Energy-Efficient Sensor Selection for Data Quality and Load Balancing in Wireless Sensor Networks

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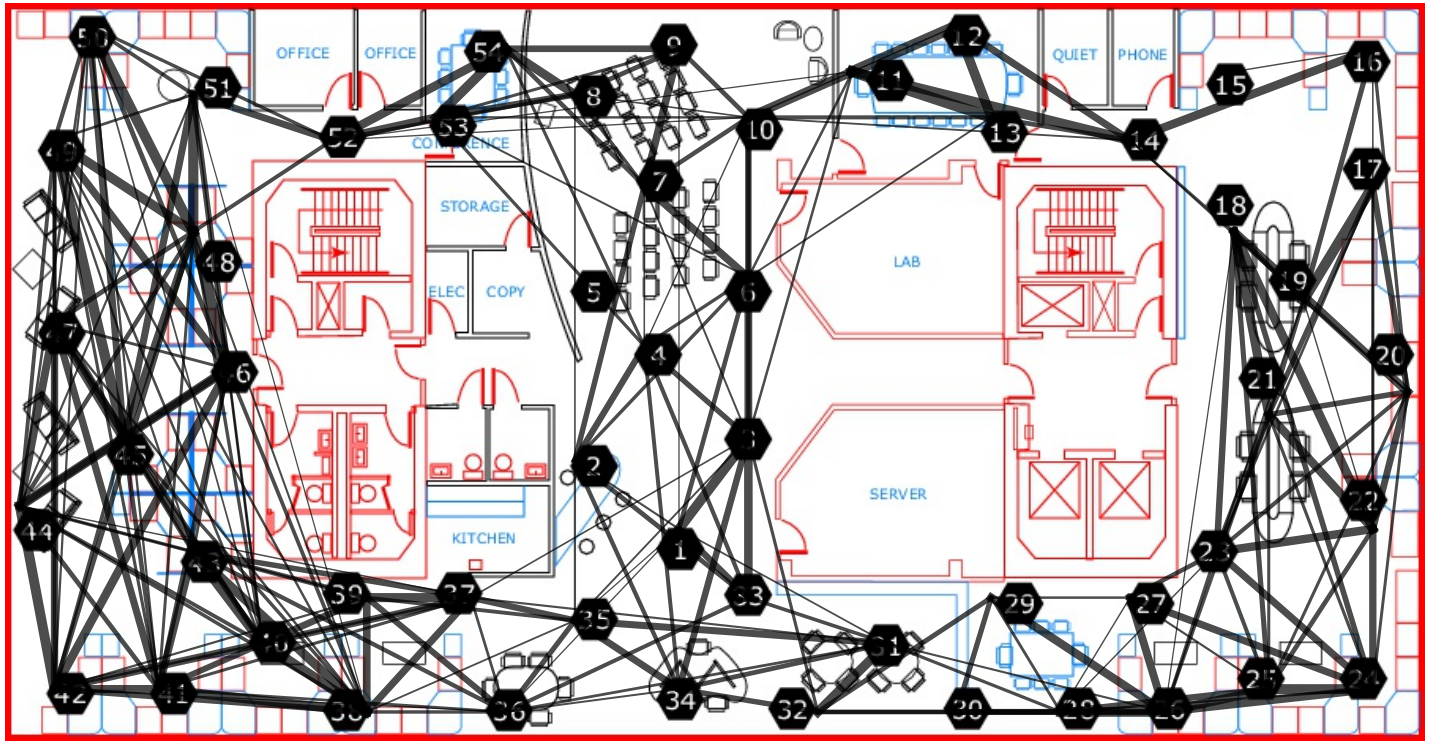
Motivation and Goal

Collect high quality data efficiently using sensor nodes:

- Increase network life-time and energy-efficiency
- Energy load balancing
- Consider link quality and routing
- Exploit spatio-temporal correlation



Contributions and Highlights

- Introducing adaptive sensing with belief propagation (ASBP) protocol.
- The formulation of the active sensor selection optimisation problem.
- Construct a *graph* model for WSN with spatio-temporal data correlation to be used by belief propagation.
- The effect of data quantisation on the data correlation.

Adaptive Sensing with Belief Propagation (ASBP) protocol

- Conserve energy by predicting missing data and using links with better quality.
- Objective:
  - Maximise the link quality of the multi-hop path to the sink.
  - Select a set of active sensors for data collection.
  - Minimise the correlation of the data between the active sensors.

Adaptive Sensing with Belief Propagation (ASBP) protocol (continued)

ASBP has two phases:

- *Phase 1:* All sensors collect data in the sensing field.
  - Only 20 readings are required.
  - Link quality is estimated.
  - Correlation coefficient matrix is constructed.
  - Select a set of active sensors by solving an optimisation problem.
- *Phase 2:* Sensing phase.
  - Only the active sensors are sensing and transmitting data.
  - Base station uses belief propagation (BP) to reconstruct the missing data.

Model

- Decision variables:

$$x[s] \in \{0, 1\},$$

1 if sensor s is selected, 0 otherwise $s \in S$

- Objective function:

$$\texttt{maximise} \quad \sum_{s \in S} E[s]^{\alpha} \cdot u[s]$$

  - S: Set of all sensor nodes.
  - α: Weight Constant (typically 0.5).
  - E: Residual energy.
  - $u[s]$: Data utility of the sensor s.

Model - Constraints

- Data utility constraints, $\forall s \in S$:

$$u[s] = w_1 \cdot x[s] \cdot q[s] - w_2 \cdot \sum_{\substack{s' \in S, \\ s' \neq s}} x[s] \cdot x[s'] \cdot C[s, s']$$

- Routing constraints, $\forall s \in S$:

$$q[s] = \max_{p \in P[s]} \left(B[n_p] \cdot \prod_{(s', s'') \in p} \left(x[s''] \cdot L[s', s''] \right) \right)$$

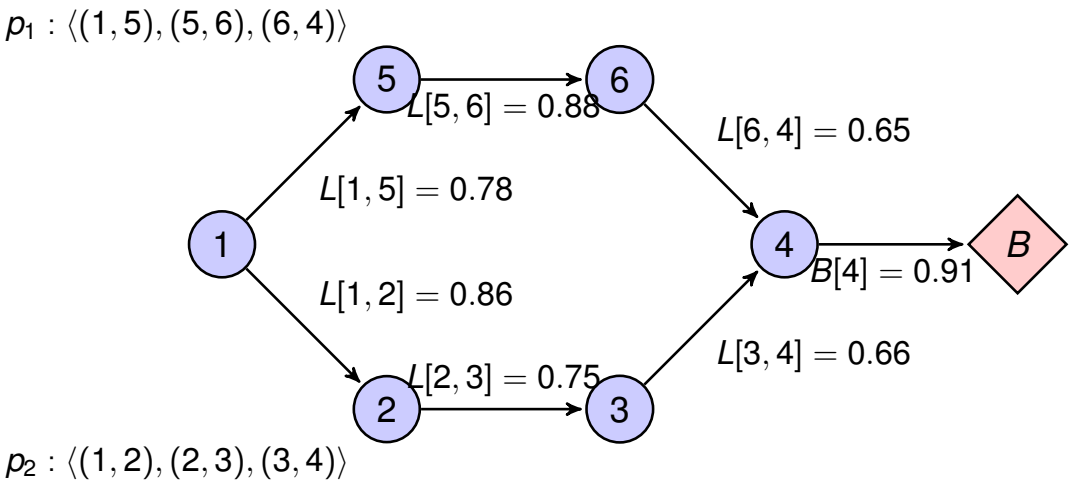
- Path quality constraints:

$$\forall s \in S, \quad q[s] \geq x[s] \cdot t$$

- Active sensor constraints:

$$\sum_{s \in S} x[s] \geq m$$

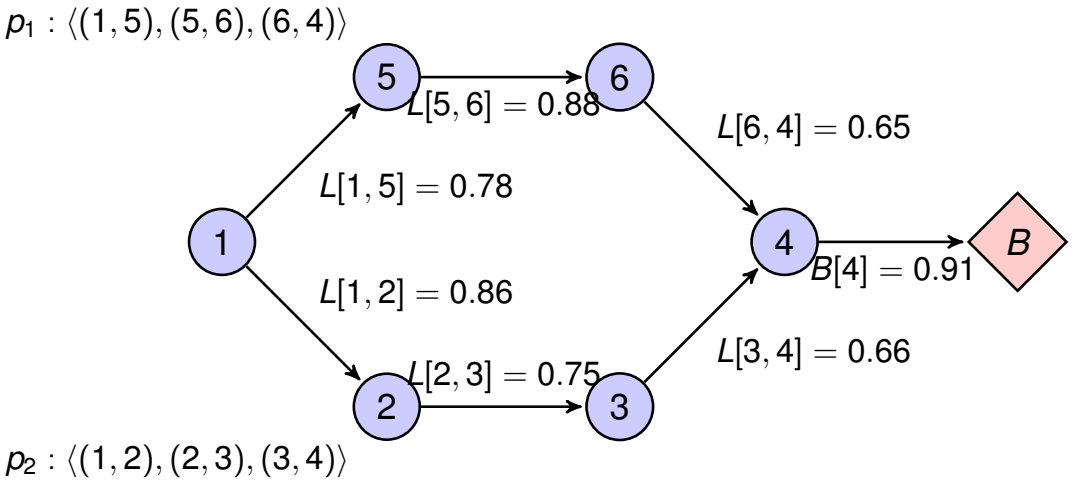
Implied Constraints



- Intersection of paths between two end-points:

$$\forall s \in S \quad (x[s] = 1) \implies \left(\bigwedge_{s' \in P_{\cap}[s]} x[s'] \right) = 1$$

Routing Constraint - Example



$$q_{p_1}[1] = L[1,5] \cdot L[5,6] \cdot L[6,4] \cdot B[4] = 0.406$$

$$q_{p_2}[1] = L[1,5] \cdot L[5,6] \cdot L[6,4] \cdot B[4] = 0.387$$

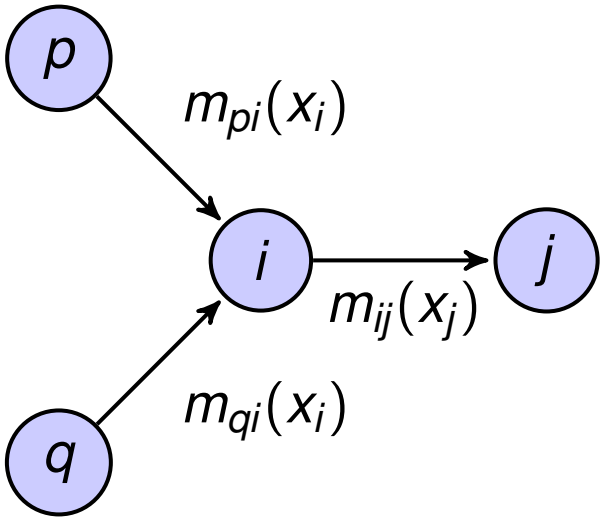
$$q[1] = \max(x[5] \cdot x[6] \cdot x[4] \cdot q_{p_1}[1], x[2] \cdot x[3] \cdot x[4] \cdot q_{p_2}[1])$$

- Routing constraints, $\forall s \in S$:

$$q[s] = \max_{p \in P[s]} \left(B[n_p] \cdot \prod_{(s',s'') \in p} (x[s''] \cdot L[s',s'']) \right)$$

Belief Propagation (BP)

- BP is a classic algorithm for performing inference on graphical models, Yedida *et al.* [YFW03]
  - Infers the underlying event from the observations.



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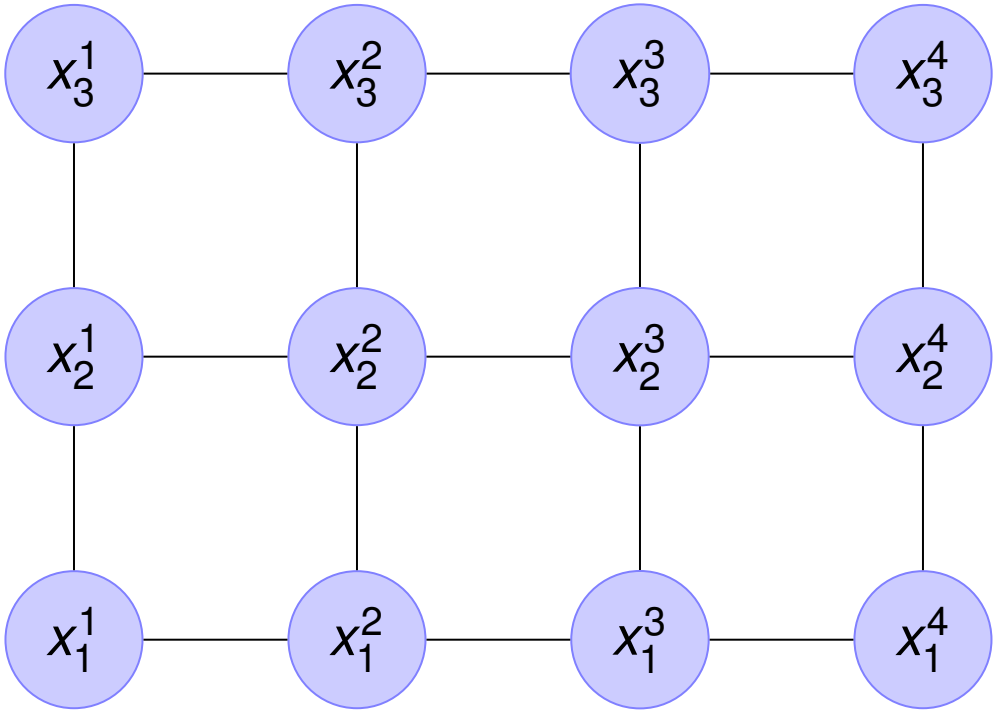
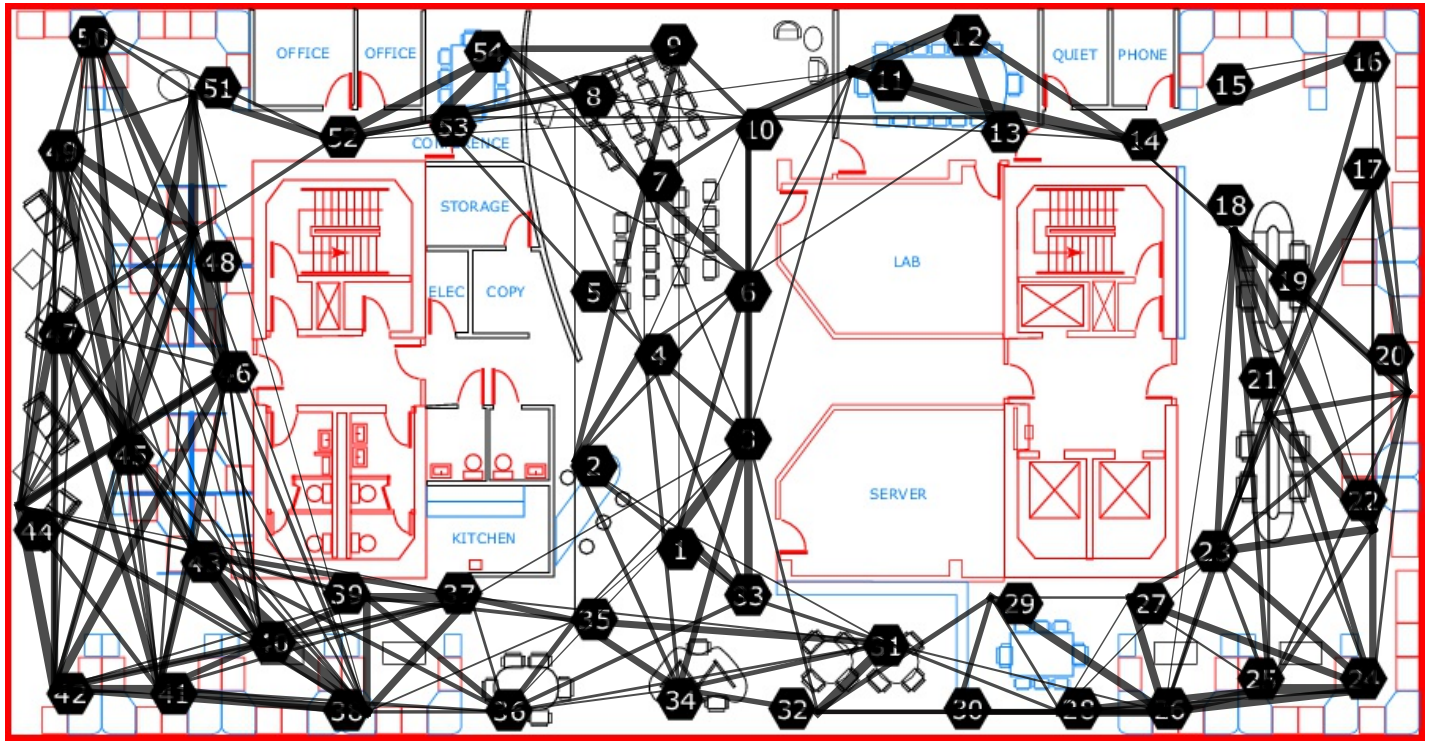
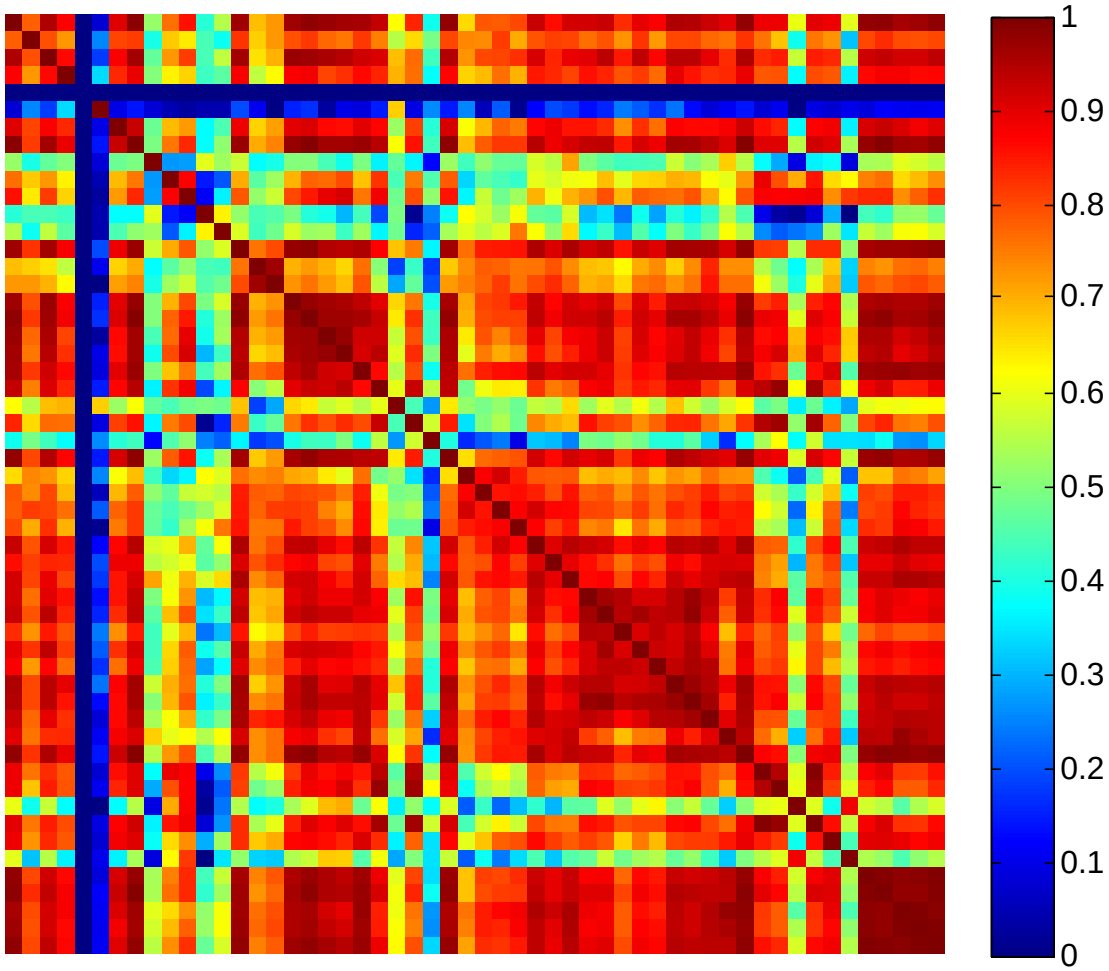


Instance Data

- Real data from Intel Berkeley Research Lab.
- 54 sensor nodes.
  - Temperature, light intensity, humidity, and voltage.
  - Link quality estimations.



Results: Correlation and Quantisation



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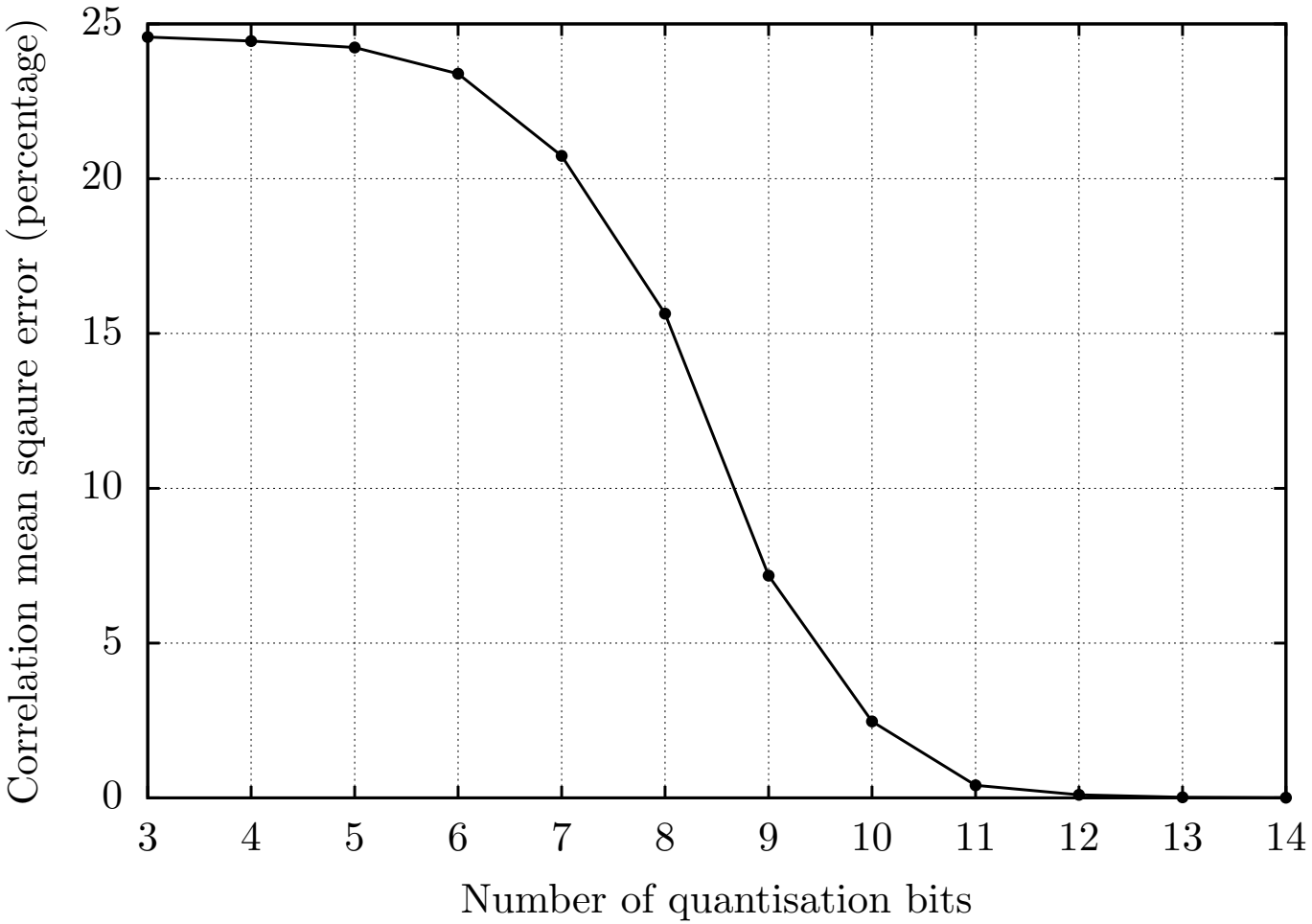
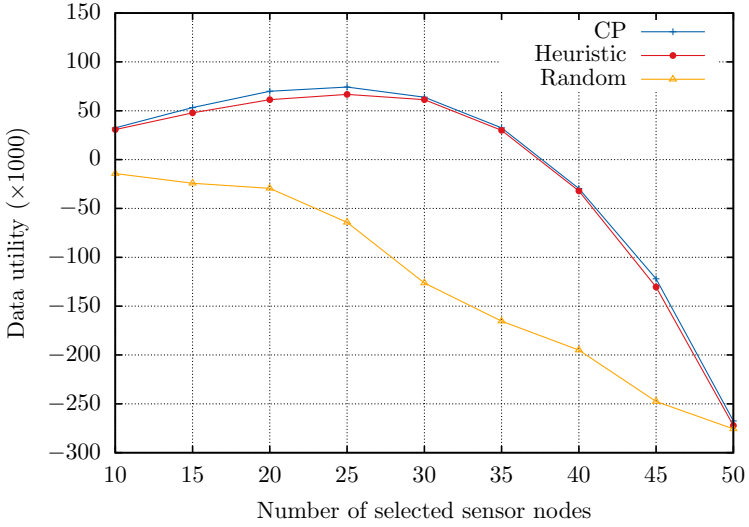
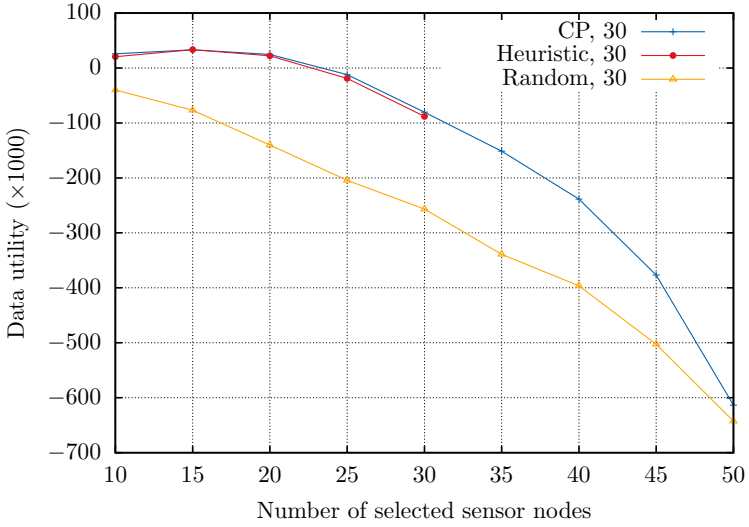


Results: Data Utility

- The optimum balance between link quality and correlation is achieved by selecting 25 active sensor nodes of 54.



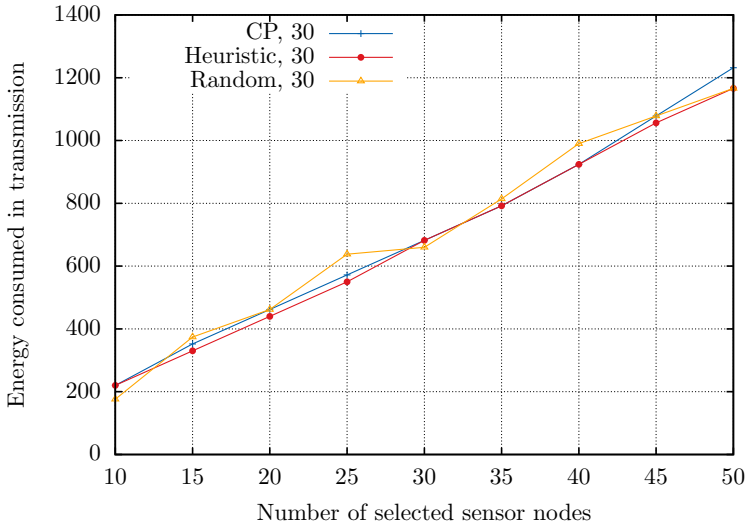
(a) Minimum 30% base station link quality



(b) Minimum 70% base station link quality

Results: Energy Consumption

- Save up to 80% energy by selecting only 10 active sensor nodes in each round.



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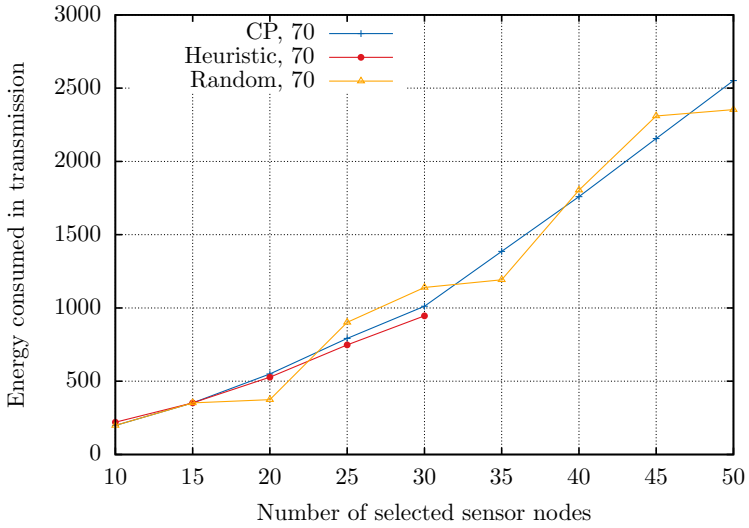
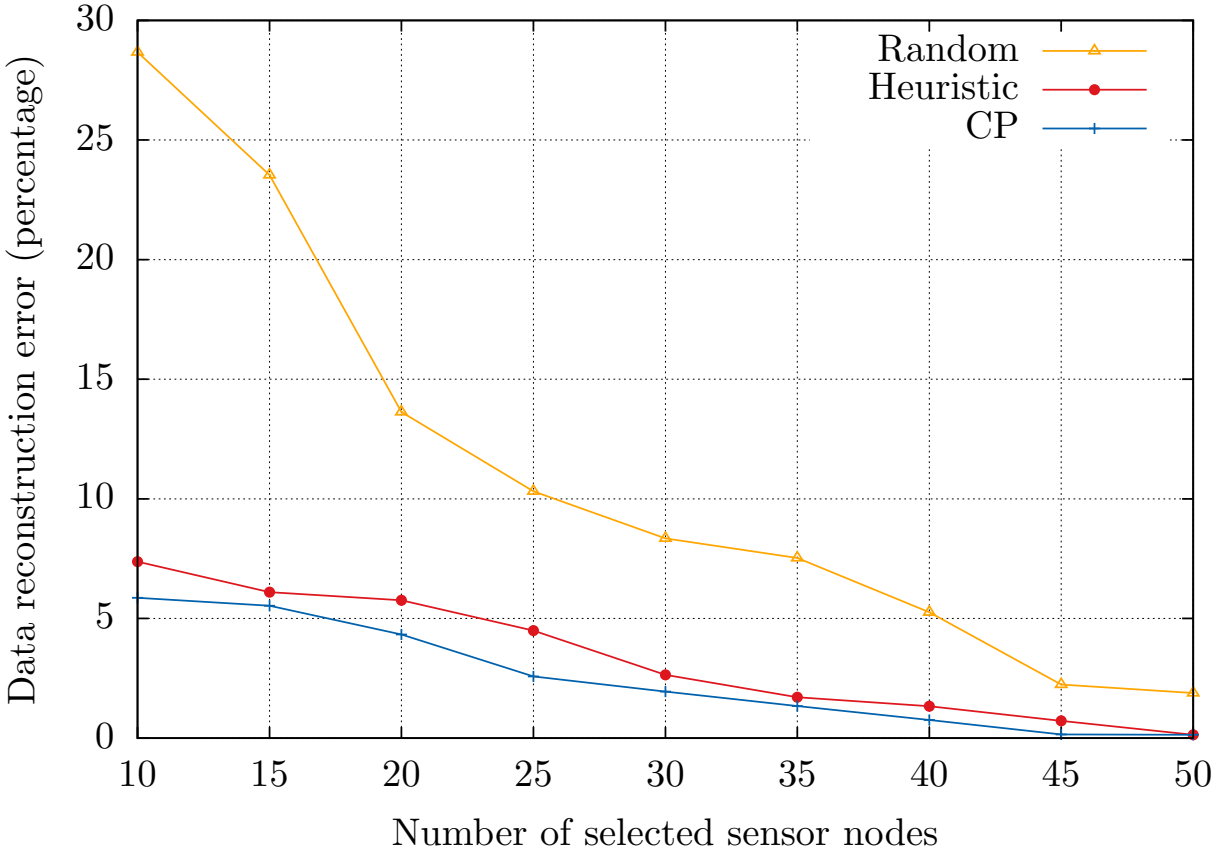


(b) Minimum 70% base station link quality

Belief Propagation Prediction Error

- BP with only 10 active sensor nodes achieves on error prediction of 6%.
- Standard deviation of the error for 10 sensors is only 12%.



Summary and Conclusion

- Effective to use constraint programming (CP).
- Proof of optimality with CP and good quality local optimum with greedy.
- ASBP works best for environment with spatio-temporal correlation in data.
- ASBP saves up to 80% energy while maintaining load balancing.
- BP predicts the missing data *iteratively* as the stream of data is received.
- Collaborative sensing with mobiles and wireless sensors can provide high sensing quality with reduced deployment cost.

Future Work

- Distributed implementation for real deployment.
- Integrate adaptive sampling rate into ASBP.
- Multi-sink scenarios including mobile sinks.

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Questions

- Thank you!
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Jonathan S. Yedidia, William T. Freeman, and Yair Weiss, *Exploring artificial intelligence in the new millennium*, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2003, pp. 239–269.