Paper presentation on

CARD: Context-Aware Resource Discovery for mobile Internet of Things scenarios

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Device Discovery

- Objective – Guarantee awareness about presence of other devices in the nearby for neighbors to be able to communicate

Motivation

- Seamless interconnectivity of devices
- Heterogeneity of devices
- Mobility – static vs mobile
- The design of efficient discovery approach
- Discovery Latency

CARD

- Context-Aware Resource Discovery
- Learning-based discovery framework
- Leverage ML techniques
- Can be plugged in on top of existing asynchronous neighbor discovery protocols
- Distributive approach

Related Work

- Probabilistic approach based on Statistical Properties
  - Detrimental to sparse network scenario
- Deterministic approach guarantee overlapping of times
  - Disco
  - U-Connect
  - Searchlight
  - Cons – energy wastage when devices out of range
- Reinforcement Learning Framework

System Model

- Multiple mobile IoT nodes that encounter opportunistically along their path different statically deployed IoT nodes.

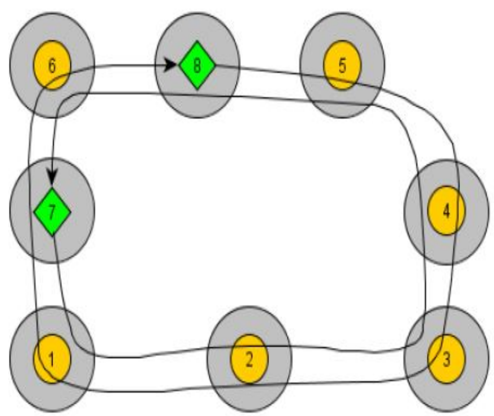


Fig. 1: Network Scenario

System Model (Continued)

- Keywords – Contact, Contact Duration, Inter-contact time, Periodicity

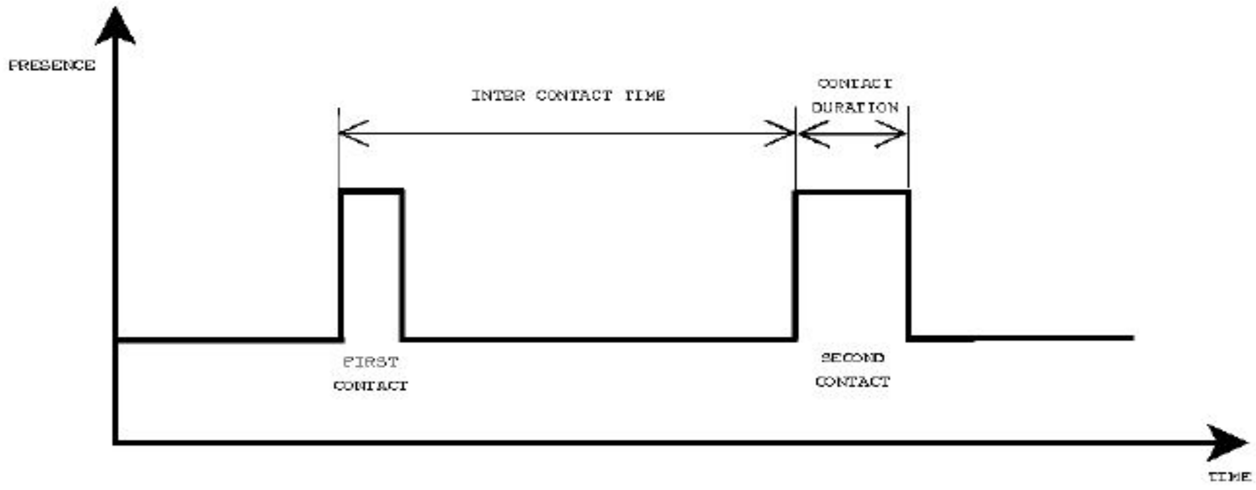


Fig. 2: Presence of other nodes in communication range over time

CARD – learning Model

- Based on Q-learning Model (Watkins)

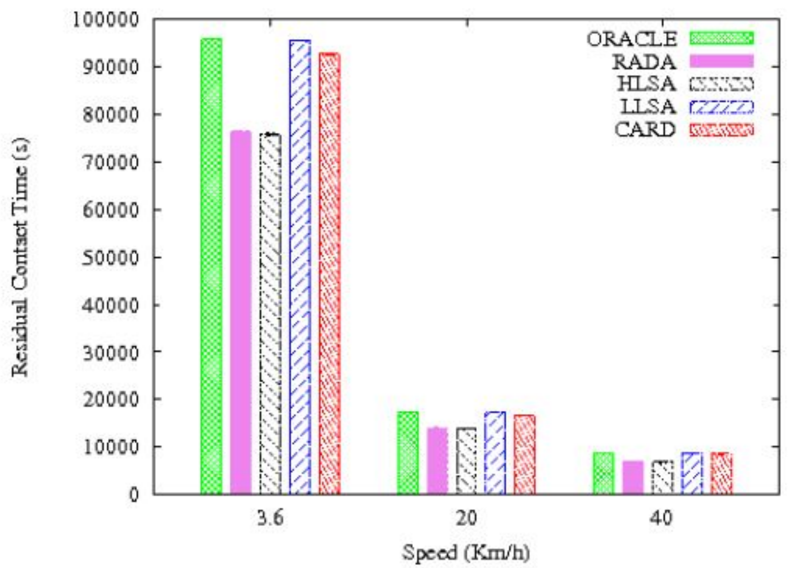
Algorithm 1: Q-Learning (Watkins, 1989)

Initialize $Q(s, \alpha)$ arbitrarily;
repeat
    Initialize s;
    repeat
        Choose α from s using policy derived from Q (e.g. ϵ-greedy);
        Take action α, observe r, s';
        $Q(s, \alpha) := Q(s, \alpha) + a * [r + \gamma * max_{\alpha'} Q(s', \alpha') - Q(s, \alpha)]$;
        $s := s'$;
    until ;
until s *is terminal*;

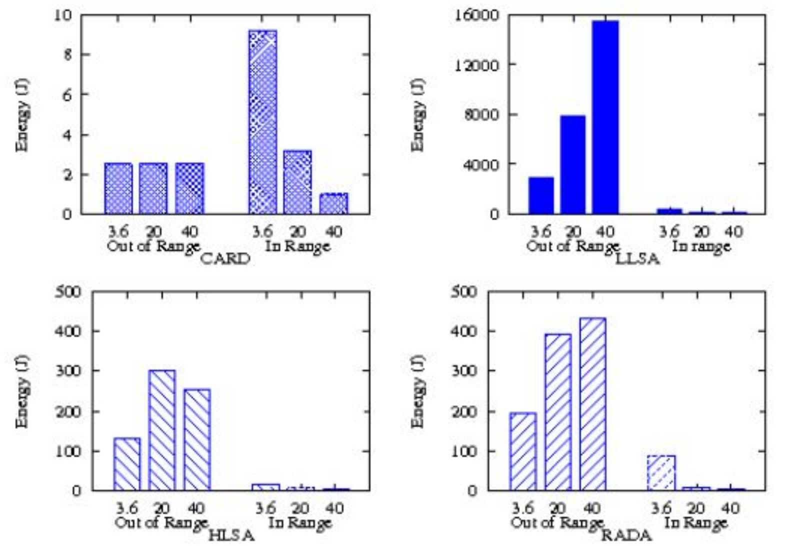
CARD – learning Model (Cont..)

- Benefits of Q-learning:
  - Simplicity of the computation
  - Convergence to a global optimum, avoids local optima
- Q-learning states and actions
- Actions - 2 types
  - Low latency high energy discovery
    - Low Latency Sub-Action (LLSA)
  - High Latency low energy discovery
    - High Latency Sub-Action (HLSA)

Evaluation - Deterministic



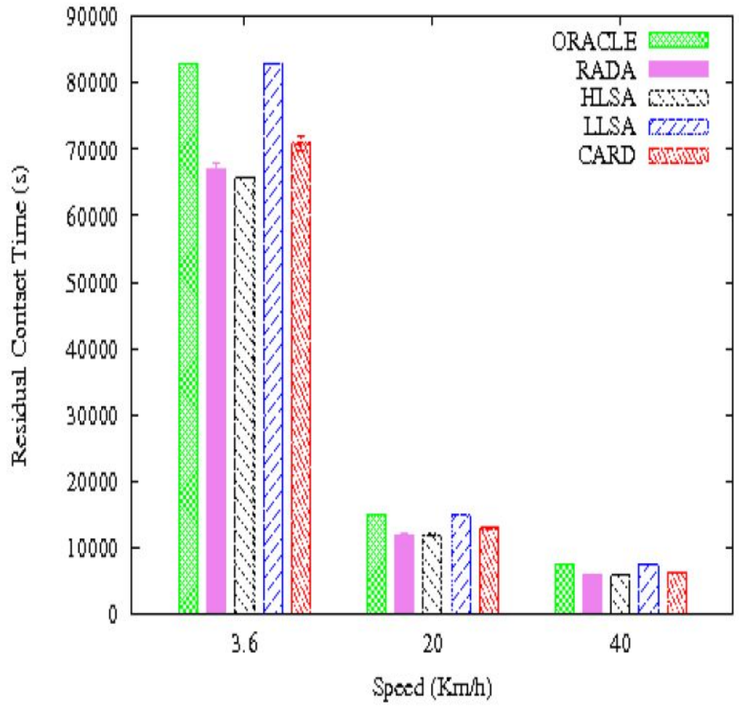
(a) Total Cumulative Residual Contact time



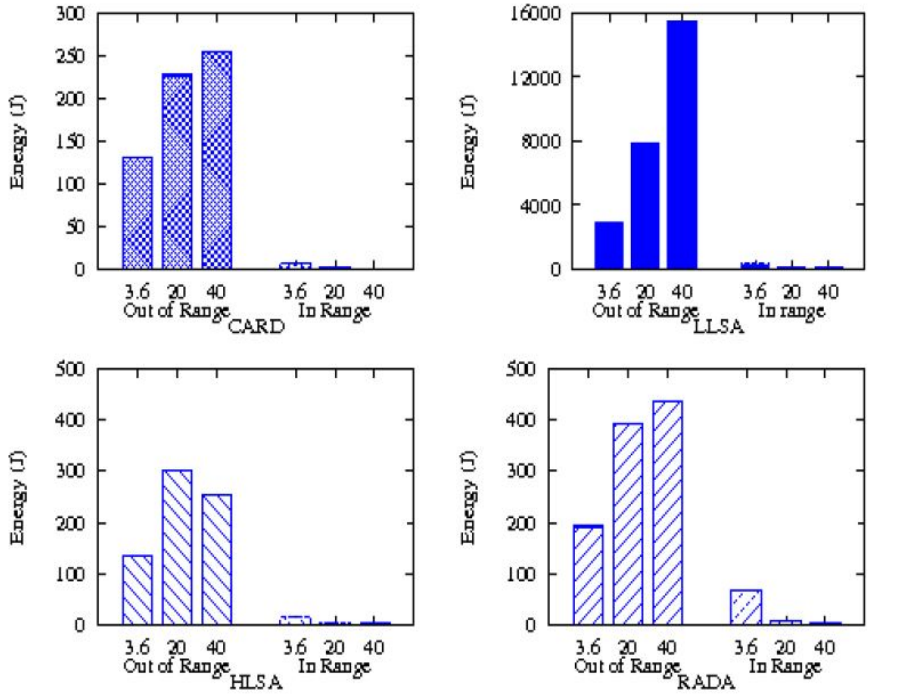
(b) Total energy consumed for the discovery process

Fig. 3: Deterministic Mobility Pattern

Evaluation – Multi. Deterministic



(a) Total Cumulative Residual Contact time



(b) Total energy consumed for the discovery process

Evaluation - Gaussian

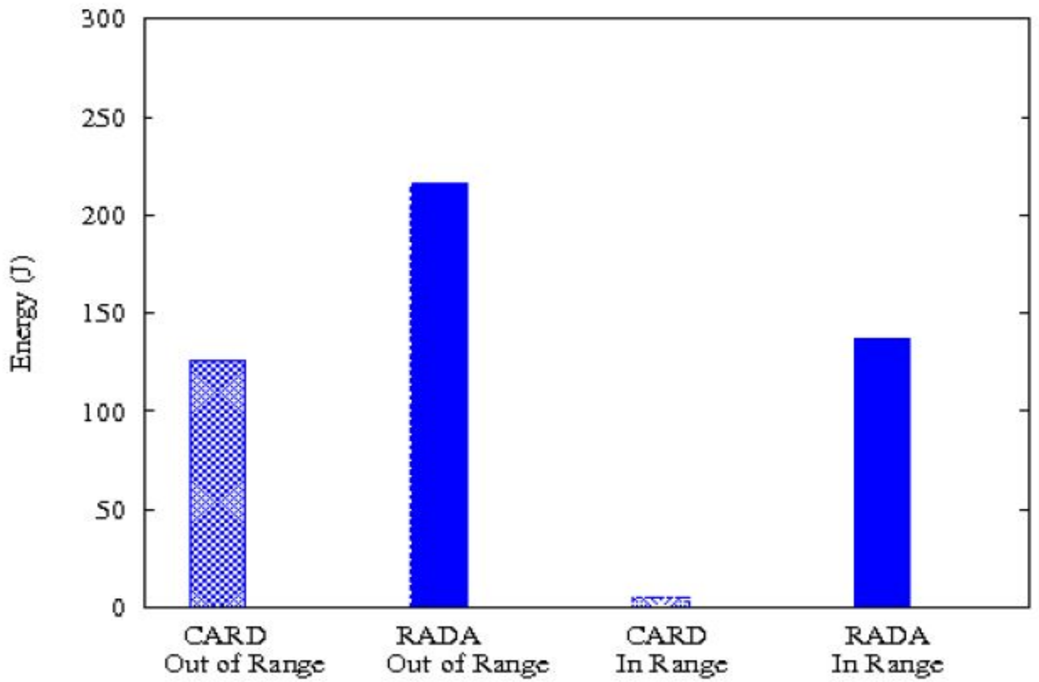


Fig. 7: Total energy consumed for the discovery process (Gaussian)

Evaluation – Real World Traces

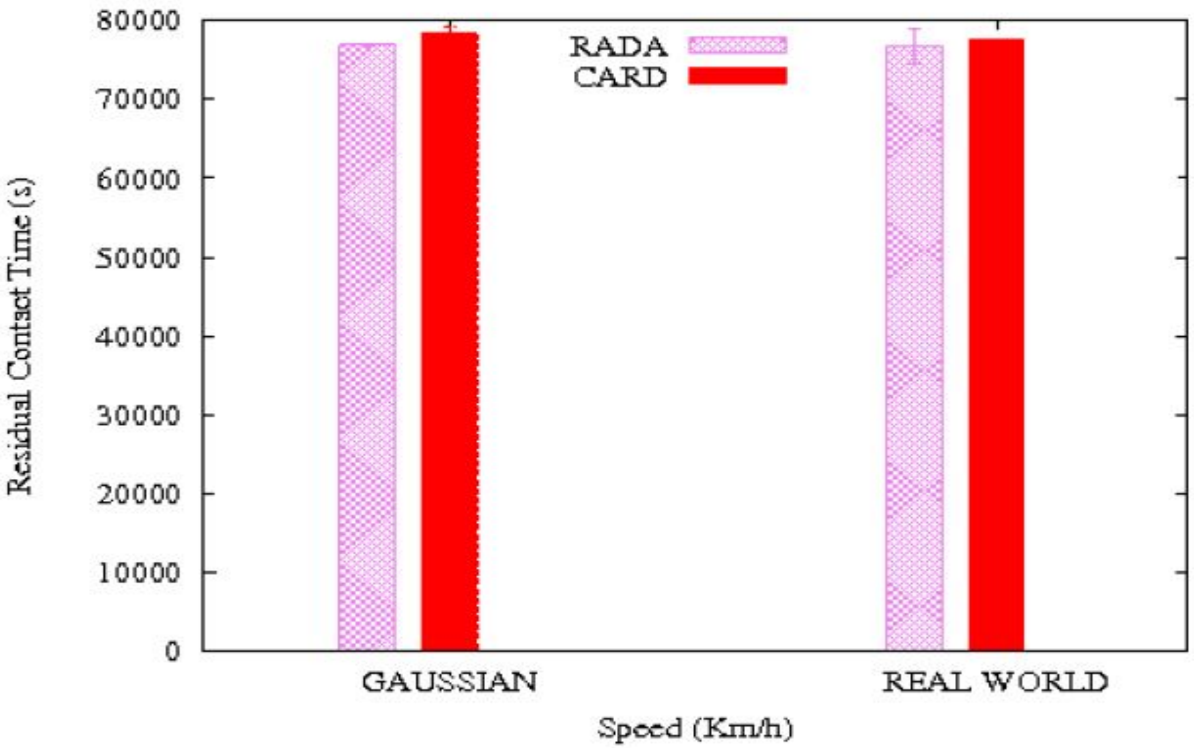


Fig. 5: Total Cumulative Residual Contact time

Contribution

- Leveraging ML techniques into learning based discovery approach
- Pluggable to current async protocols
- Adaptable to differecnt contact patterns
- Introducing CART as less energy consuming, low latency technique in the current state-of-the-art techniques to device discovery.
- Energy constraint IOT device

Limitations

- Scalability
- Noise distribution
- Specific communication pattern
- Less adaptive to changes
- Validity of data – Fully simulation based

Thanks!!!

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Questions ??