Addressing the Deployment Challenges of the Wireless IoT with Stochastic Geometry Modeling

G. Liodakis[1,2], I.O. Vardiambasis[1], A. Maras[2]

[1] Technological Educational Institute of Crete,
Department of Electronic Engineering
[2] University of Peloponnese,
Department of Informatics and Telecommunications

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Motivation and contributions

- **Motivation:**

  To shed some light on the network deployment challenges for the wireless IoT realization

- **Main contributions:**

✓ To point out the effectiveness of various spatial point process (PP) models for the performance evaluation of wireless IoT architectures.

✓ To propose performance metrics well-suited for overall the wireless IoT landscape.

✓ To provide a unified performance evaluation framework that couples IoT node design (connectivity options, powering through energy harvesting) with deployment issues, through spatial PP modeling.

Wireless IoT (1/2)

- **The term "wireless IoT" generally refers to physical devices embedded with sensors and wireless connectivity, that are able to communicate with one another and with the users, as well as becoming an integral part of the Internet.**

- Based on the geographic distribution of the wireless IoT devices, IoT applications can be categorized as:

✓ **Personalized IoT applications** (e.g., health and fitness monitoring)

✓ **Localized IoT applications** (e.g., home automation tasks in a smart home)

✓ **Wide-area IoT applications** (for the provision of a series of public services in a smart city).

Wireless IoT (2/2)

- The architecture of a wireless IoT implementation is usually implemented with:

✓ IoT devices/nodes/smartphones

✓ IoT gateways (data aggregators)

✓ IoT application servers.

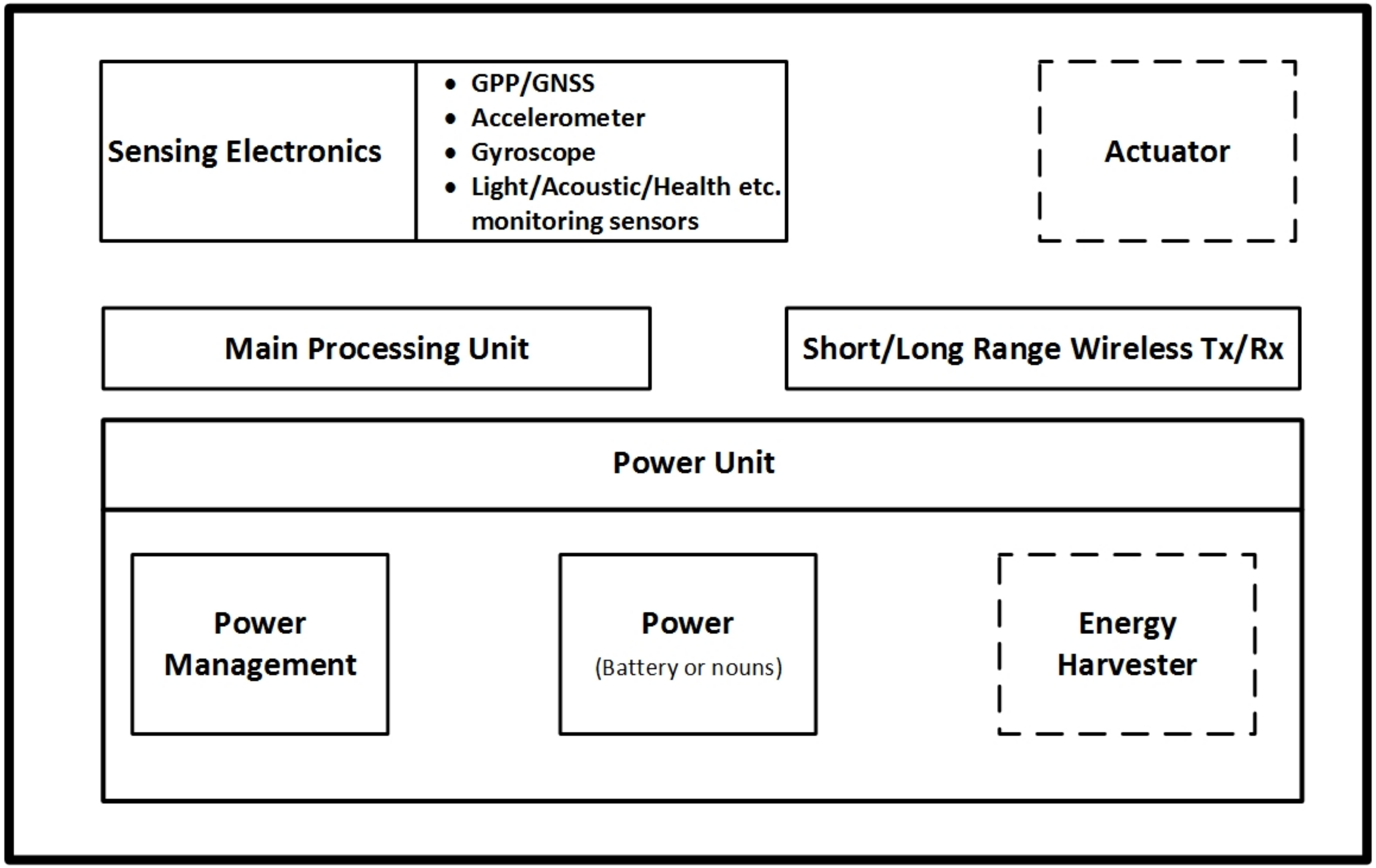
- Design aspects of an IoT device:

✓ Hardware design (circuit design, size, cost, etc.)

✓ Power provision and energy efficiency

✓ Wireless communication options

General architecture of a wireless IoT node



Location and Spatial PPs

- The location of a wireless network entity is of primary importance for the provision of wireless communication services (e.g. the location-based services of current cellular networks).
- The same, also, holds for the wireless IoT landscape:
- ✓ Sensors detect what is happening at a certain location
- ✓ For moving IoT nodes the changing spatial relationship among them may be of value for context-aware IoT applications
- ✓ The location of IoT nodes is of great concern for wireless access management, resource allocation, and interference management in order to satisfy specific QoS constraints of IoT applications.
- By using spatial PP models, we can capture and model various sources of uncertainty:
- ✓ The spatial distribution of the wireless IoT nodes
- ✓ The random nature of the wireless channel
- ✓ The spatial distribution of energy harvesters for powering purposes

PPs for modeling and performance evaluation

- Spatial PPs provide analytical models that apply **on average** for all wireless network realizations, including their performance evaluation, though **only** in some special cases closed-form expressions are derived.
- These expressions relate spatially averaged performance metrics to the wireless network deployment parameters and other communication engineering variables.
- In such a way, **not only** network deployment guidelines for optimization purposes, **but also** network behavior insights are obtained, without resorting to costly and time consuming simulations.

From SINR to communication performance metrics

- **Coverage propability** (p_{cov}): It is the complementary cumulative distribution function of SINR and id defined as the probalitily that the SINR goes above a certain threshold T_{th}.

$$P_{cov} \triangleq \mathbb{P}[\mathrm{SINR} > T_{th}]$$

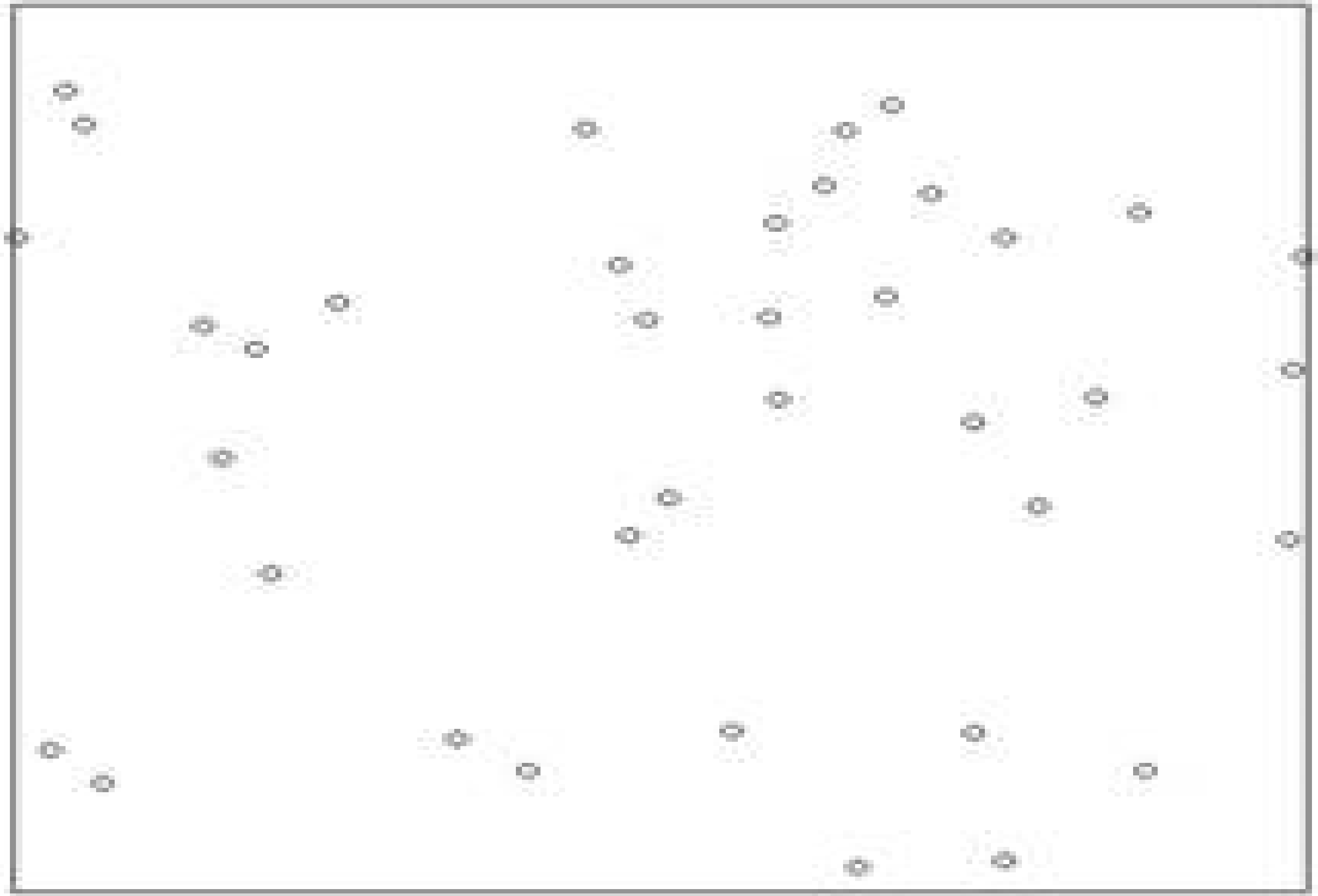
- Outage probability (p_{out}): It is defined as the probability that the SINR goes below the specified T_{th} value.

$$P_{out} \triangleq \mathbb{P}[\mathrm{SINR} < T_{th}]$$

- ***k-coverage probability*** ($p_{k\text{-}cov}$): It is defined as the probability that k IoT gateways are in the communication range of each IoT device.
- ***Gateway association probability*** (p_{ga})
- **Ergodic link rate** (R): This metric measures the expectation of the long-term achievable rate that a typical communicating (i.e., SINR> T_{th}) IoT node or gate experiences averaged over for the PP under consideration *and* over the distribution of channel and interference states.

$$R \triangleq E[\log(1+\mathrm{SINR})]$$

Realization of a Homogeneous Poisson PP (HPPP) with λ=30



Properties and weaknesses of the HPPP model

• Suitable to model a network with infinite many nodes that are randomly *and* independently (i.e., no spatial correlation) distributed over a given service area.

• HPPP is a model for which the distribution of the distance between the nodes is known.

• Popular model due to its tractability (due to its stationarity and the Slivnyak's theorem).

• Many "operations", such as independent thinning and superposition, on a HPPP preserve its "Poisson law".

But…

• Node locations of real networks are spatially dependent (i.e., HPPP is not an accurate model for interference evaluation).

Furthermore, in some instances, both spatial and temporal correlation is introduced for the aggregate interference (e.g., between different time slots if the receiver is equipped with a single antenna).

Evaluation of p_{cov} for a k-tier HPPP wireless IoT architecture (1/2)

- In case k=2:

✓ First tier: Macro BSs
✓ Second tier: IoT Gateways
✓ Third tier: IoT nodes

$$\mathrm{SINR}(\mathbf{X}_i) = \frac{P_i H_{\mathbf{X}_i} \|\mathbf{X}_i\|^{-\alpha}}{\sum_{j=1}^{k} \sum_{X \in \Phi_j \backslash \mathbf{X}_i} P_j H_{\mathbf{X}} \|\mathbf{X}\|^{-\alpha} + \sigma^2} = \frac{P_i H_{\mathbf{X}_i} \|\mathbf{X}_i\|^{-\alpha}}{I(\Phi \backslash \{\mathbf{X}_i\}) + \sigma^2}$$

$$P_{cov}\left(\{\lambda_i\}, \{T_{th,i}\}, \{P_i\}\right) = \mathbb{P}\left(\bigcup_{i \in \{1,2,\ldots,k\},\, \mathbf{X}_i \in \Phi_i} \mathrm{SINR}(\mathbf{X}_i) > T_{th,i}\right)$$

Evaluation of p_{cov} for a k-tier HPPP wireless IoT architecture (2/2)

$$P_{cov}\left(\{\lambda_i\},\{T_{th,i}\},\{P_i\}\right)=$$

$$=2\pi\sum_{i=1}^{k}\lambda_i\int_0^{\infty}\exp\left(-x^2\left(\frac{T_{th,i}}{P_i}\right)^{2/\alpha}\cdot\zeta(\alpha)\cdot\sum_{m=1}^{k}\lambda_m P_m^{2/\alpha}\right)\cdot\exp\left(-\frac{T_{th,i}\,\sigma^2}{P_i}x^\alpha\right)\cdot x\,dx$$

$$\zeta(\alpha)=\frac{2\pi^2}{\alpha}\csc\left(\frac{2\pi}{\alpha}\right)$$

- Interference-limited (no-noise) case:

$$P_{cov}\left(\{\lambda_i\},\{T_{th,i}\},\{P_i\}\right)=\frac{\pi}{\zeta(\alpha)}\cdot\frac{\sum_{i=1}^{k}\lambda_i P_i^{2/\alpha}T_{th,i}^{-2/\alpha}}{\sum_{i=1}^{k}\lambda_i P_i^{2/\alpha}}$$

- Same per-tier T_{th}:

$$P_{cov}\left(\lambda,T_{th},P\right)=\frac{\pi}{\zeta(\alpha)\,T_{th}^{2/\alpha}}$$

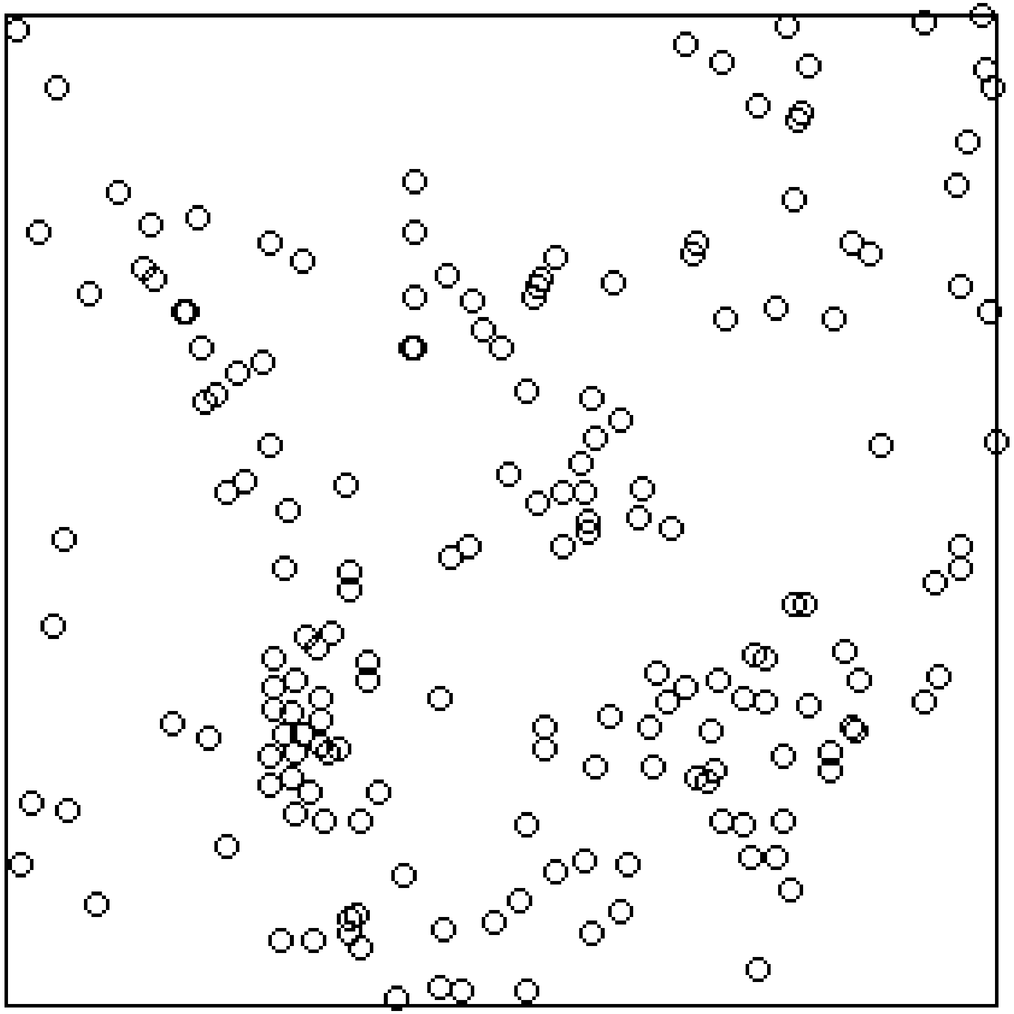
The a-Ginibre PP (a-GPP) for modeling repulsion

- The a-Ginibre PP lies between the Poisson and Ginibre (a=1) PPs.
- The points of an a-Ginibre PP are more regularly located than PPPs.
- The a-GPP is a thinned GPP.
- The a-GPP models repulsion through a soft-core process.
- The degree of repulsion is tunable by the value of a (a-Ginibre for macro BSs, PPP for wireless IoT aggregators).

PPs for modeling “attraction” for the data aggregation process in wireless IoT

- Poisson cluster PP
- Cox cluster PP
- Neyman-Scott PP
- Matern cluster PP
- Thomas cluster PP

Matern Cluster spatial process
(λ_{parent}=30 and $\lambda_{offspring}$=4)



Energy harvesting for the wireless IoT

- Energy harvesting may be employed for various wireless IoT applications in a smart city contex:

✓ Traffic congestion

✓ Noise monitoring

✓ Waste management

✓ Smart parking, etc.

- RF energy harvesting from the radio signals of different frequencies (e.g., from co-channel interference of a cellular network) may be sensed by the energy harvester of a wireless IoT device.

Energy harvesting process modeled by PPs

- PPP for modeling energy harvesters and energy aggregators
- Poisson-Boolean model
- The class of GPPs

Performance metrics for energy harvesting

- **Expectation of the energy harvesting rate**.

- **Transmission probability**: The probability that an IoT node's battery has harvested sufficient energy for transmission.

- **Transmission outage probability**: The probability that the transmission rate of an IoT node is below the desired threshold).

- **Success probability**: The probability that both transmission and radio coverage probabilities are satisfied.

LTE NB-IoT and LoRa main physical parameters

Standard / Parameter	LTE NB-IoT	LoRa
Frequency	Guard band & In-band options	867 – 869 MHz (in Europe)
Bandwidth	200 kHz	125 kHz (DL) 125/250 kHz (UL) (for Europe)
Duplex mode	Half duplex (FDD only)	Yes
Transmit power	20 dBm	14 dBm (for DL and UL in Europe)
Typical coverage range	5 km	Rural: 10-15 km Urban: 3-5 km
Peak data rate	DL: ~20 kbps UL: ~60 kbps	290 bps – 50 kbps (both DL and UL for Europe)
Devices per IoT gateway	~ 50,000	~ 10,000 (from real experimentation)
Power efficiency	Very high	Medium high
Complexity	Very low	Low

Conclusions

- The maturity of stochastic geometry modeling in other fields (MANETs, cellular, sensor networks) can be quite effective for the performance evaluation and dimensioning of the wireless IoT ecosystem.
- PP models can capture **sources of uncertainty** that affect the design of wireless IoT network entities (placement, connectivity, powering).
- **Trade-offs** between the mathematical tractability provided by the various PP models and the suitability of these models for the real world IoT implementations, should be achieved.
- Although most wireless IoT applications are more **coverage-centric deployments** than capacity-centric deployments, the individual requirements of the wireless IoT architectures and applications, should be considered.
- **Standardization** for wireless IoT system architecture *and* low-power long range communication systems will facilitate the performance evaluation framework.