Automated Construction of Fast and Accurate System-Level Models For Wireless Sensor Networks

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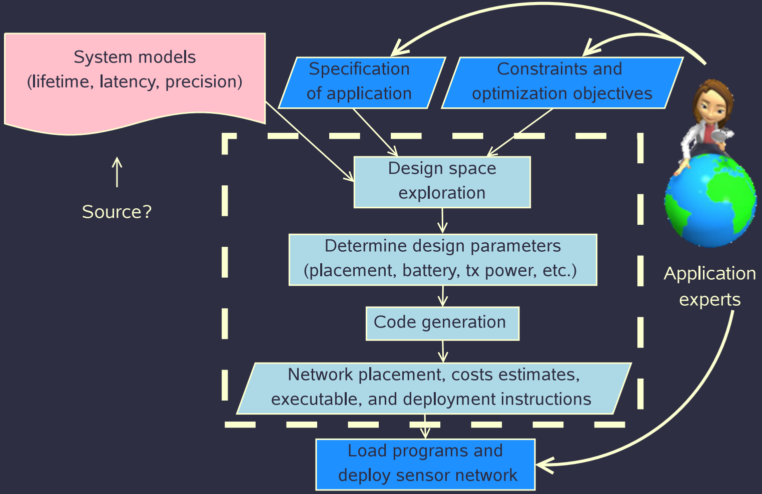
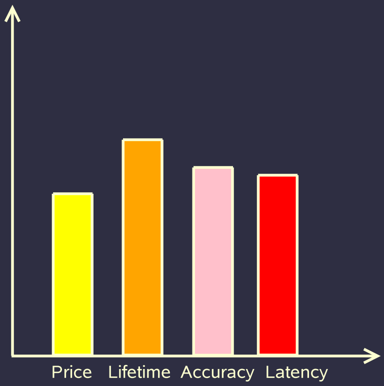
Outline

Toward synthesis of wireless sensor networks



Motivation

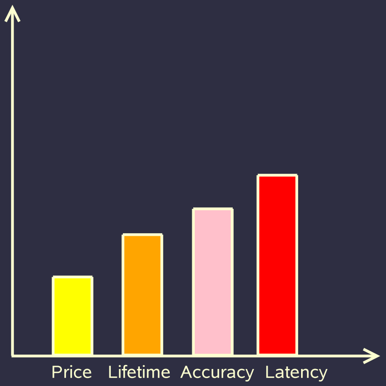
Costs and performance



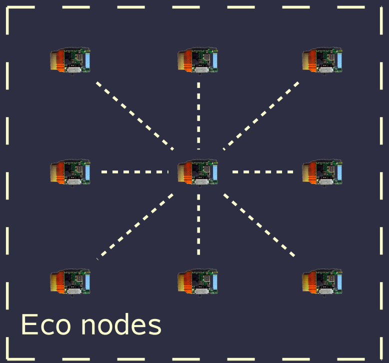
Sensor network design

Motivation

Costs and performance



Sensor network design



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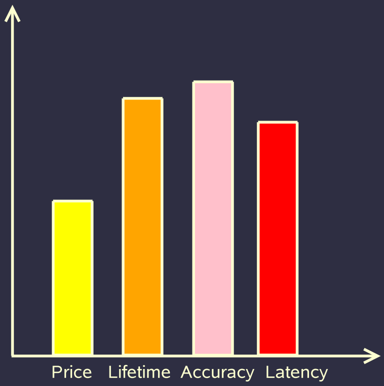
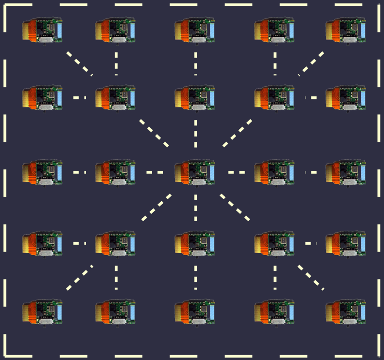


Sensor network design



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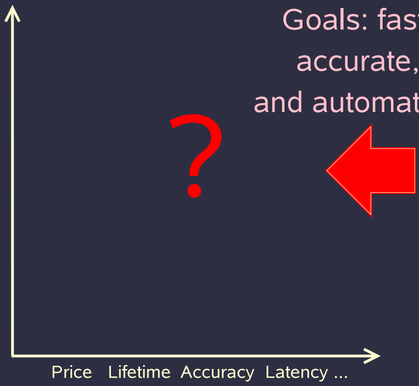
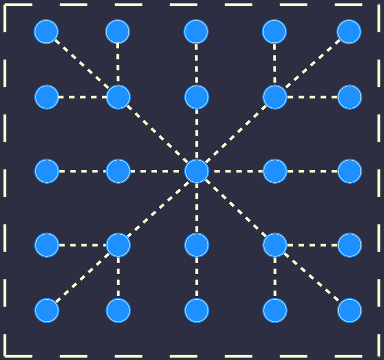


Goals: fast,
accurate,
and automated.

Sensor network design



Alternatives to estimate quality of prospective designs

Analytical

Understand interactions between system components, simplified assumptions, quick to evaluate.

Detailed network and reliability simulation

More accurate, longer evaluation time.

Deployment

Most costly and most accurate, difficult to evaluate long-term behaviors.

Key ideas: build analytical models based on simulation results using statistical modeling methods

- Models should be fast to evaluate.
- As accurate as detailed simulation.
- Generalize and automate model construction.
- Reduce simulation runs with adaptive sampling.
- Model system-level performance metrics that application experts can appreciate.

System lifetime

Duration from the start of operation until the sensor network ceases to meet its operating requirements.

Existing definitions

Time to first node failure, N node failure, % node failure, network connectivity.

Application experts care about quality of data (data-centered applications).

We propose a more general application-level definition based on sampling density that decouples specification from implementation.

Briefly, the network is alive if spatial and temporal sampling density requirements are honored.

Related work I

Modeling

- Use statistical methods or machine learning techniques to model performance and power consumption for micro-architectural design space exploration.
- Lee ASPLOS'06, Ozisikyilmaz DAC'08, Cook DAC'08.
- Was not applied to wireless (sensor) networks.

Related work II

Sensor network lifetime

- Most existing work ignores node-level fault processes.
- Aging analysis in large-scale wireless sensor networks (Lee, Ad Hoc Networks'08).
  - Analytical models for network connectivity analysis.
  - Consider both battery depletion and node reliability.

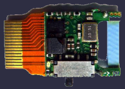
Sensor node lifetime modeling

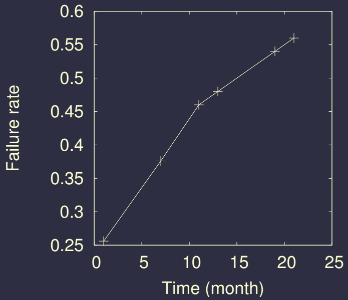
- A 15 × 15 mm, 1 μA, reliable sensor-net module: enabling application-specific nodes (Yamashita IPSN'06).
  - Measured node fault process by accelerated aging.
  - Fit to Weibull distribution.

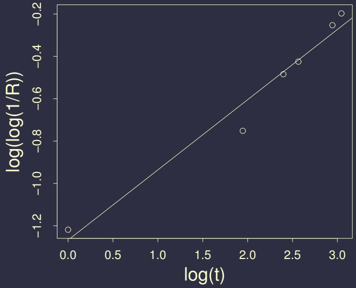
Outline

Node-level fault process modeling

Tracked status of 250 Eco nodes for 21 months.







Good fit to Weibull. SRE $= 0.08$, $R^2 = 0.96$.

Nodes are heavily used between measurements.

Battery energy dissipation modeling

Assume a constant deliverable energy capacity that is independent of variation in discharge rate.

Battery is depleted when total consumed energy equals the rated battery capacity.

Accurate when battery's internal resistance and device current are low.

Our model generation technique could be used with more complex battery models.

Outline

1. Introduction
2. Node-level modeling
3. System-level model construction
4. Evaluation

System-level model construction I

Model inputs (predictor variables)

Design parameters: network density, network size, battery capacity, radio transmit power, sampling density, sampling frequency, aggregation.

Model outputs (response variables)

- Performance metrics: system lifetime, data delivery latency, etc.
- Directly reflect (system-level) application requirements from an application expert's perspective.

System-level model construction II

Training data (samples)

- Simulation results from detailed wireless sensor network simulator – SIDnet-SWANS [Ghica Sensys'08].
- Use realistic simulation models, e.g., wireless communication models that consider signal attenuation, interference, and contention.

Adaptive sampling

- Start with sparse uniform sampling.
- Add samples in rough regions (difference in output value between adjacent sample points larger than a threshold).
- Acquire desired model accuracy with a small number of simulations.

System-level model construction III

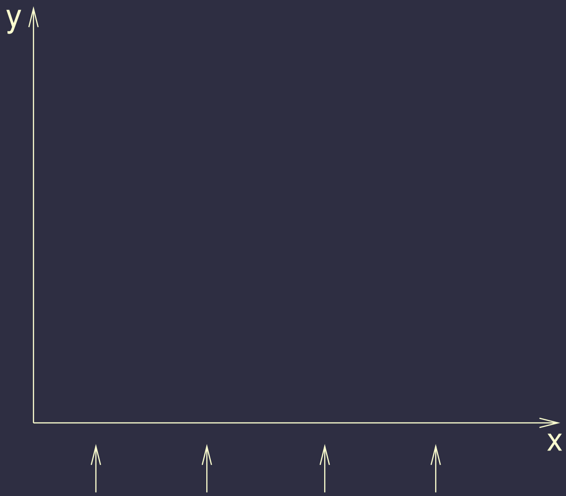
Statistical modeling methods considered

- Polynomial regression: response = polynomial function of predictors + random error.
- Kriging: interpolation method based on the spatial distribution of known values.

Model evaluation

- Run 10-fold cross validation 50 times with different random seeds.
- Model error $E = \sqrt{\sum_{i \in T} (y_i^p - y_i^s)^2 / |T|}$
  - y_i^p: predicted value, y_i^s: actual value, T: sample set.

Example for adaptive sampling



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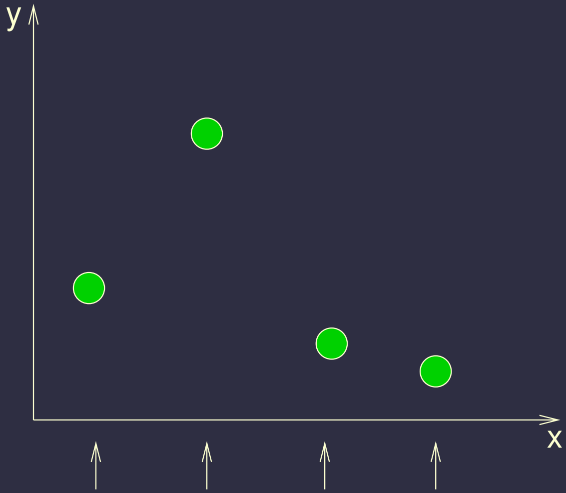

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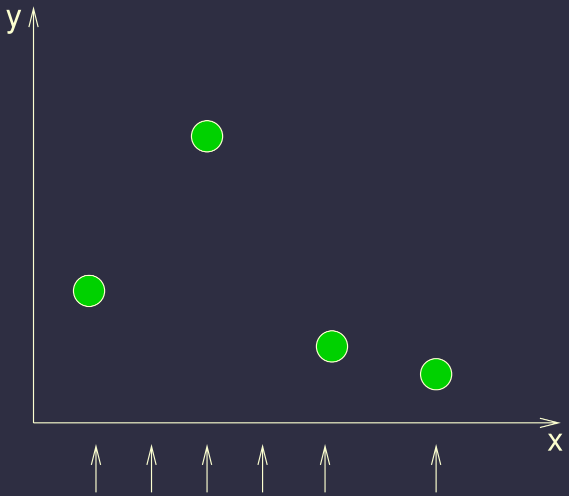

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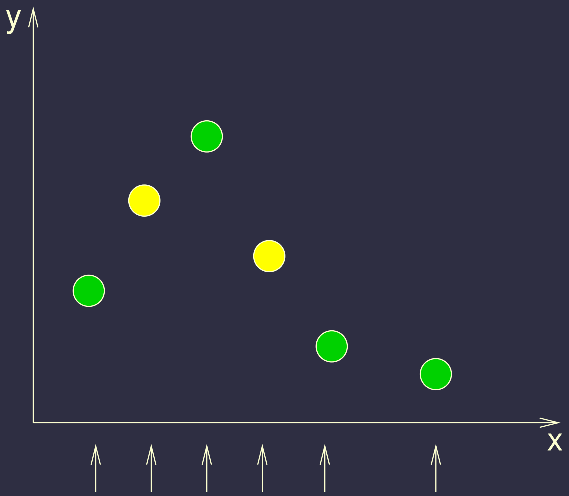
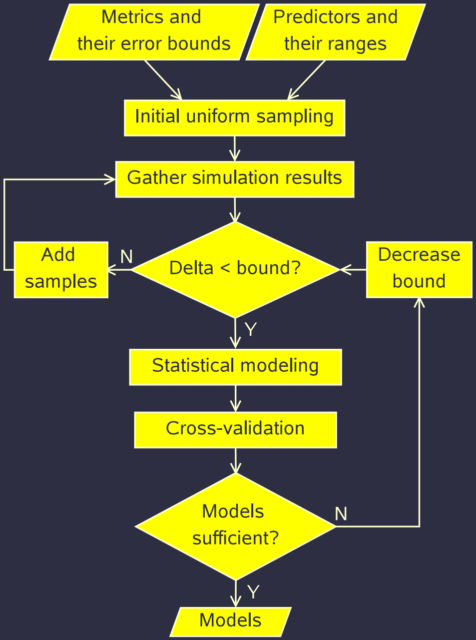


Automated model construction



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System lifetime modeling

System lifetime definition: time elapsed since start of operation until the spatial density of promptly delivered data drops below a threshold specified by the application developer.

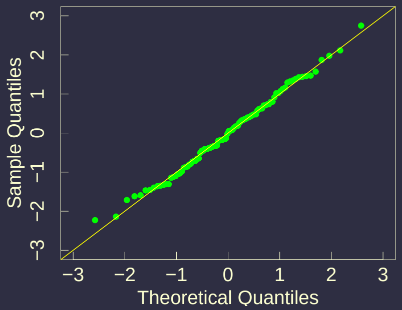
Domain of applications and assumptions

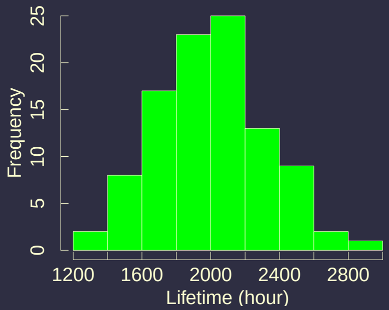
- Applications: periodical data gathering from a stationary sensor network. No aggregation or perfect aggregation.
- Sensor nodes uniformly distributed in a 2D grid.
- Sink node at the center.
- Homogeneous sensor nodes, same lifetime fault model.
- Sensor node fault modeled by independent Weibull processes.
- A node failure disconnects the affected node from the network.
- Dynamic data collection tree.

System lifetime modeling

- Different node failure sequence maps to different system lifetime.
- Assume system lifetime has Gaussian distribution.
- Use Monte Carlo simulation to map one design to one lifetime distribution.
- Run simulations in parallel on a cluster of machines.

System lifetime distribution

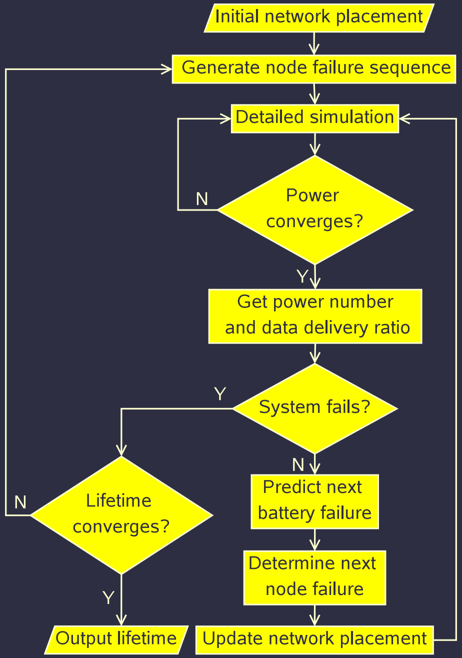




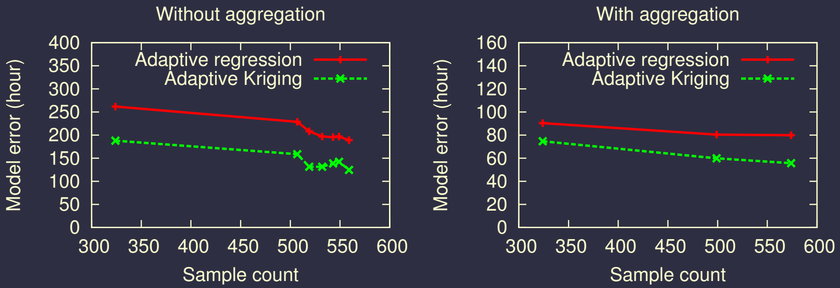
Normality tests shows the hypothesis is acceptable.

Average p-value is 0.54 for 100 instances.

Monte Carlo simulation



System lifetime modeling results



Design space contains 405,790 solutions.

Built model with 3.6% error by simulating only 0.27% of the solutions.

Total CPU time is approximately 8 weeks.

Comparison with an analytical model

Analytical model for aging analysis (Lee 2008)

- Compute degradation in network connectivity due to node-level faults and battery depletion.
- Unit disk model for wireless communication.
- Ignore interference and contention.

Comparison results

- Use our technique to build a model for network connectivity.
- Our model has an error of 72 hours (2.1% of average lifetime).
- Lee's model has an error of 525 hours (15% of average lifetime).

Caveats

Effectiveness of our technique relies on the ability to accurately estimate relevant quality metrics through simulation or measurement.

Model construction time may be infeasible for applications with arbitrary sensor positions or network traffic patterns.

Conclusions

An automated technique for generating system performance models for wireless sensor networks.

Used our technique to build a system lifetime model, considering both node-level fault processes and battery depletion.

Proposed a system lifetime definition to capture application-level requirements.

Lifetime model with 3.6% error was generated with simulating 0.27% of the solutions in the design space.

Reduced error by 13% compared with the most advanced analytical model.

Acknowledgment

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Q&A

Thank you

Example of the design space