Each cell  $V_{x_i}(\pi)$  is set of points which are closest to that node

- **Delaunay graph:**  $G(\pi, E)$

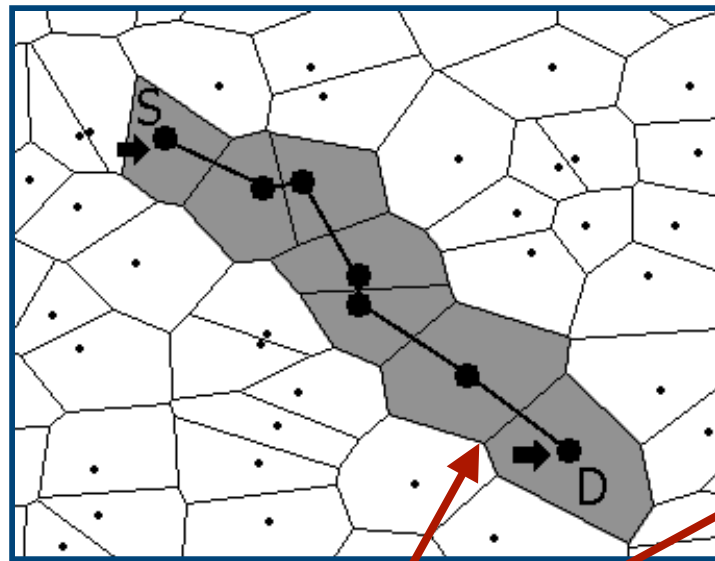
- $E$  : edges placed between nodes whose cells share a face

- **Shortest Delaunay route:**

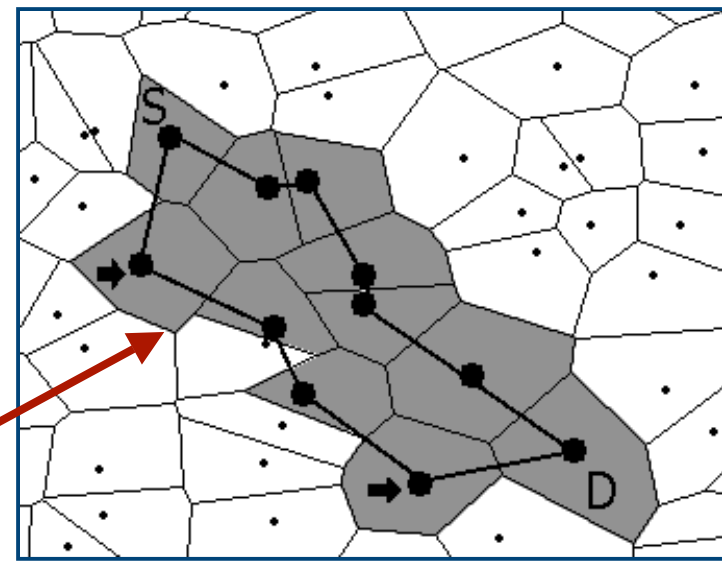
- Shortest Euclidean norm route on  $G(\pi, E)$



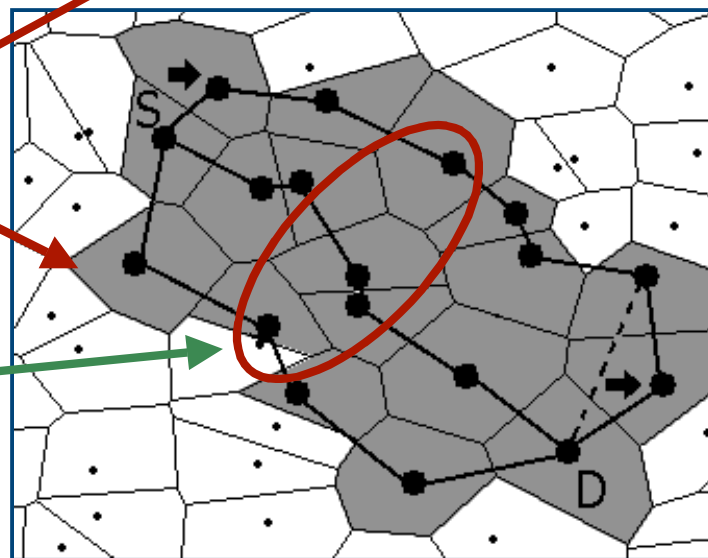
# Multipath routing: geometric construction



$w=1$



$w=2$



$w=3$

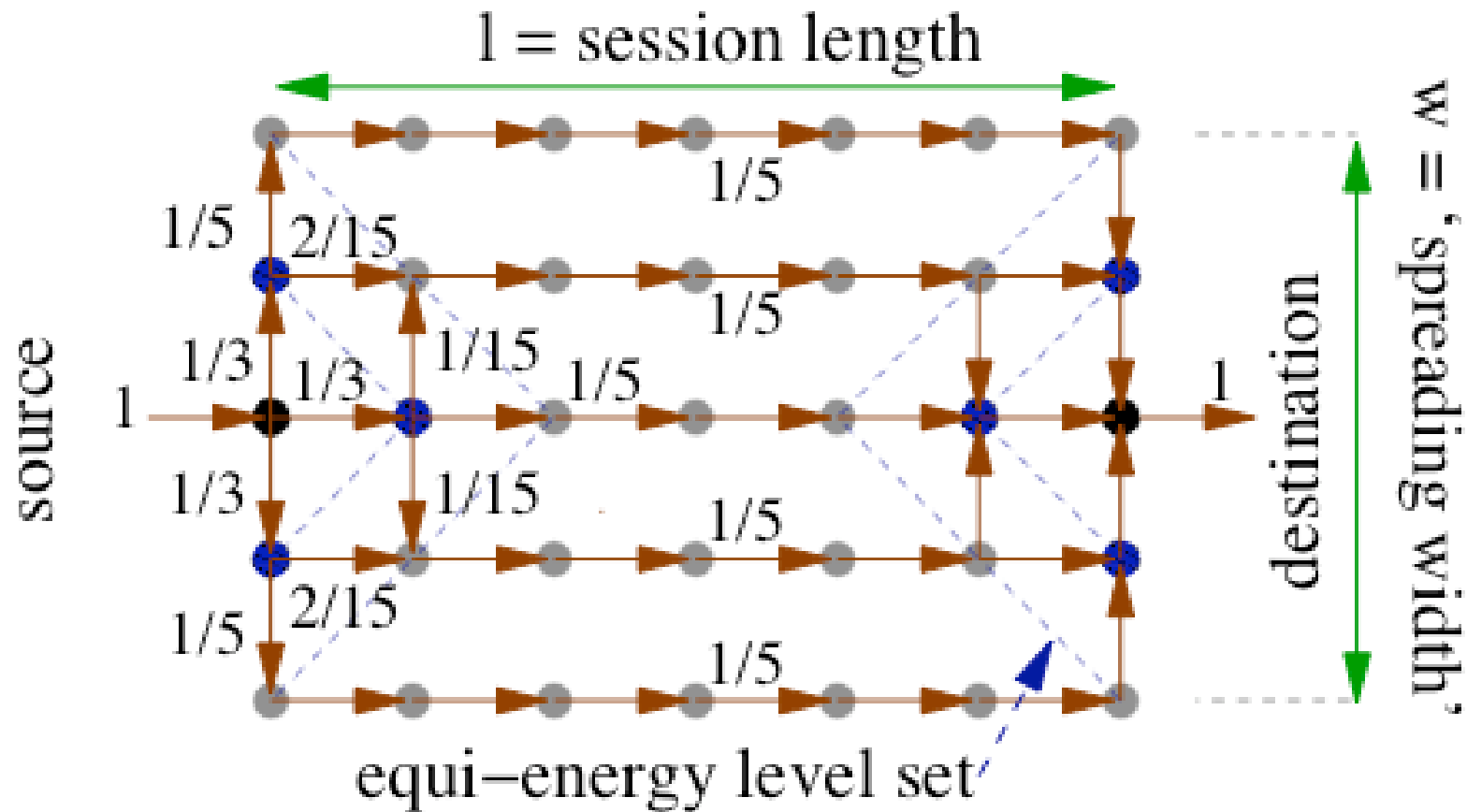
Spatial  
'footprints'

Flow/Energy  
balancing

Multipath  
routing with  
increasing  
spreading  $w$

# Energy Balancing- Lattice Model

- Rectangular spatial footprint. Good flow balancing ?



# Continuum Model

- Ad hoc nodes: infinitesimal units of space
- Traffic loads: random process of energy footprints
  - Session locations (offered load) prior to time  $t$

$$\Pi_t = \{X_i | i = 1, 2, \dots\} \sim \text{Poisson PP}(\lambda t)$$

- Footprints- reflecting degree of spreading

$$\{\Phi_i | i = 1, 2, \dots\} \text{ i.i.d. translation invariant}$$

- Balancing of energy- reflecting flow across footprint

$$h(x, \Phi_i) \text{ energy burden density}$$

# Continuum Model

- Cumulative energy burden - shot noise process

$$E(x, t) = \sum_{X_i \in \Pi_t} h(x - X_i, \Phi_i)$$

**Theorem:** (asymptotic normality)

$$\mu(t) = \mathbf{E}[E(0, t)] = \lambda t \mathbf{E}\left[\int_{\Phi_0} h(x, \Phi_0) dx\right]$$

$$\sigma^2(t) = \mathbf{Var}[E(0, t)] = \lambda t \mathbf{E}\left[\int_{\Phi_0} h(x, \Phi_0)^2 dx\right]$$

$$\frac{E(0, t) - \mu(t)}{\sigma(t)} \rightarrow N(0, 1) \text{ as } t \rightarrow \infty$$

Evaluate  
impact of  
spreading  
mechanism  
on spatial  
energy  
burdens

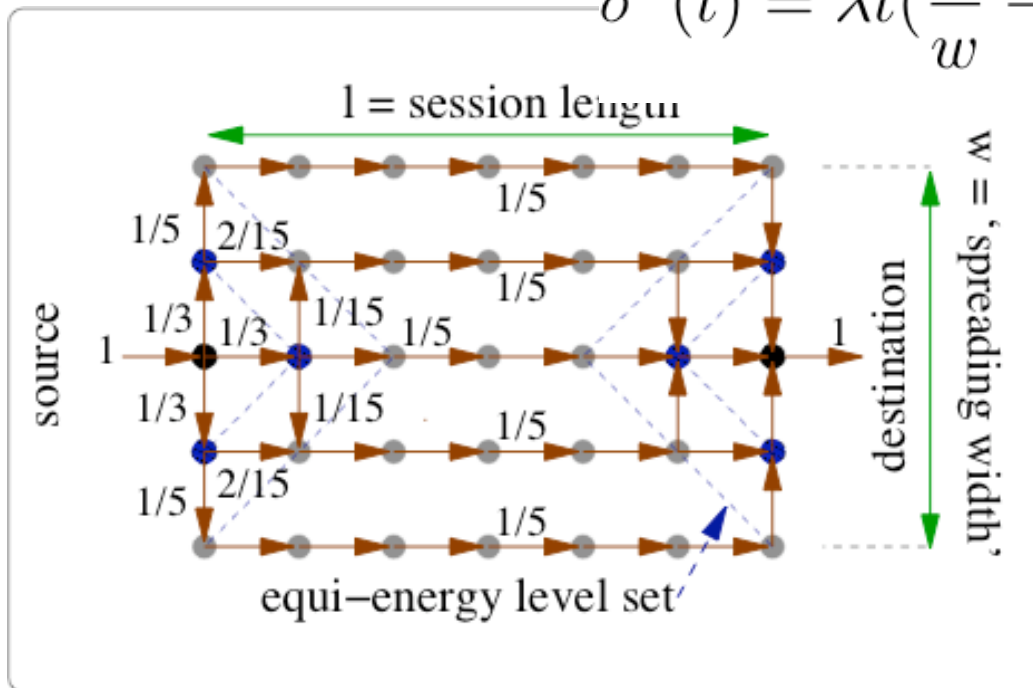
[Heinrich & Schmidt]

# Lattice model: A parametrized energy balancing strategy

**Lemma:** min variance energy balancing strategy subject to flow conservation and equal flow on mid-section nodes of rectangular footprint gives:

$$\hat{\mu}(t) = \lambda t \left( l + \frac{w}{2} - \frac{1}{2w} \right)$$

$$\hat{\sigma}^2(t) = \lambda t \left( \frac{l}{w} - \frac{1}{2} \left( 1 + \frac{1}{w^2} \right) + \sum_{k=1}^{\frac{w+1}{2}} \frac{2}{2k-1} \right)$$



Spreading Cost  
 Increasing  $w \rightarrow$   
 increasing mean &  
 decreasing  
 variance

# Optimizing Energy Balancing:

## Non replenishing case

- $b$  = battery capacity    $t$  = desired network lifetime
- Prob. of depletion by  $t$  for **typical** location/node

$$P(E(x, t) > b) \approx \phi\left(\frac{b - \mu(t)}{\sigma(t)}\right) = \phi(r(t))$$

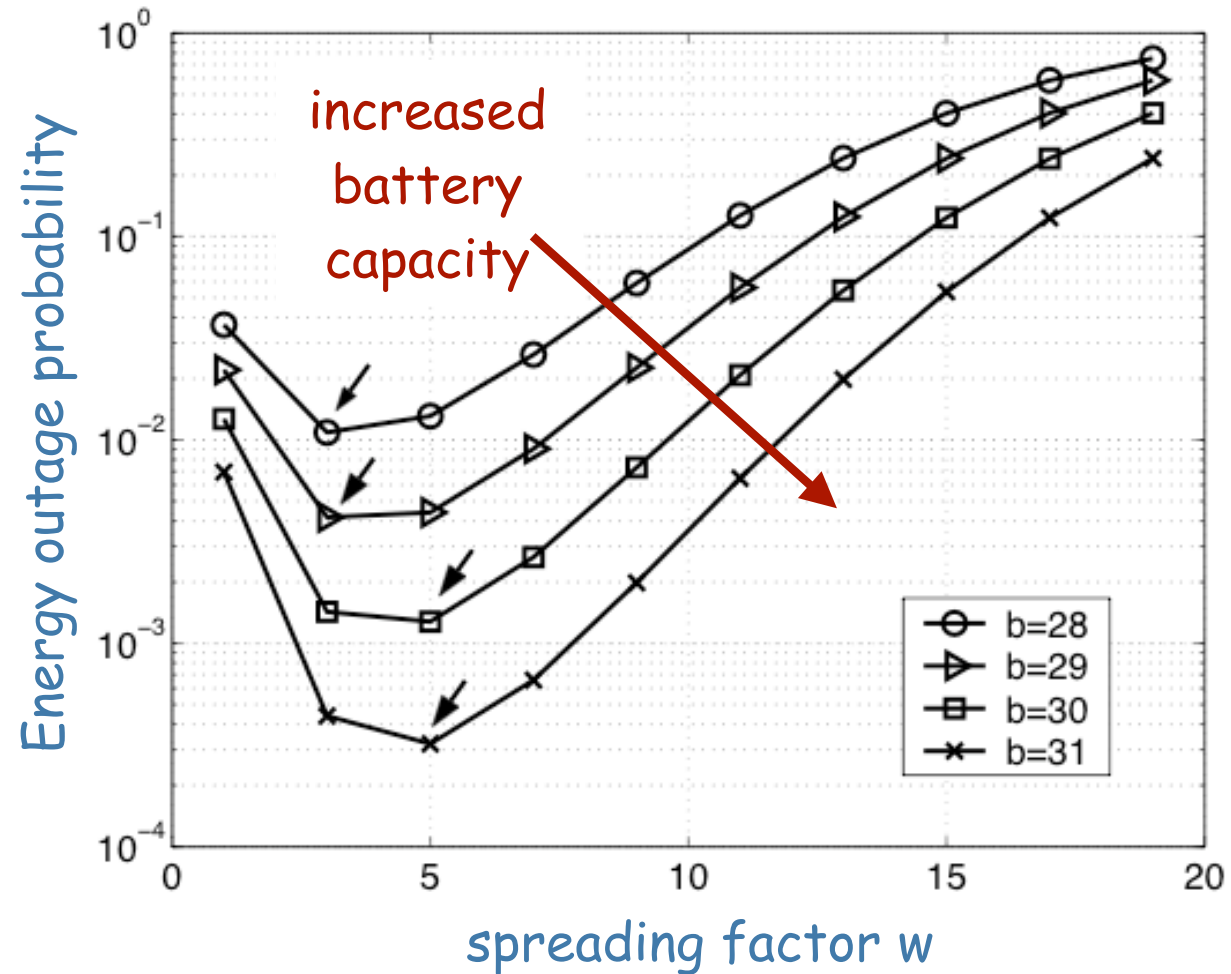
- Prob. of depletion by  $t$  of any location within  $A$

$$P(\sup_{x \in A} E(x, t) > b) \approx H_\alpha a^{2/\alpha} r(t)^{4/\alpha} \phi(r(t))$$

$\alpha, a$  : depend on spatial correlations of energy  
burden field

[Adler, Aldous]

# Optimizing non replenishing scenario: Example



- Larger battery capacity should increase spreading

# Optimizing Energy Balancing:

## Nodes with replenishing capability

- Simple discrete-time model with batch arrivals (of energy burdens) :

$$W_{n+1} = \max[W_n + S_n - c, 0]$$

Energy burden on node at the beginning of slot  $(n, n+1]$       New energy burdens on node for slot  $(n, n+1]$       Energy replenishing rate per slot

- How does energy balancing strategy impact tail asymptotics of stationary distribution ?

$$\lim_{b \rightarrow \infty} \frac{1}{b} \log P(W > b) = -\theta^*$$

# Optimizing Energy Balancing:

## Nodes with replenishing capability

- Theorem: Under our modelling assumptions if 'energy queue' is stable, i.e.,

$$\lambda E\left[\int_{\Phi_0} h(x, \Phi_0) dx\right] < c$$

then the asymptotic tail exponent satisfies

$$\theta^* : \Lambda(\theta^*) = 0, \Lambda'(\theta^*) > 0$$

where

$$\Lambda(\theta) = \lambda E\left[\int_{\Phi_0} (e^{\theta h(x, \Phi_0)} - 1) dx\right] - c\theta$$

[Kelly, Whitt & Glynn, De Veciana & Walrand]

# Optimizing network with replenishing

## Example

- Using grid model,  $l=8$ ,  $\lambda=1$  and  $c^*$  is critical rate for  $w=7$

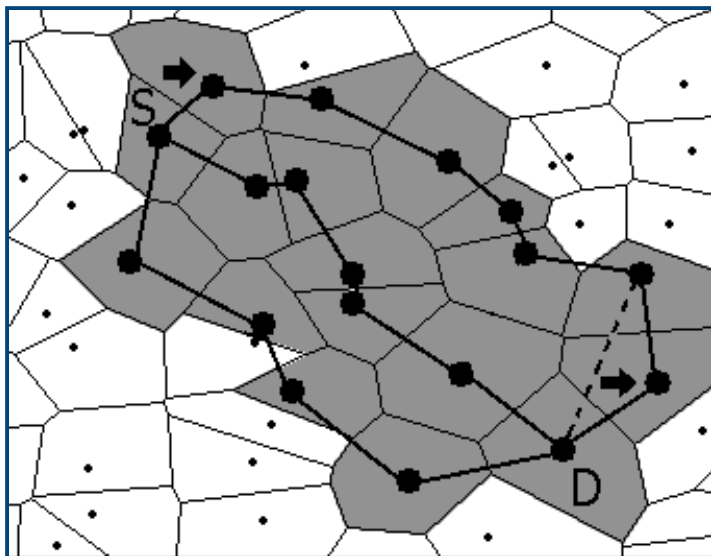
Asympt. Decay rate $\theta^*$		
Spreading factor $w$	Replenishing rates	
	$c=1.2 c^*$	$c=2.0 c^*$
1	0.8673	1.7125
<b>3</b>	<b>1.2506</b>	2.7080
<b>5</b>	1.0965	<b>2.7593</b>
7	0.7965	2.6831

- Optimal tradeoff between maintaining stability and reducing energy burden variability.

# Simulations: proactive multipath routing

## Setup

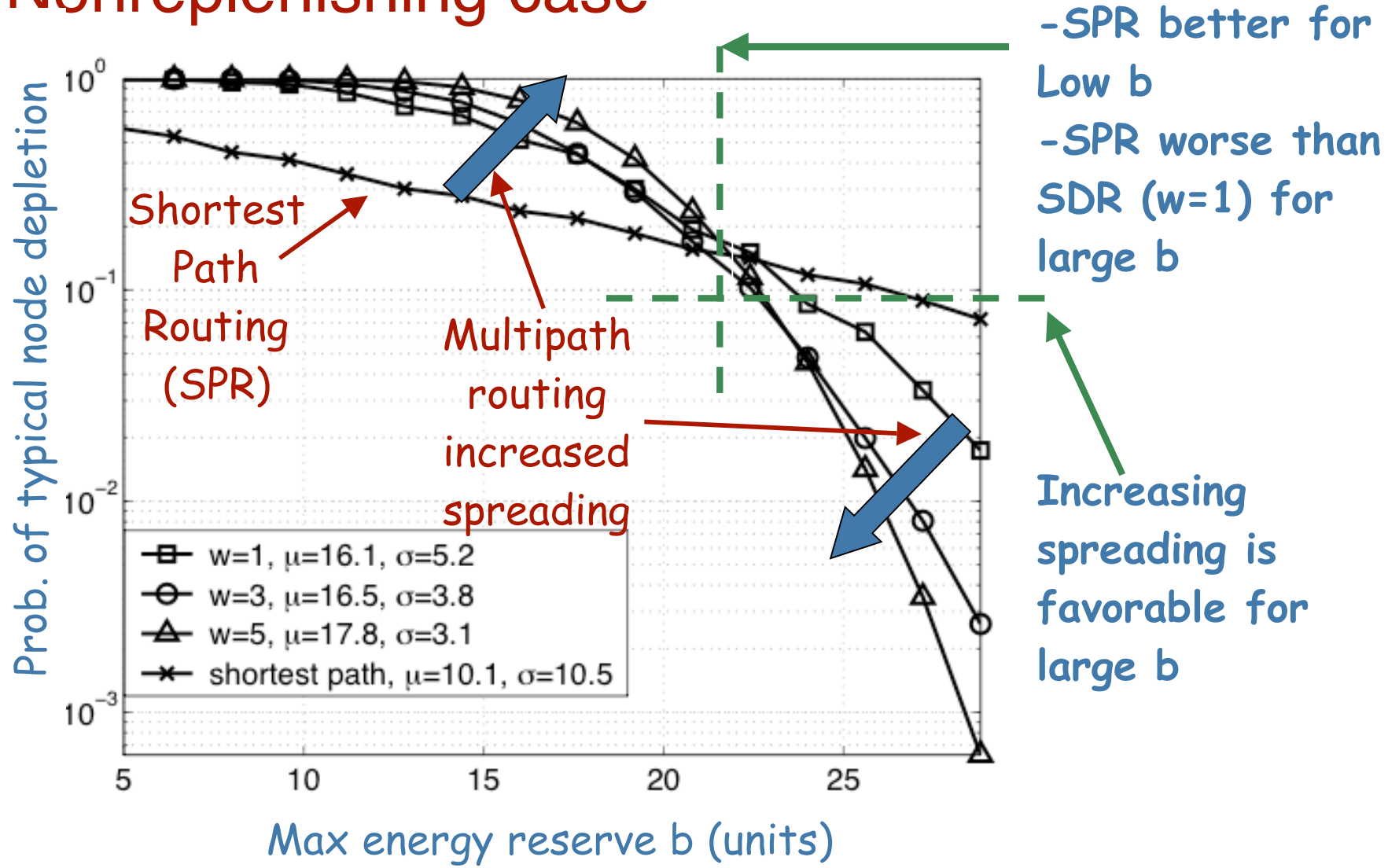
- 400 nodes locations on  $20 \times 20$  square Poisson PP with unit rate
- Source-destination selected at random
- Multipath routing based on geometric construction for different spreading factors  $w$



- Flow balancing mimics our optimal assignment
- Find probability that a randomly selected node is depleted of its energy reserve  $b$

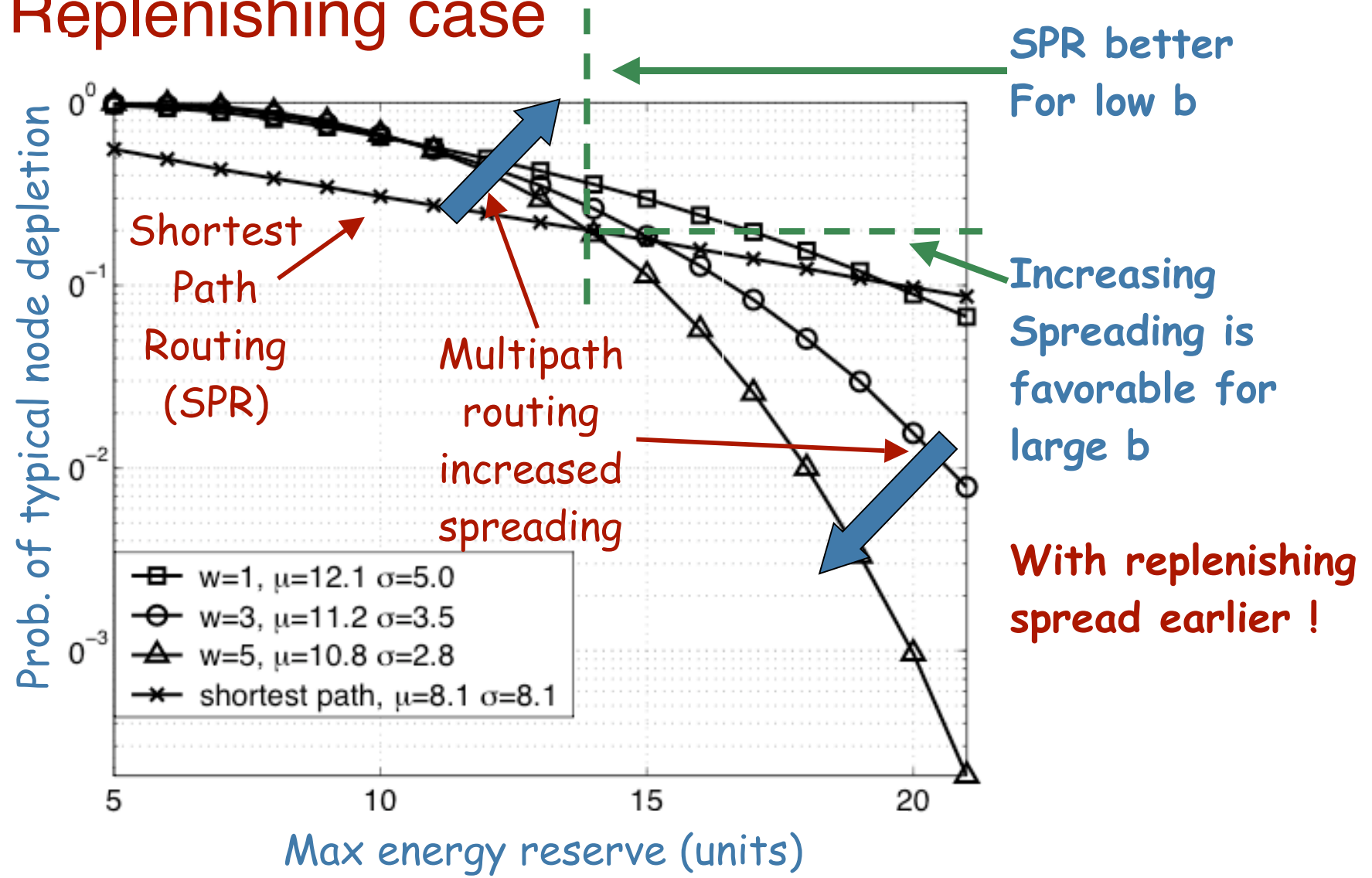
# Simulations: Proactive multipath routing

## Nonreplenishing case



# Simulations: Proactive multipath routing

## Replenishing case



# Summary and ongoing work - Part 1

- Investigate `optimal' energy balancing strategy
  - Tradeoff: spreading to decrease variability versus energy cost of achieving spreading
- Stochastic geometric framework and simple queuing models enable study
- Ongoing
  - Continuum optimization - `optimal' routing shape
  - Dynamic spreading based on stream characteristics
  - `Knock on' effects in space - when to routing around depleted regions ?

# Part 2: Routing hierarchies in wireless sensor networks using compression and sink nodes

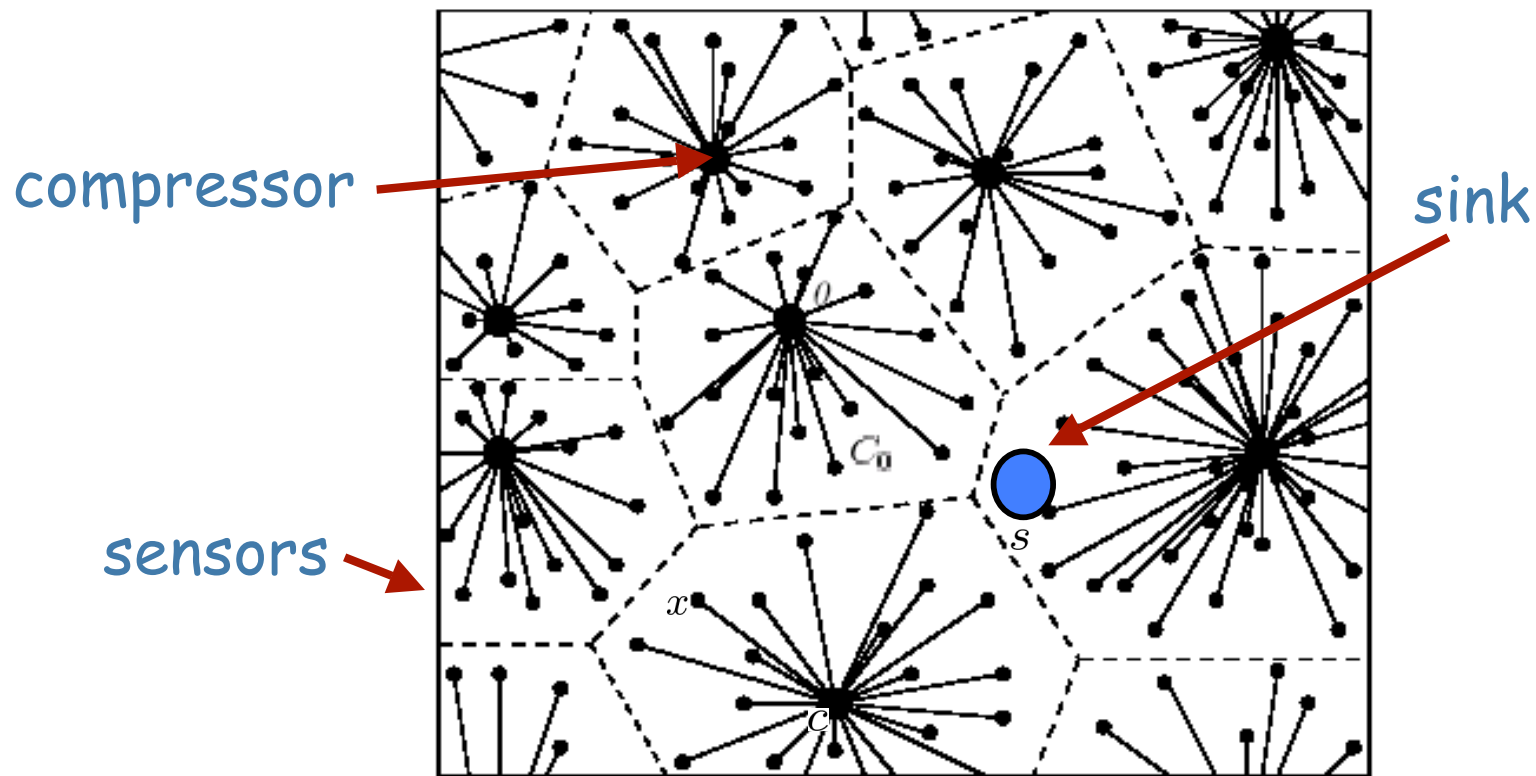
- **Traffic and Network model**
  - Sensors generate stream of data packets which are routed via ad hoc network to set of sink nodes
  - Possibility of data/header compression of correlated/redundant data along intermediate nodes
- **Problem:** What is the best way to organize compression & aggregation along with routing so as to minimize network's overall energy burden.

# Hierarchical Network Organization

## Model

- Locations of sensors, compressors, and sinks follow homogenous Poisson PPs

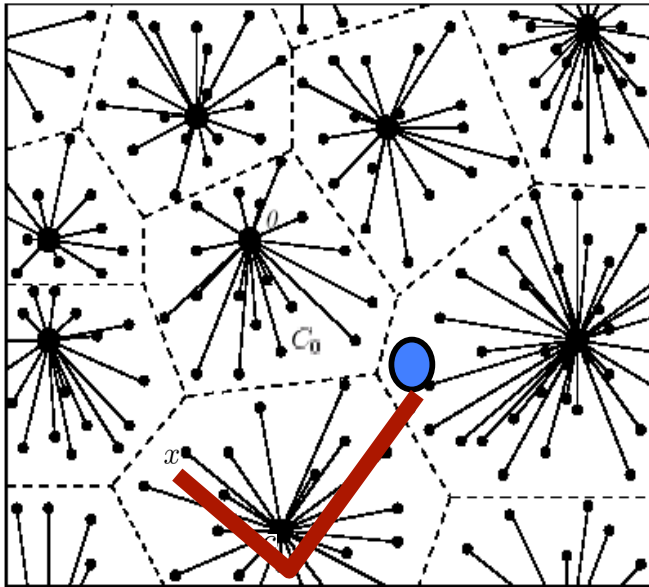
$\Pi_0, \Pi_1, \Pi_2$  with intensities  $\lambda_0, \lambda_1, \lambda_2$



# Hierarchical Network Organization

## Model

- Sensors generate packet rate  $\lambda$  at unit rate
- Energy cost between two locations is proportional to distance  $d(x,y)$  (i.e.,  $\sim$  #of hops) and packet rate
- Compression ratio is roughly  $\alpha$



Energy cost  $e(x)$  for  
sensor at location  $x$

$$e(x) = d(x, c) + \alpha \cdot d(c, s)$$

Distance to  
compressor  $c$

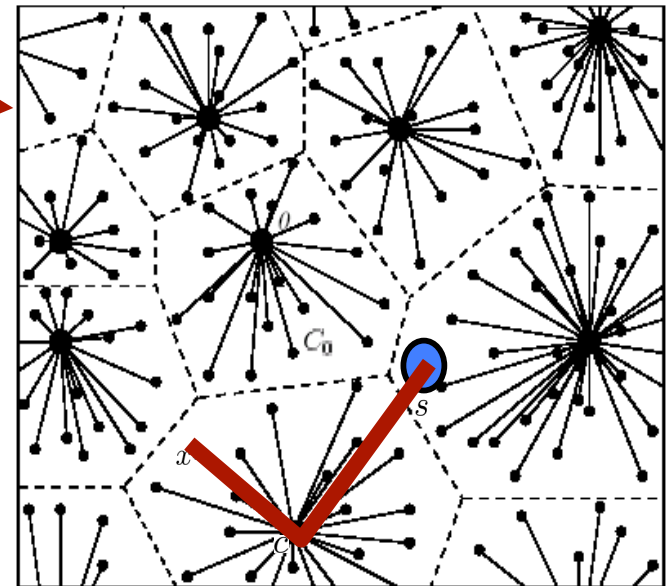
Distance from  
compressor  
to sink  $s$

# Hierarchical Network Organization

- **Problem:** What is routing/compression hierarchy which minimizes overall energy burden?
- Possible solution: route to closest compressor (or sink) and then from there to the sink

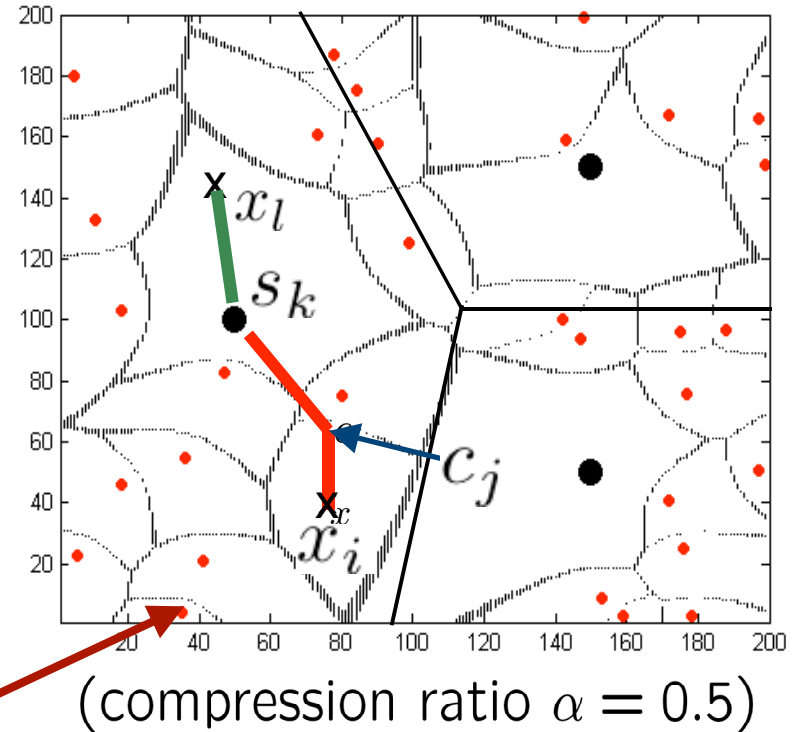
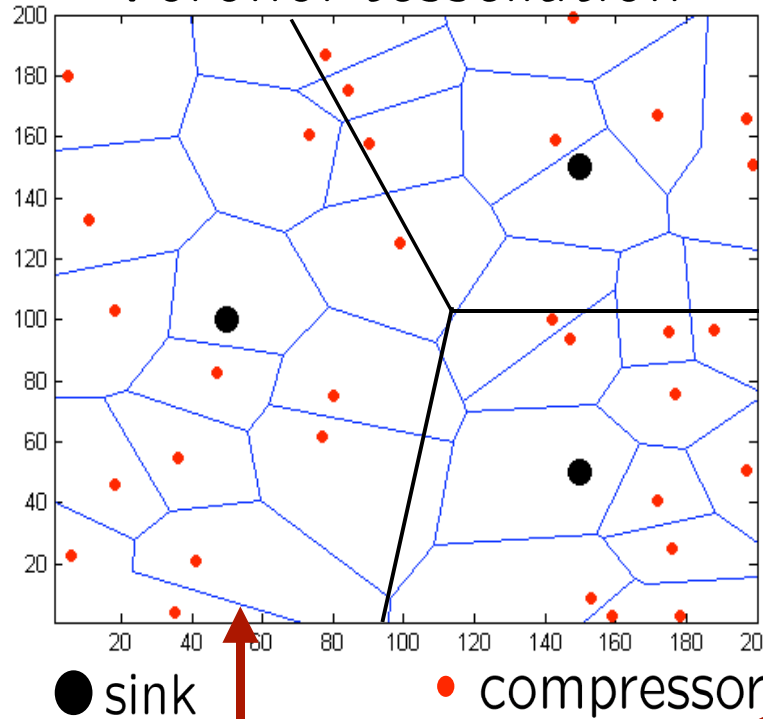
- Voronoi tessellations \*
- But is this optimal?

- **Theorem:** The minimum avg. energy cost hierarchy is associated with a *Johnson-Mehl tessellation*



\*[Baccelli et al.: Average cost analysis for Voronoi hierarchies]

# Voronoi tessellation



$$V_{y_i}(\pi_1, \pi_2) = \{z \in \mathbf{R}^2 \mid |z - y_i| < |z - y_j|, \forall y_j \in \pi_1 \cup \pi_2\}$$

$$T_{y_i}(\pi_1, \pi_2) = \{z \in \mathbf{R}^2 \mid |z - y_i| + \alpha|y_i - s_V(y_i)| < |z - y_j| + \alpha|y_j - s_V(y_j)|, \forall y_j \in \pi_1 \cup \pi_2\}$$

**JM:** compressor `seeds' start growing at times prop. to distance from closest sink - hyperbolic faces.

# Analysis of energy cost

- Avg. cost for a typical sink:

$$E_2^0 \left\{ \sum_{c_j \in \Pi_1 \cap V_0(\Pi_2)} \left[ \underbrace{\alpha |c_j| \mathcal{N}_{c_j}^\alpha}_{\substack{\text{\# sensors} \\ \text{associated with} \\ \text{compressor } c_j}} + \underbrace{\sum_{x_i \in \Pi_0 \cap T_{c_j}^\alpha(\Pi_1, \Pi_2)} |x_i - c_j|}_{\substack{\text{sensors to} \\ \text{compressor}}} \right] \right. \\
 \left. + \underbrace{\sum_{x_i \in \Pi_0 \cap T_0^\alpha(\Pi_1, \Pi_2)} |x_i|}_{\substack{\text{sensors directly} \\ \text{to sink at origin}}} \right\}$$

Expectation wrt Palm prob. sink process i.e. sink at origin

# Analysis of Energy Cost

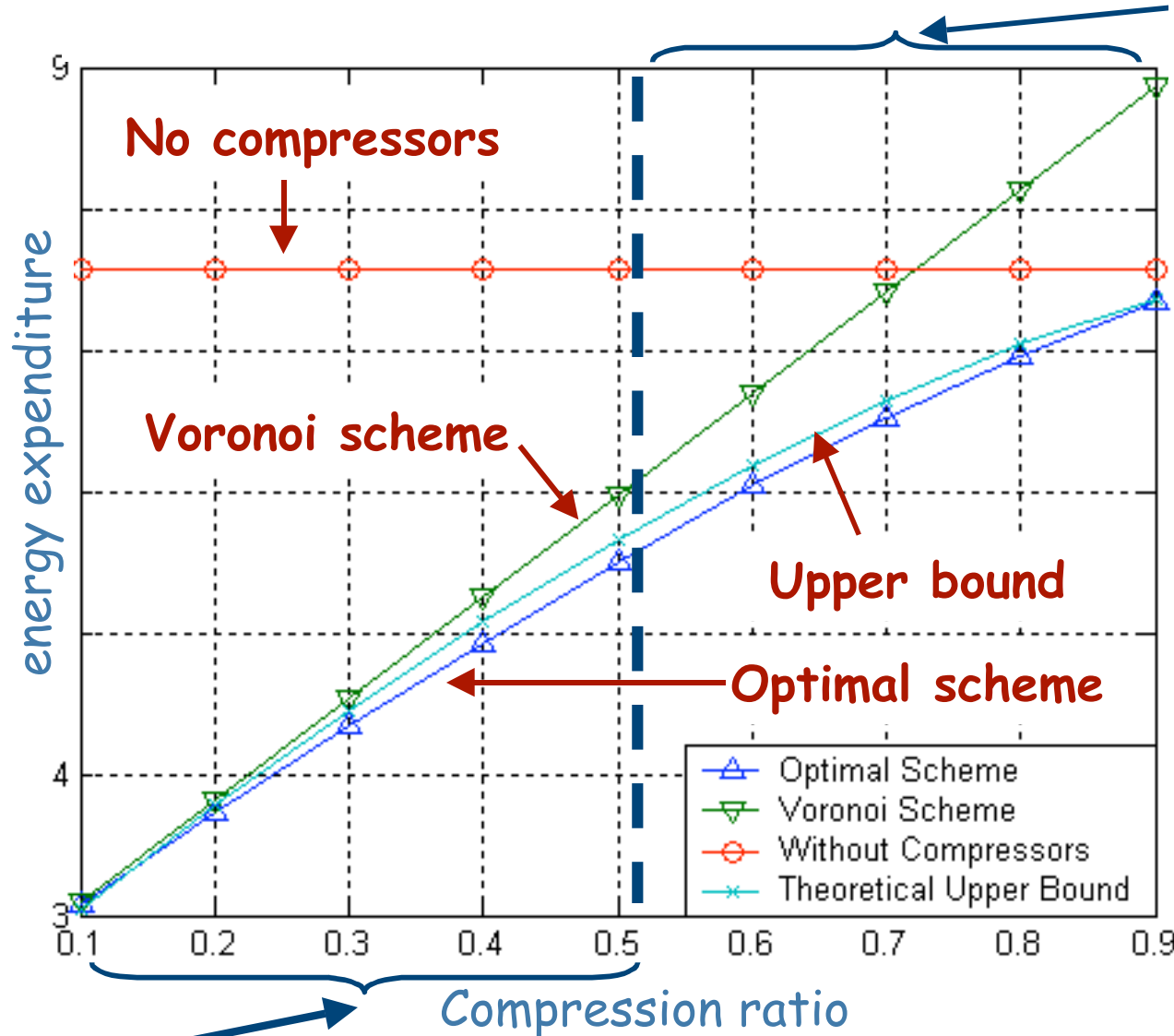
- **Theorem** a tight upper bound on energy cost is given by

$$\frac{\lambda_0}{\lambda_2} \left\{ \frac{\alpha}{2\sqrt{\lambda_2}} + \frac{1 - \alpha}{2\sqrt{\lambda_2 + \frac{\lambda_1 f(\alpha)}{\pi}}} \right\}$$

$f(\alpha)$  = area of  $\alpha$  skewed Cartesian oval

- $\alpha=0$  -> avg. costs to closest sink/compressor  $\frac{1}{2\sqrt{\lambda_1 + \lambda_2}}$
- $\alpha = 1$  -> avg. costs to reach closest sink  $\frac{1}{2\sqrt{\lambda_2}}$

# Performance Comparison



For moderate compression optimal gives 8-28% savings over Voronoi

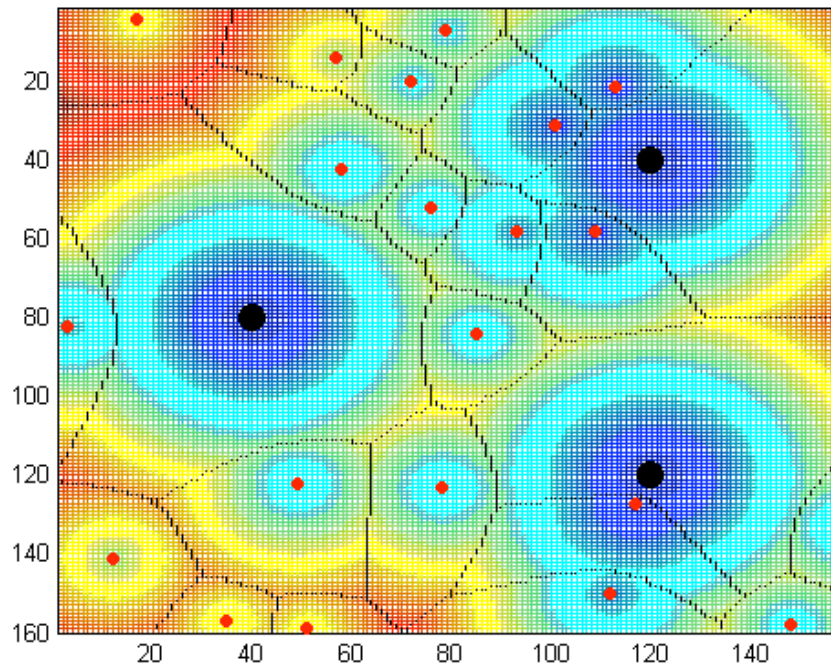
For high compression Voronoi acceptable

# Results and extensions

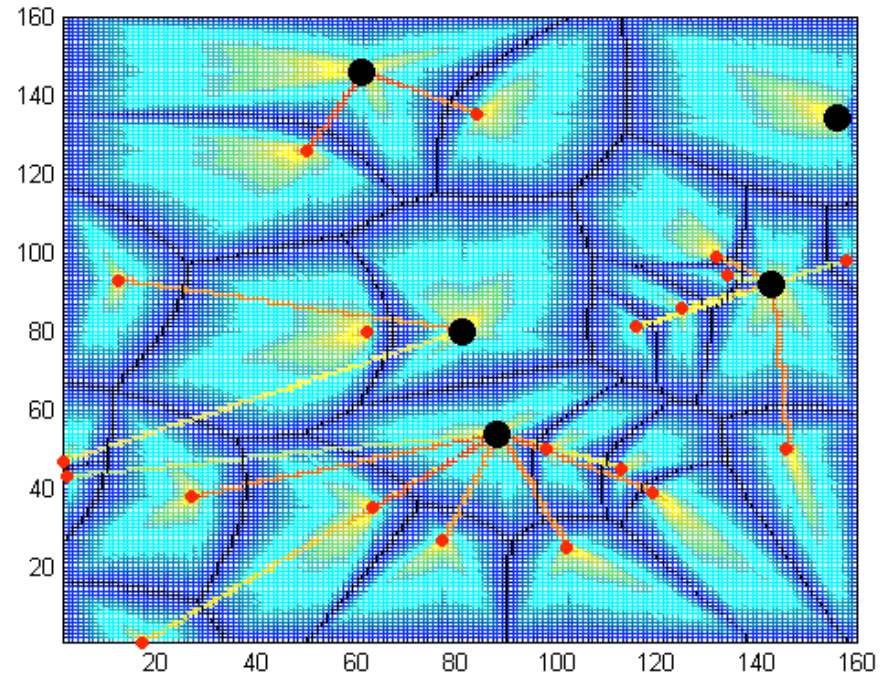
- Analytical results for mean energy costs for optimal hierarchy associated with Johnson-Mehl tessellation
  - *Permit optimization of densities of compressors/sinks etc. based on compression ratio and system capacity*
- Extensions: optimal hierarchy associated with non-linear energy costs
  - One/two hop model, i.e., direct transmission to sink or relaying via compressor to sink.
  - Capture wireless channel's signal decay (path loss)

# Energy and 'Congestion' Fields

● compressor ● sink



Energy field associated with carrying traffic from given location  $e(x)$



Cummulative energy field associated with ALL traffic traversing\* given location with straight line routing

# Summary - Part 2

- JM tessellation outperforms Voronoi scheme significantly when the density of compressors is fairly high, otherwise, *Voronoi scheme is as good as optimal scheme.*
- In one/two-hop cases, the gain from the optimal tessellation is much larger, however, as path-loss exponent increases, the role of compression becomes negligible
- *Congestion* is a severe impairment for the system design – detecting or switching compressors/sinks is unavoidable, but what is the best strategy? Further study

# Outgoing comments.

- Stochastic geometry & queueing provides a concrete way to study spatial processes and interactions in ad hoc wireless and sensor networks.
- Energy balancing-> optimal tradeoffs
  - Dynamic vs static settings, e.g., traffic/nodes
- We are looking to further refine these ideas and provide a more comprehensive view including some dynamic aspects of spatial interactions among user's traffic.

# Spatial Dimension in Wireless and Sensor Networks

- Plays critical role in determining
  - Connectivity, capacity/interference patterns, energy expenditures, sensing coverage, protocol performance
  - Difficulties: complexity of environment, number of users/sensors, and mobility
- Challenges
  - Devise tools enabling modeling, analysis, and design of incorporating space/location
    - Macroscopic modeling via stochastic geometry
  - Develop more efficient system designs and optimized protocols

# Performance Comparisons

- Energy savings of the optimal scheme, relative to Voronoi scheme, depends on the compression ratio with increasing sensitivity as density of compressors decreases

