Joint Energy Management and Resource Allocation in Rechargable Sensor Networks

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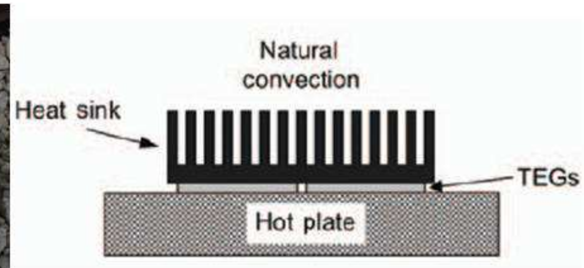
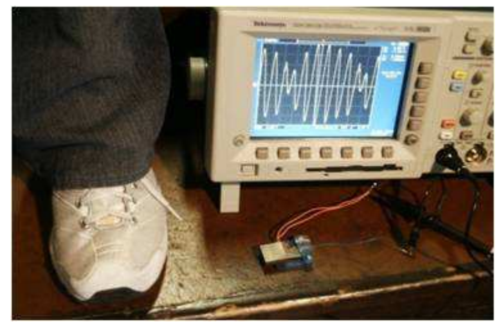
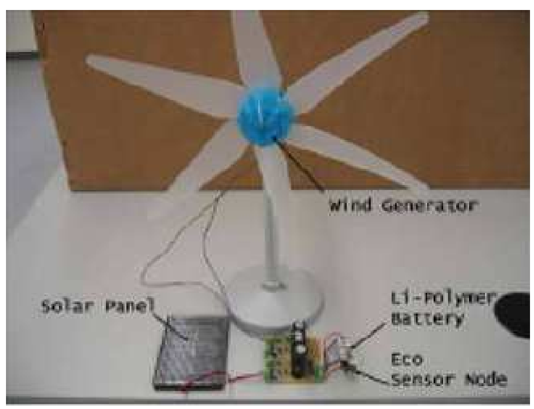
Environmental Energy Harvesting

- Many technologies available for harvesting energy in different forms

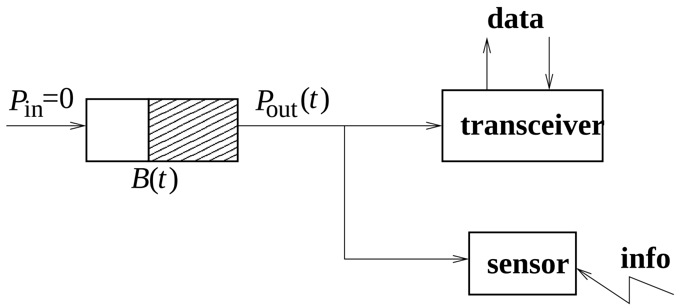
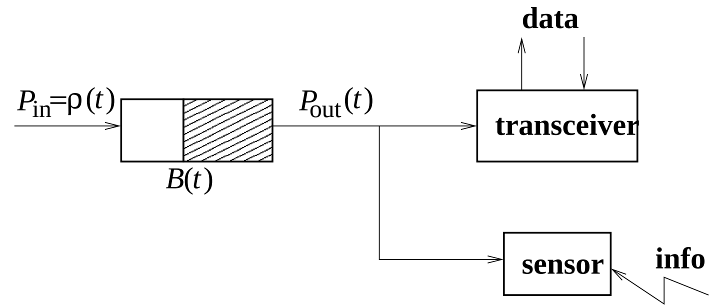






, etc.

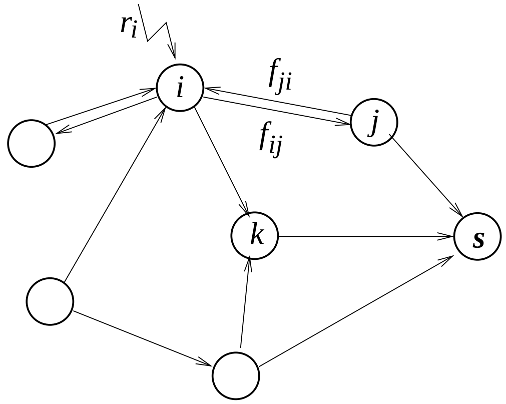
Energy Management - Different Paradigm

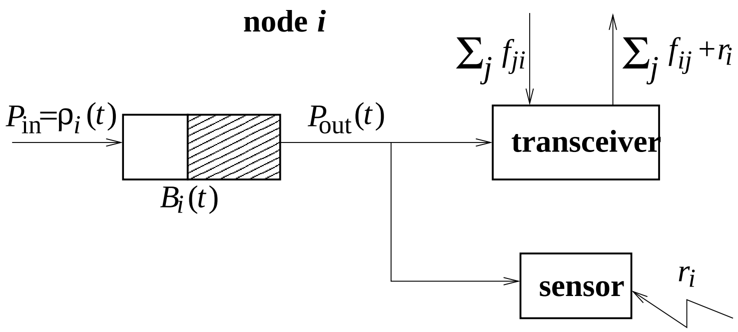
	Classical	With replenishment
		
lifetime:	$< \infty$	∞
purpose:	$\max \int_0^{\text{lifetime}} \text{utility}(t)\ dt$	$\lim_{T\to\infty} \max \frac{1}{T} \int_0^T \text{utility}(t)\ dt$
undesirable:	empty battery	empty or *full* battery
challenge:	extend lifetime	perpetual operation with variable P_{in}

Q: Energy management a straightforward extension or fundamentally different?

A: Close to the latter.

Network Utility Maximization





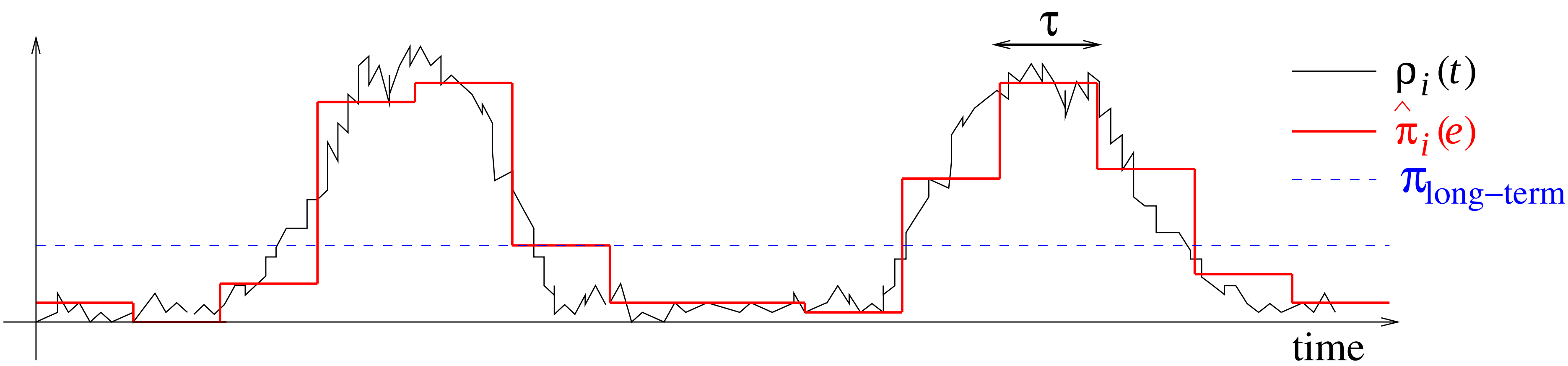
$$
\begin{array}{lll}
\max_{r_i, f_{ij}} & \sum_i \log r_i & \\
\text{subject to} & \sum_j f_{ij} \geqslant \sum_j f_{ji} + r_i, \quad \forall i \neq s & \longrightarrow \text{flow balance} \\
& P_{\text{in}} \geqslant \underbrace{\sum_j \lambda_{ij}^{(\text{tx})} f_{ij} + \sum_j \lambda_{ji}^{(\text{rx})} f_{ji}}_{\text{fixed xmit and recv power}} + \lambda_i^{(\text{sn})} r_i & \longrightarrow \text{energy conservation} \\
& \mathbf{f} \in \Pi & \longrightarrow \text{achievable rate region}
\end{array}
$$

But

P_{in} is neither a constant nor perfectly known

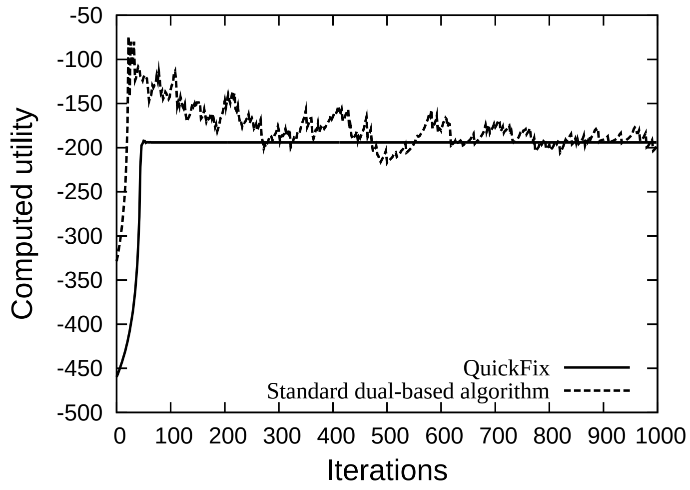
Battery is finite

Dynamic Problem



Option	$\mathbf{E}_{\text{in}}$	Issue
(1)	$\rho_i(t)$	complexity/convergence overhead
(2)	$\pi_{\text{long-term}}$	finite battery $\rightarrow$ extended periods of discharge
(3)	$\hat{\pi}(e) = \frac{1}{\tau} \sum_{t=(e-1)\tau+1}^{e\tau} \hat{\rho}_i(t)$	finding optimal tradeoff between overhead and discharge probability

Overhead and Discharge Rate



- Too slow a convergence in general networks.
  - Need to choose $\tau \gg 1$
  - High battery discharge rate

$\Rightarrow$ Need to sacrifice performance for perpetual operation

$\rightarrow$ Convergence: Assume/generate DAGs

$\rightarrow$ Discharge rate: SnapIt

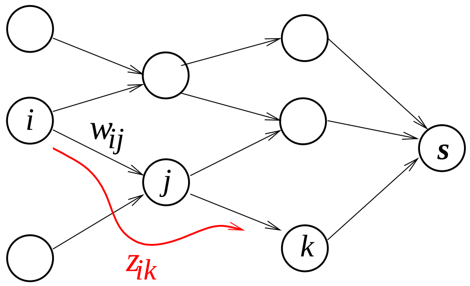
Resource Allocation over DAGs

w_{ij}: fraction of node i
traffic over *link* ij

$z_{ik}(\mathbf{w})$: fraction of node i
traffic over *node* k

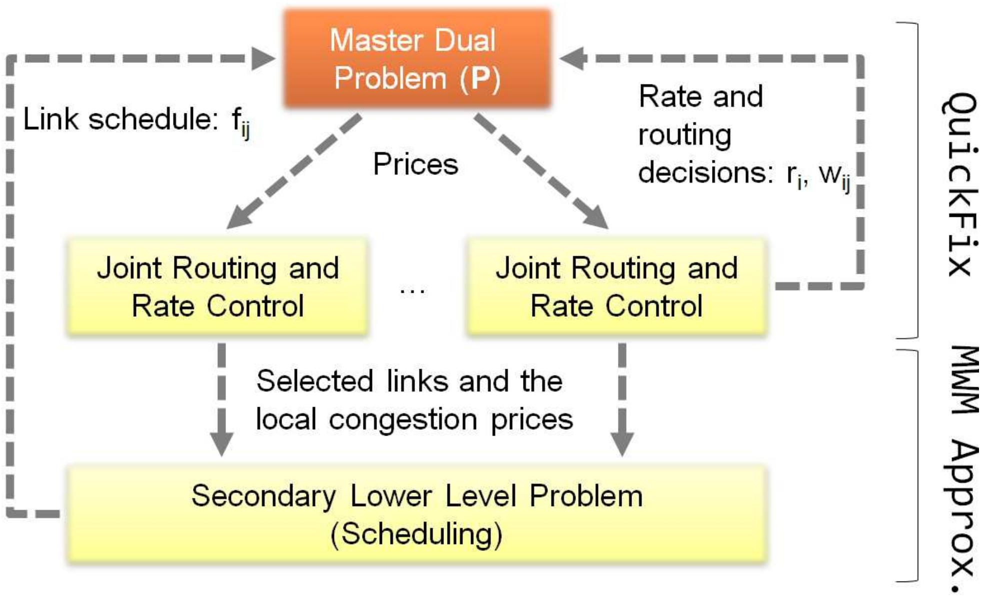
$z_{ik}(\mathbf{w}) = w_{ij} w_{jk}$

rewrite problem in terms of $\mathbf{z}$ and $\mathbf{w}$



- The structure of the DAG enables efficient solutions
- QuickFix Algorithm
  - Dual decomposition $\rightarrow$ subgradient-based distributed solution
  - Efficient joint updates exploiting DAG structure

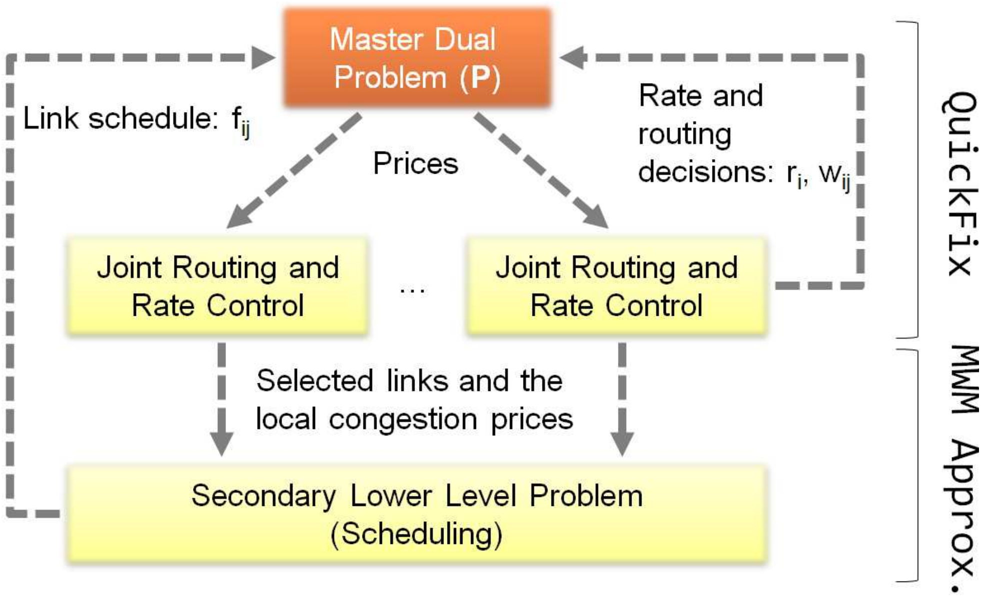
QuickFix - Dual Decomposition Approach



Notes:

MWM scheduler: weight is a combined battery/data queue state

QuickFix - Dual Decomposition Approach

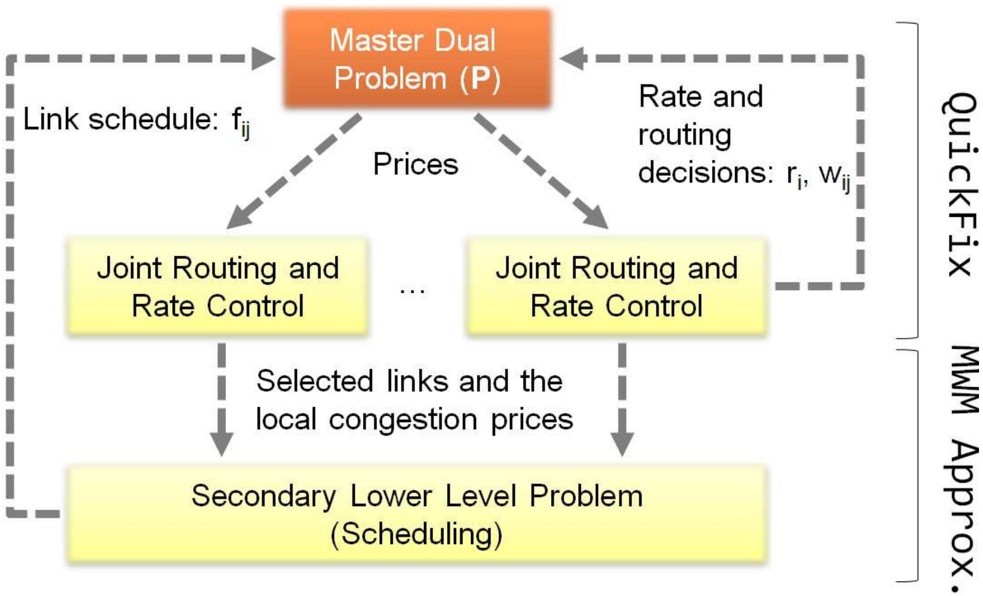


Notes:

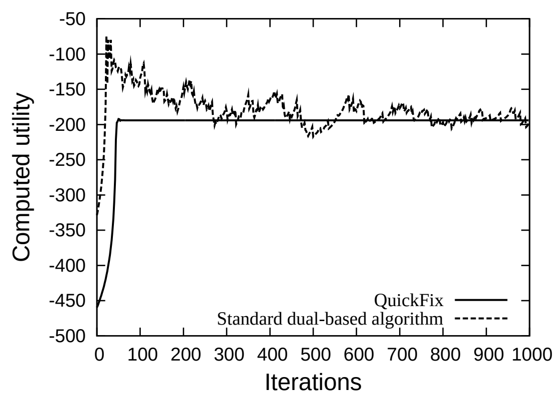
Two phases of QuickFix iterations:

1. Aggregate prices: parents $\rightarrow$ children, update r_i^*
2. Aggregate traffic: children $\rightarrow$ parents, update prices

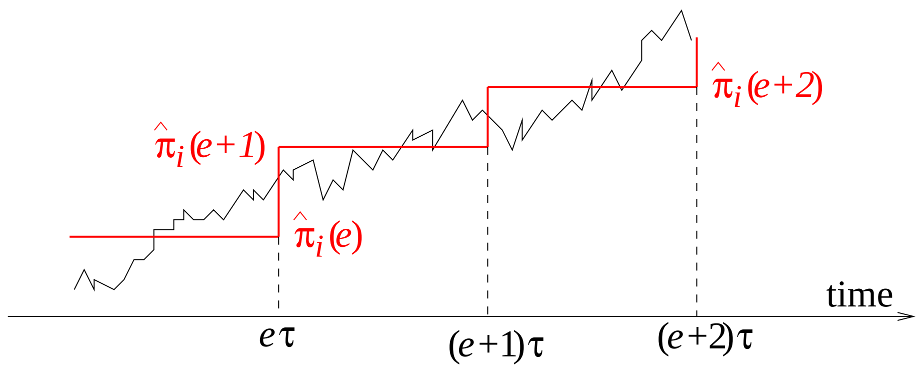
QuickFix - Dual Decomposition Approach



Notes:



SnapIt - Localized Energy Management

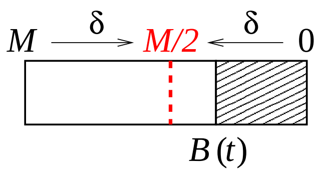


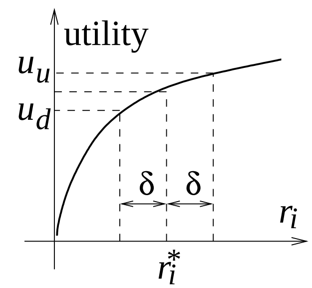
Cumulative energy mismatch: $\sum_e \left[\sum_{t=(e-1)\tau+1}^{e\tau} \rho_i(t) - \hat{\pi}_i(e)\right]$

- Issue - **finite battery size** causes:
  - Unbiased estimator $\Rightarrow$ 0 battery drift $\longrightarrow$ high discharge rate
  - Biased estimator $\Rightarrow$ very high discharge rate or inefficient replenishment
- Solution: Adaptively control drift

SnapIt - Localized Energy Management

$$B(t) \leqslant M/2 \Rightarrow r_i^* - \delta$$
$$B(t) > M/2 \Rightarrow r_i^* + \delta$$





Q1: What performance is lost due to $r_i^* \mp \delta$?

Q2: How much is discharge probability reduced with δ drift?

Theorem: If the variance, $\sigma^2_{\tilde{\rho}_i} \triangleq \mathrm{var}\left(\frac{1}{\tau_Q}\sum_{t=1}^{\tau_Q}\rho_i(t)\right)$ is bounded and the utility function is the log function, $U(\cdot) = \log(\cdot)$, then, given any $\beta \geq 1$, SnapIt achieves $p_i^{\mathrm{SnapIt}}(M_i) = \mathrm{O}(M_i^{-\beta})$ and $\bar{U}_i^* - \bar{U}_i^{\mathrm{SnapIt}} = \Theta\left(\frac{\log M_i}{M_i}\right)$ with the choice of $\delta_i = \frac{\beta\sigma^2_{\tilde{\rho}_i}\log M_i}{\lambda_i^{(\mathrm{sn})} M_i}$.

$\Rightarrow$ Optimal utility & low discharge rate possible simultaneously.

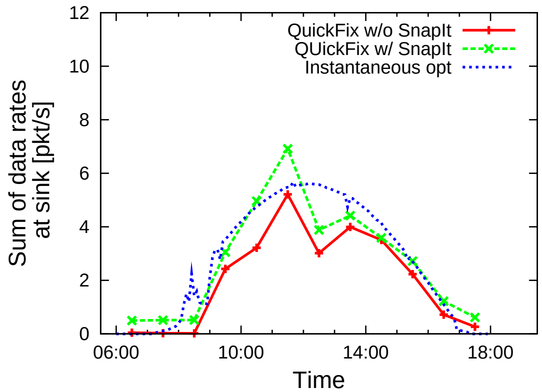
Simulations - Parameters

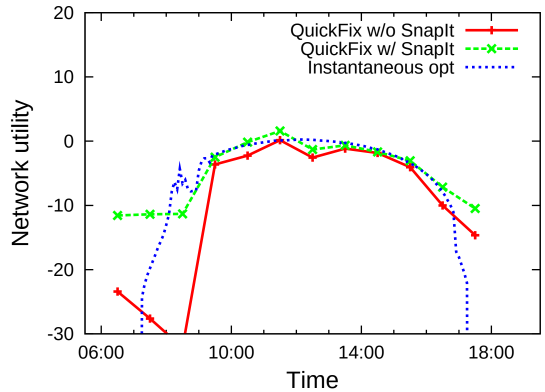
- A 67-node testbed with topology created based on an actual local testbed
- Recharging profiles based on real solar radiation measurements from NREL
- $\lambda_i^{(\mathrm{sn})} = 105\mu W$, $\lambda_i^{(\mathrm{tx})} = 63\mu W$, $\lambda_i^{(\mathrm{rx})} = 69\mu W$, $\alpha = 0.001$, $\delta_i = 0.1 r_i$
- $\tau = 1$ hour and 1 iteration every 5 minutes

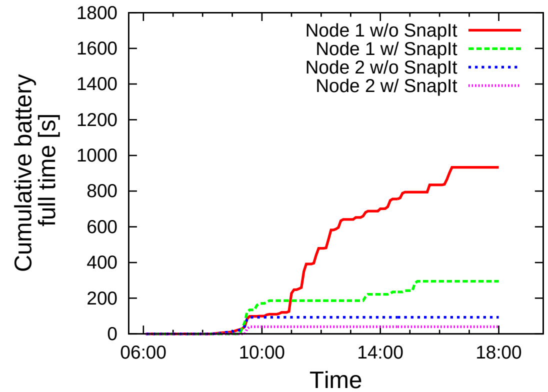
Simulations - Sum Rate and Network Utility

Sum rate | Network utility | Cumulative full/empty time

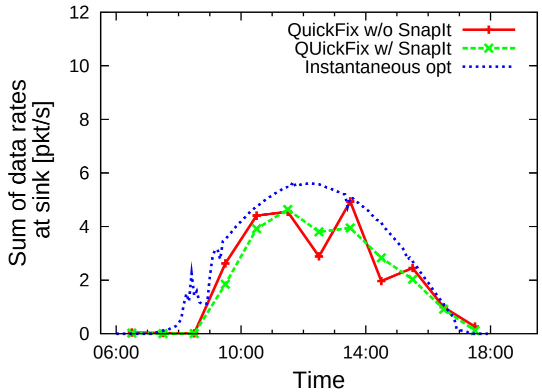
Initial battery - high

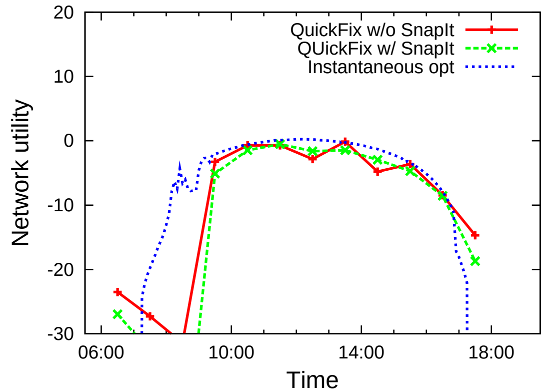


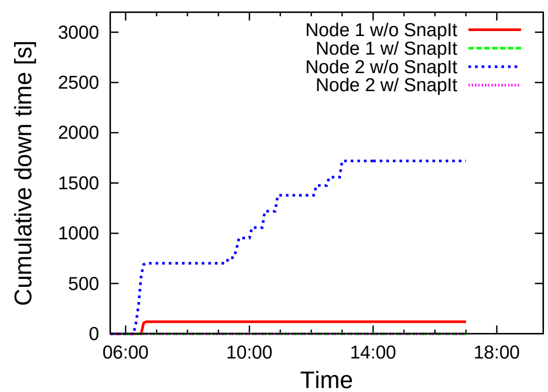




Initial battery - low





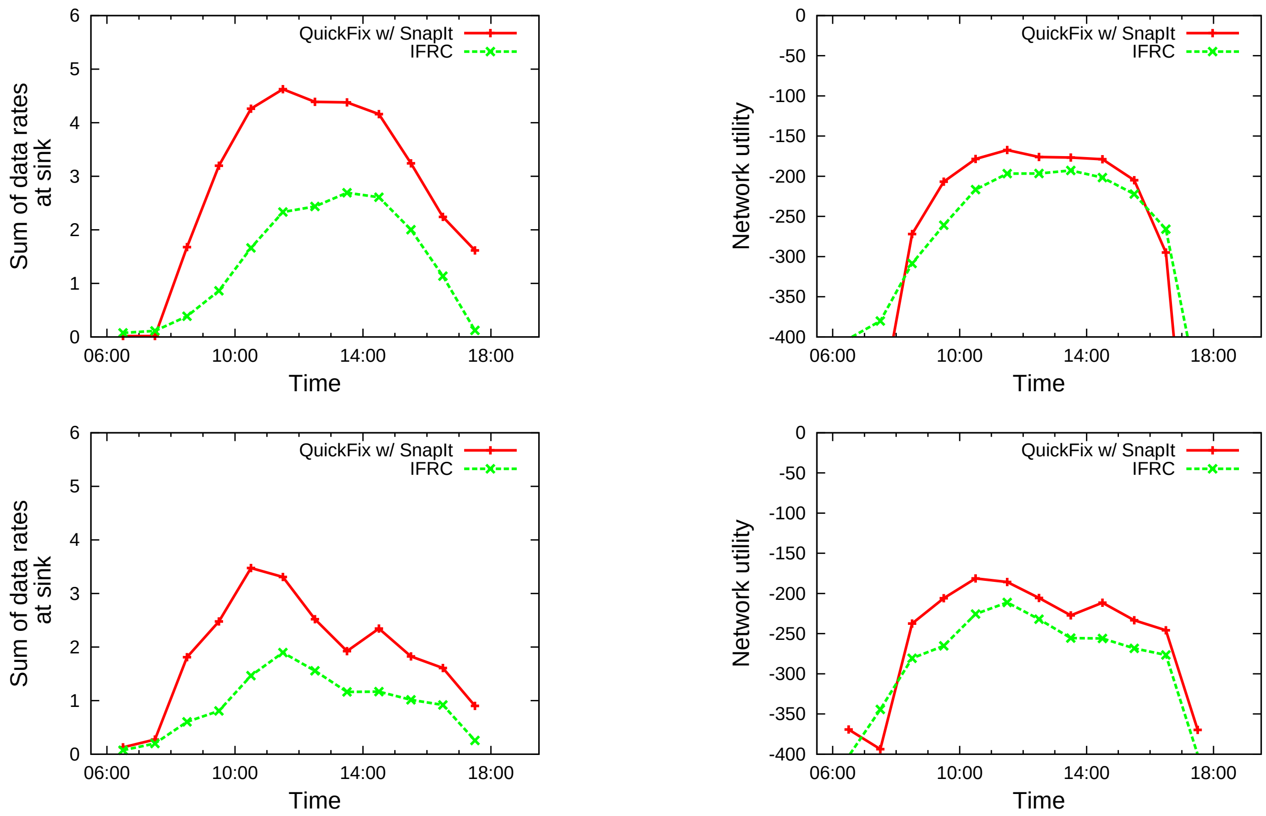


Simulations - Sunny/Cloudy Day vs. IFRC

Sum rate | Network utility

Sunny day

Cloudy day



Summary and Future Work

- QuickFix + SnapIt to achieve optimal network utility
  - Addressed convergence issue associated with variable replenishment
  - Addressed (finite) battery discharge rate due to variable replenishment
- Can we improve the convergence issue without the DAG assumption/construction?
- Can we combine battery control with data queue control to achieve low discharge and data buffer overflow rates?