Modeling Energy Constrained Routing in Selfish Ad Hoc Networks

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Nodes in ad hoc networks are energy constrained and potentially selfish. Defining rational and optimal behavior is complicated.

The effects of selfishness have been widely studied.

But the effects of energy not.

- Intuitively, when nodes condition their behavior on their energy, this leads to a more balanced resource usage.
- Thus, energy optimization may well be the rational strategy.
- Accordingly, in order to act optimally, a node should try to model the energy of other nodes.

Questions:
- How to capture this formally?
- How to build mechanisms that allow nodes to act optimally?
• We present a game theoretic model that
  – models the energy of the nodes and links it with the behavior of nodes
  – models the effect of selfishness

• We also present a mechanism that
  – allows nodes to learn optimal strategies over time
  – is guaranteed to converge to a sequential equilibrium point

• And present simulation results for the model
General Framework

- We consider repeated Bayesian games in an adaptive learning framework
  - agents optimize immediate (single shot) gain
    - thus differs from standard repeated games
  - agents hold theories about parameters of interest
    - in our case selfishness and energy
  - the sequence of theories forms a learning process that is adaptive if
    - the action selection probabilities of the agents eventually come close to empirical frequencies
    - and the beliefs of the agents converge.
  - closely related to stochastic approximation theory
Model Intuitively

optimize route, decide how many of the packets to send and send them
The Game Structure

• Source node
  1. Discover routes to the destination
  2. Estimate the “goodness” of the routes
  3. Select the route to use
  4. Gather feedback and update theories

• Intermediate node
  – Optimizes an utility function and selects the optimal action as given by the utility function
  – The utility function can utilize estimates about the behavior of the source
Estimating the Goodness of Routes

• Once the source has information about available routes, it calculates a score for each route

• The score combines
  – the energy and selfishness estimates
  – the importance of energy
  – the cost and the value of the packets

• We use the expected utility for a path
  – first we estimate the probability that a given number of packets arrives at the correct destination
    \[ \mu(P) = \prod (\alpha \varphi + \beta \psi) \]
  – next, we combine this with the utility of the packets
    \[ u(s, P) = \mu(P) \left[ h(s) - g(s) \right] \]
Intermediate Nodes

• The behavior strategies of the intermediate nodes are assumed to be
  – weighted linear combinations of the selfishness of the source and the remaining energy of the intermediate node
    • the weights represent importance in the individual components
  – thus we have a punishment mechanism
  – and we also have a part that depends on the current energy of the nodes
    \[ \sigma = \alpha \varphi + \beta \psi \]
Obtaining Feedback

• In order to update the theories of the nodes, they require feedback
  – i.e., how many packets finally arrived at the destination
  – in order to accomplish this, we need
    • packet timers
    • acknowledgements
  – if the packets are not acknowledged before the timer goes off, they are considered to be dropped
Learning Optimal Strategies

• It turns out that a learning process can be shown to converge to an equilibrium when
  – the beliefs are updated using the Bayes’ rule
  – strategies are selected using reinforcement learning rules and random experimentation occurs often enough
• In our case, we use the rule $1/k$, where $k$ is the current iterate, to select suboptimal actions
  – Also other rules possible, large literature on this in the field of reinforcement learning
• For the convergence proof, see the paper.
Experimental Setup

We tested the model using randomly generated network topologies

- constrained uniform deployment: nodes were not allowed to be “too close” to each other
- random waypoint model with constant speed
- Poisson distributed traffic

In each setup, the values of the importance parameters were the same for all nodes

- tested with different initial values of the importance parameters
- each initial configuration repeated 30 times

In the experiments we ignore selfishness for clarity
Results 1: Success rate of nodes

- Success rate of nodes
  - Importance of energy class varied (in steps of 0.1) between 0.0 and 1.0
  - Topmost, importance of energy = 0.0
  - Subsequent, increase by 0.1
Results 2: Amount of nodes alive

- Amount of nodes that are alive
  - Importance of energy class varied (in steps of 0.1) between 0.0 and 1.0
  - Topmost, importance of energy = 1.0
  - Subsequent, decrease by 0.1
Results 3: Packets sent and forwarded

- Amount of packets sent (left) and forwarded (right)
  - Importance of energy class varied (in steps of 0.1) between 0.0 and 1.0
  - Steepest descent, importance of energy = 0.0
  - Subsequent, increase by 0.1
Conclusions

• Our simulations indicate that energy optimization in decision making affects network lifetime – this should be the rational choice of the nodes.

• The results also indicate that nodes can learn a reasonable strategy when energy influences decisions.
  – Though the results show that this easily results in a decrease of overall performance.

  – Building mechanisms that are able to model the energy of others can prove useful in highly resource constrained environments.
Summary

• We have presented a game theoretic model that captures selfishness and resource constraints of devices
• We presented a mechanism for learning optimal strategies over time
• And we presented simulation results for the model
• Our model shows that:
  – Energy optimization is likely to be the rational choice of nodes
  – But other devices can learn to optimize their behavior also in this kind of settings