

# Operating System and Algorithmic Techniques for Energy Scalable Wireless Sensor Networks



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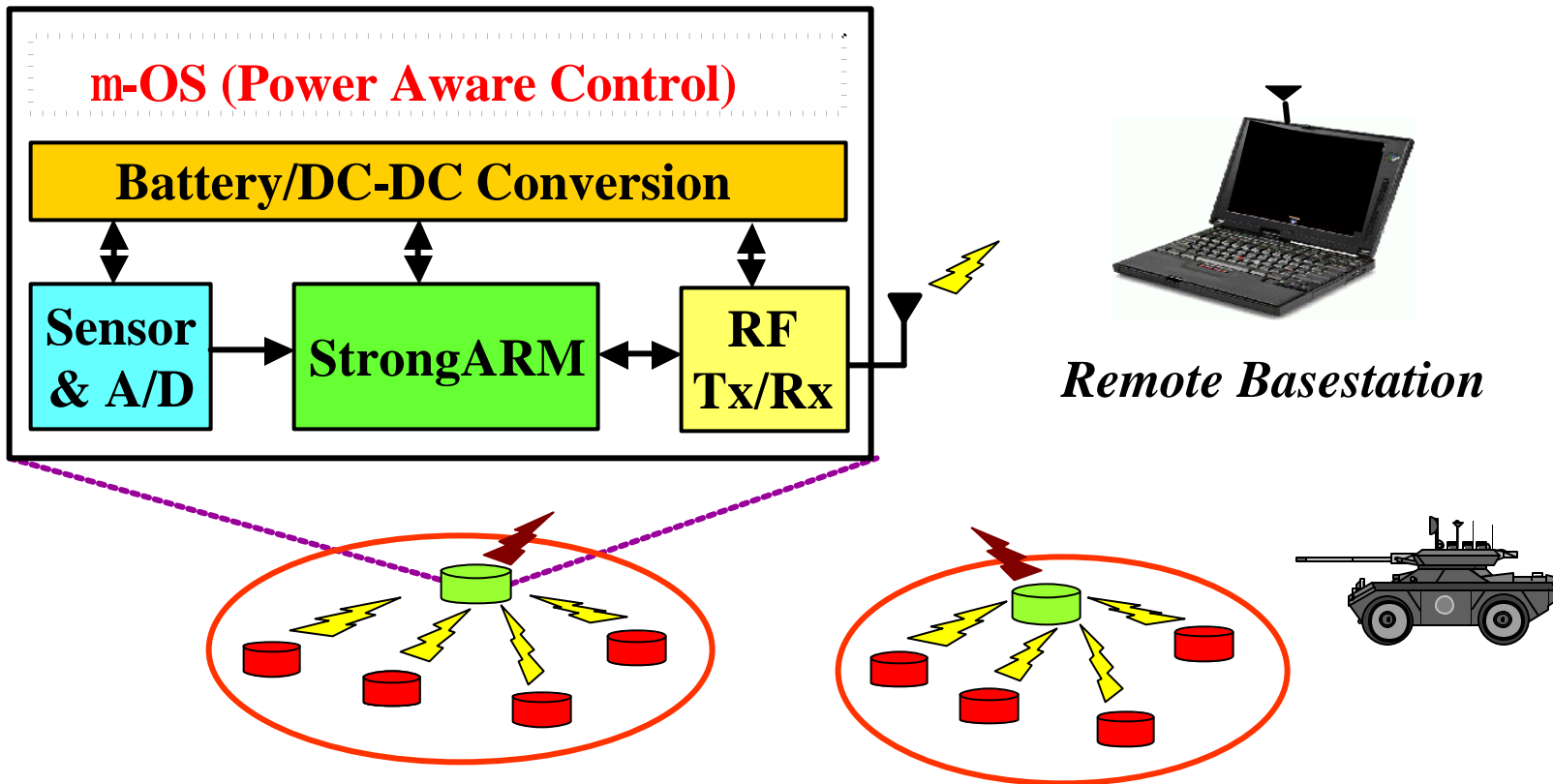


# Overview

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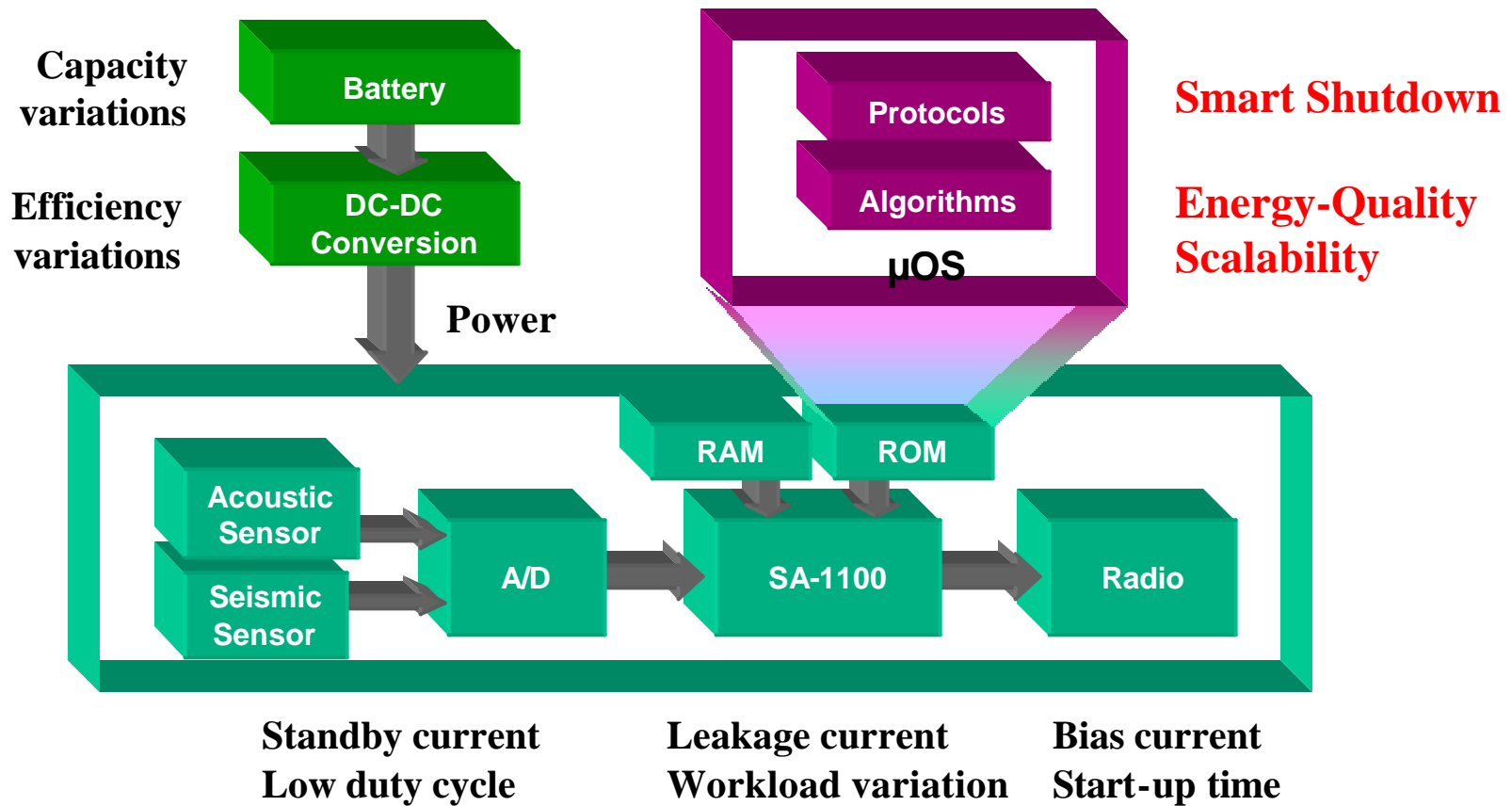
- The MIT  $\mu$ AMPS Project
  - Sensor Network and Node Model **Sensor Network**
- Power-Aware Node Model
- Smart Shutdown
  - Hierarchical Sleep States **OS**
- Energy-Quality Scalability
- Algorithmic Transformations
  - Filtering, Image Decoding Examples **Applications**

# The MIT $\mu$ AMPS Project



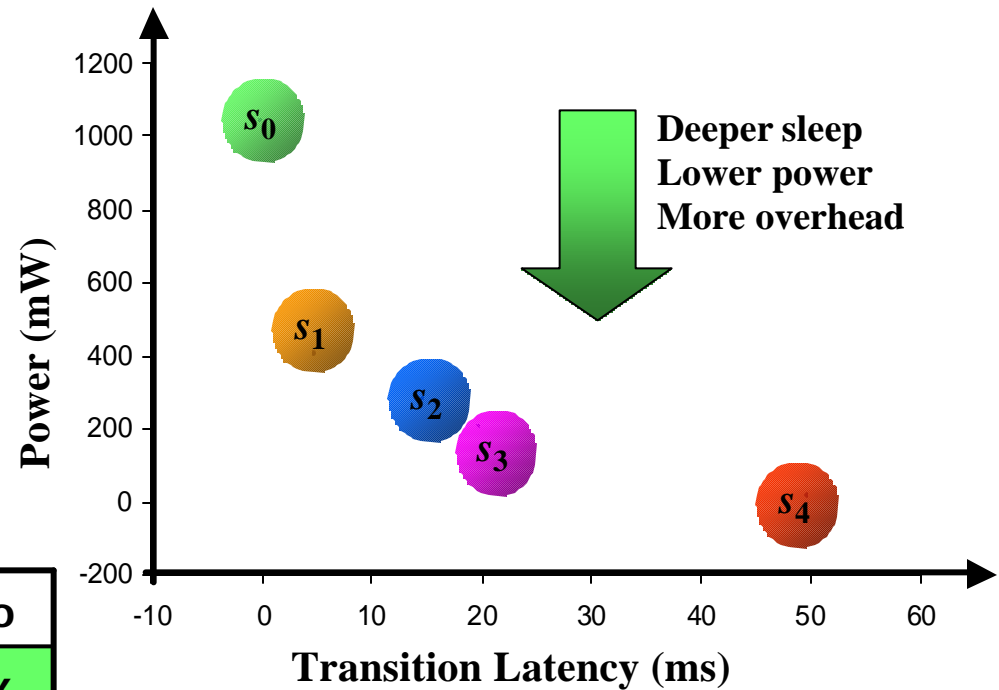
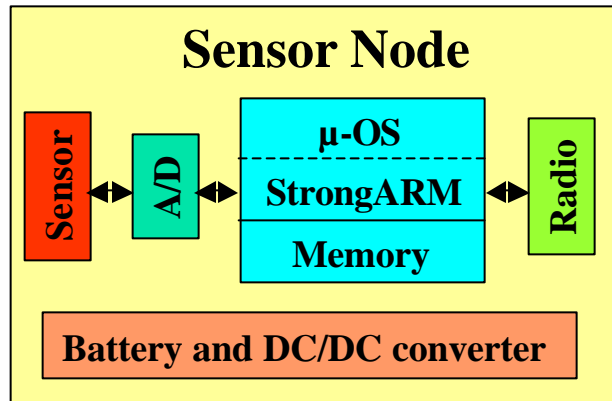
- A **universal substrate** for **power aware** data gathering from a massively distributed wireless network

# Power Aware Node



- Scalability  $\Rightarrow$  More efficient use of battery life

# OS Directed Power Management



|       | ARM    | Memory | Sensor | Radio  |
|-------|--------|--------|--------|--------|
| $s_0$ | active | active | on     | tx, rx |
| $s_1$ | idle   | sleep  | on     | rx     |
| $s_2$ | sleep  | sleep  | on     | rx     |
| $s_3$ | sleep  | sleep  | on     | off    |
| $s_4$ | sleep  | sleep  | off    | off    |

- OS must decide suitable transition policy based on observed history



# Event Model

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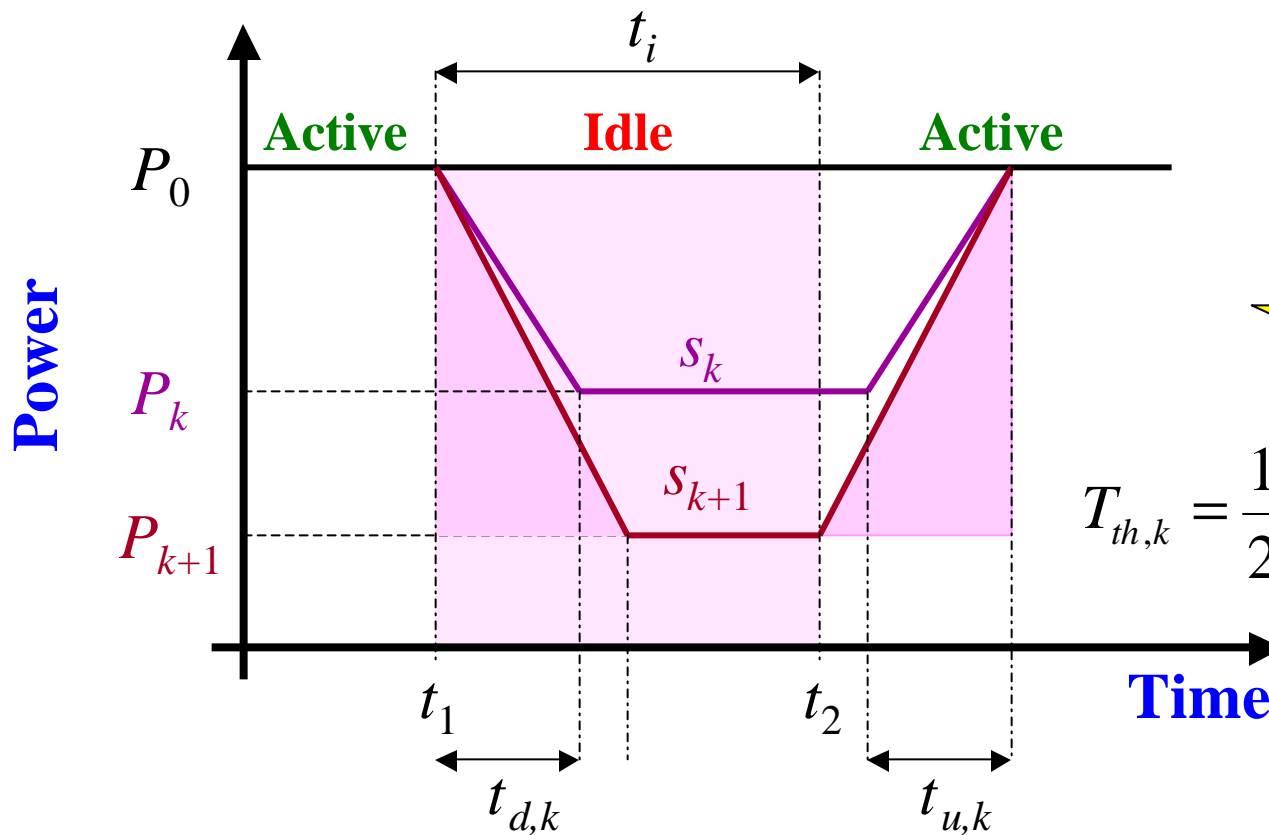
- Poisson process
  - Rate :  $\lambda_{tot} \text{ s}^{-1}$
- Arbitrary spatial distribution
  - Probability of occurred event being at node<sub>k</sub> =  $p_{ek}$
- Probability of no events at node<sub>k</sub> in time  $T_{th}$

$$p_k(T_{th}, 0) = \sum_{i=0}^{\infty} e^{-\lambda_{tot} T_{th}} (\lambda_{tot} T_{th})^i (1 - p_{ek})^i = e^{-p_{ek} \lambda_{tot} T_{th}}$$

- Probability of at least 1 event

$$p_{th,k}(T_{th}) = 1 - e^{-p_{ek} \lambda_{tot} T_{th}}$$

# Sleep State Transitions



More idle time before energy savings is positive

$$T_{th,k} = \frac{1}{2} \left[ t_{d,k} + \left( \frac{P_0 + P_k}{P_0 - P_k} \right) t_{u,k} \right]$$

- Every state has a minimum time  $t_i$  before which energy savings is negative!

# Typical Thresholds and Policy

|       | Power (mW) | Transition Time (ms) | $T_{th,k}$ (ms) |
|-------|------------|----------------------|-----------------|
| $s_0$ | 1040       | -                    | -               |
| $s_1$ | 400        | 5                    | 8               |
| $s_2$ | 270        | 15                   | 20              |
| $s_3$ | 200        | 20                   | 25              |
| $s_4$ | 10         | 50                   | 50              |

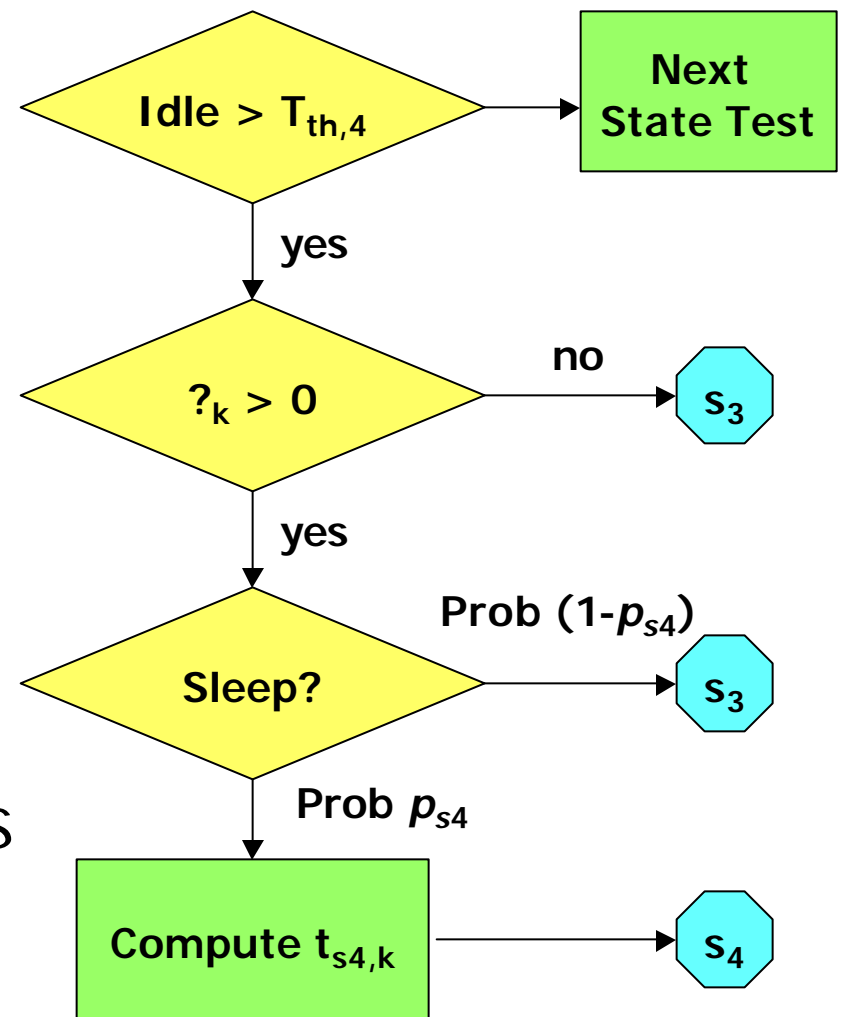
- Transition to  $s_k$  if probability of at least one event is greater than a constant ( $p_{th0}$ )

# Missed Events

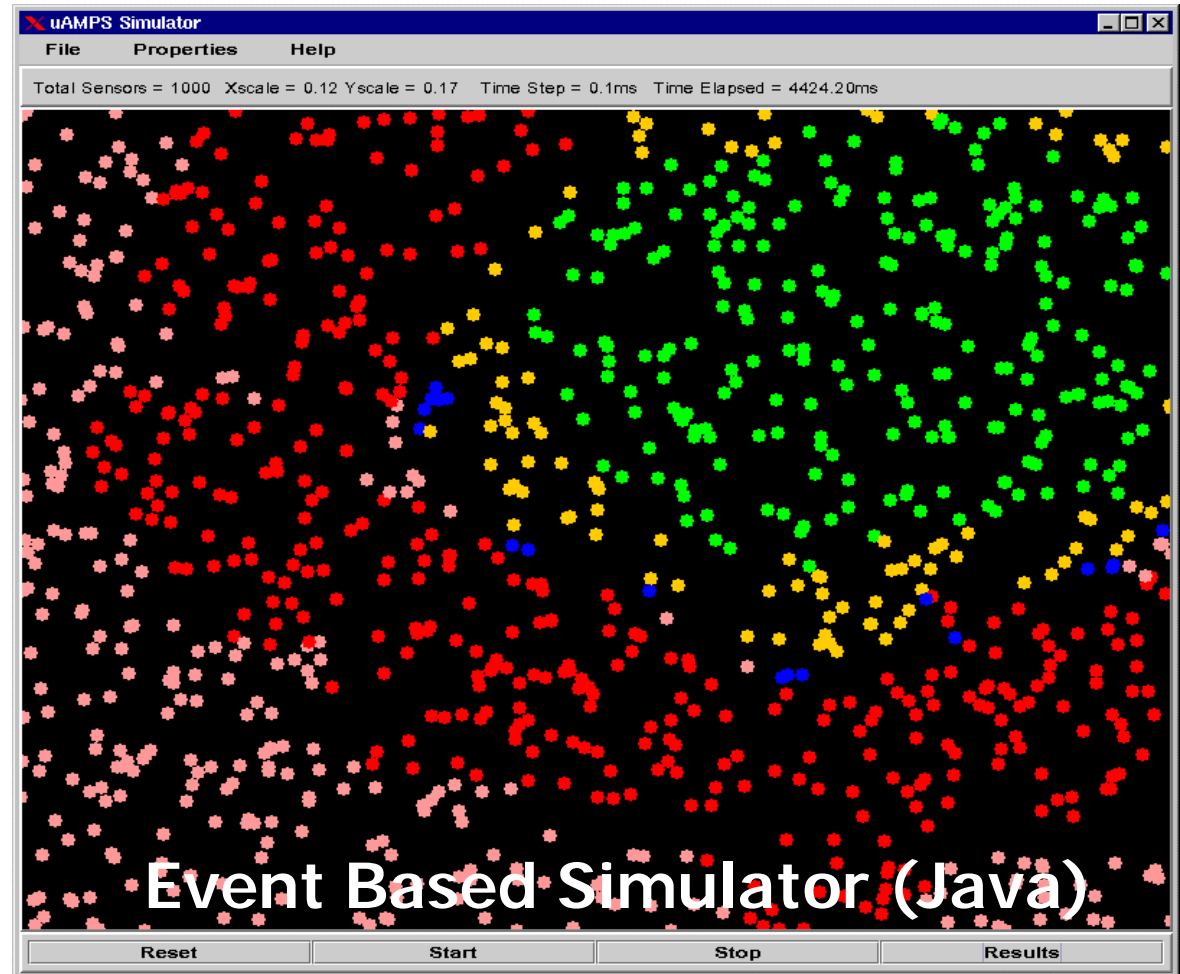
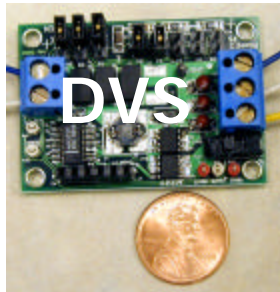
- State  $s_4$  is 'completely off'
  - Disallow  $s_4$  – Critical sensing
  - Selectively disallow  $s_4$ 
    - If idle > threshold, sleep with probability  $p_{s4}$
    - Wake up after a time

$$t_{s4,k} = -\frac{1}{I_k} \ln(p_{s4})$$

- Overall 2 system parameters
  - $p_{th0}$  and  $p_{s4}$



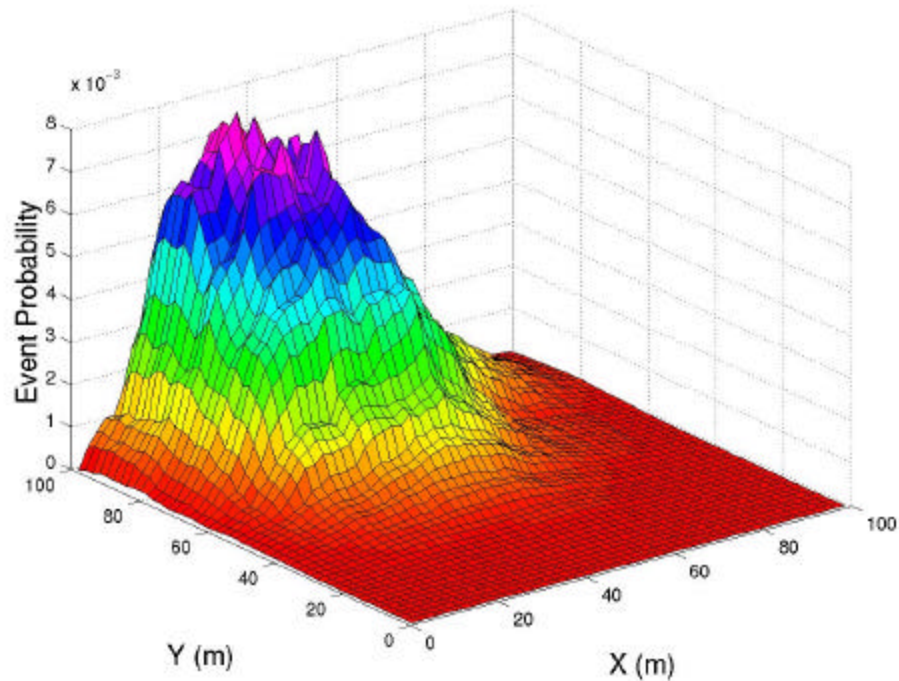
# Simulation Infrastructure



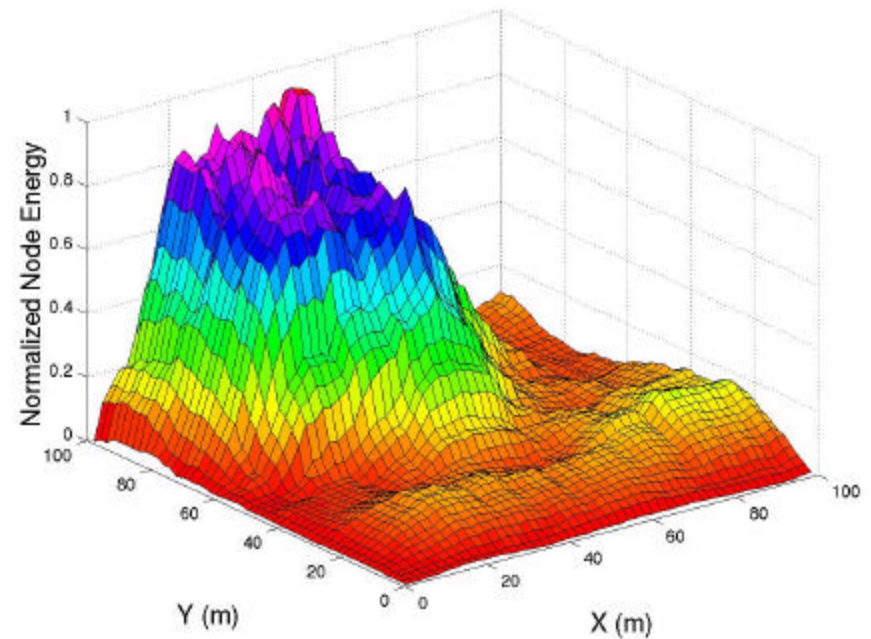
- Node models from actual hardware

# Results

## Spatial Event Distribution

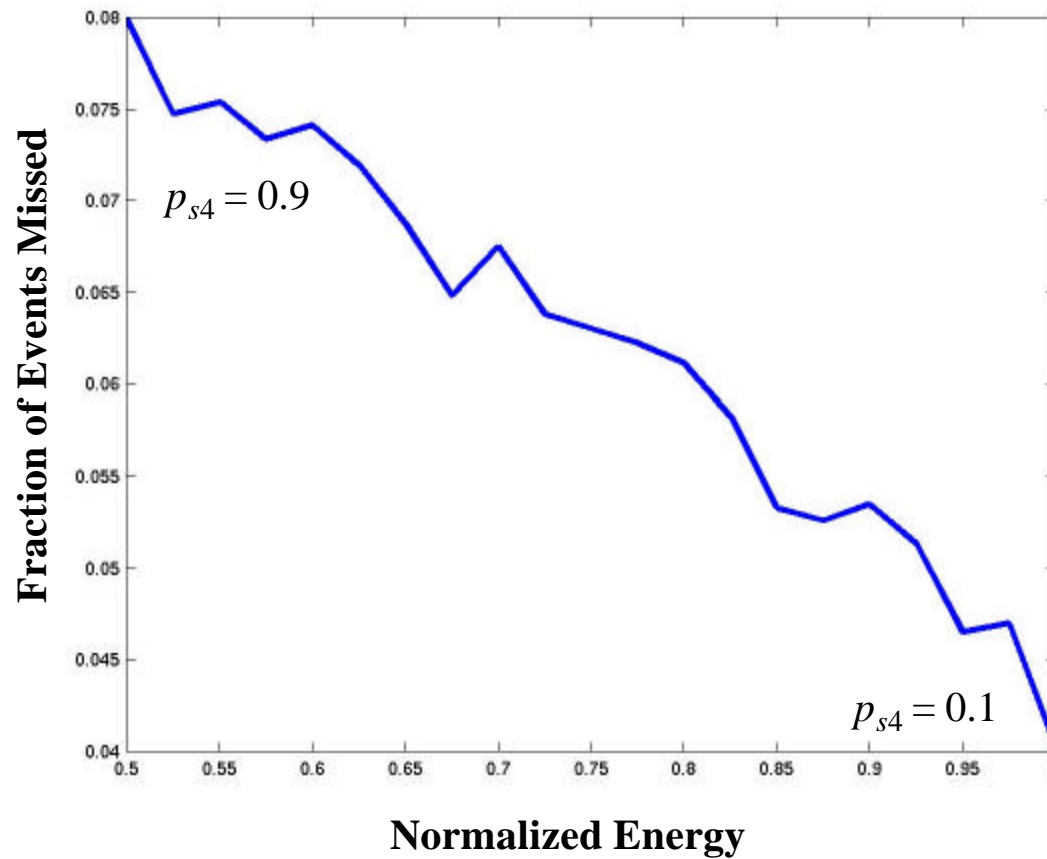


## Spatial Energy Consumption



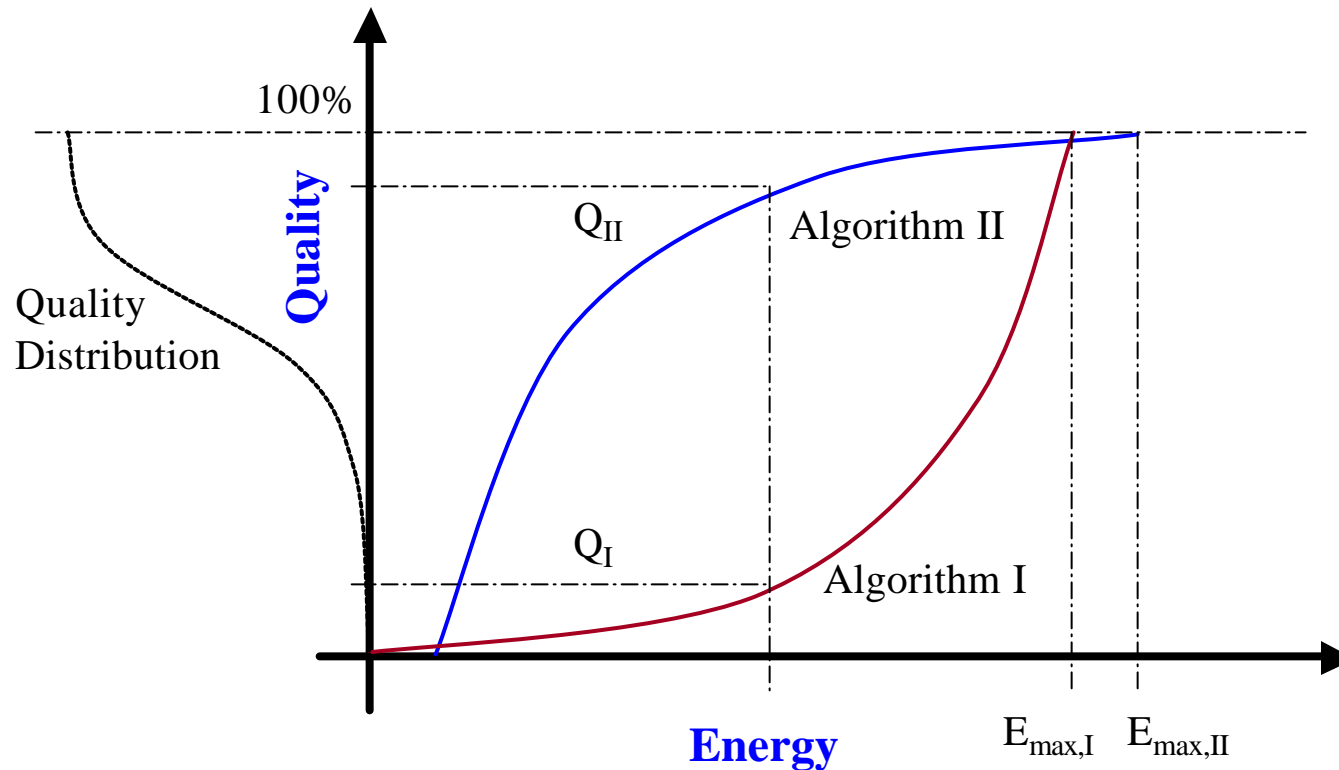
- Energy Consumption Tracks Events

# Results



- Scalable degradation in event detection

# Energy Scalable Applications

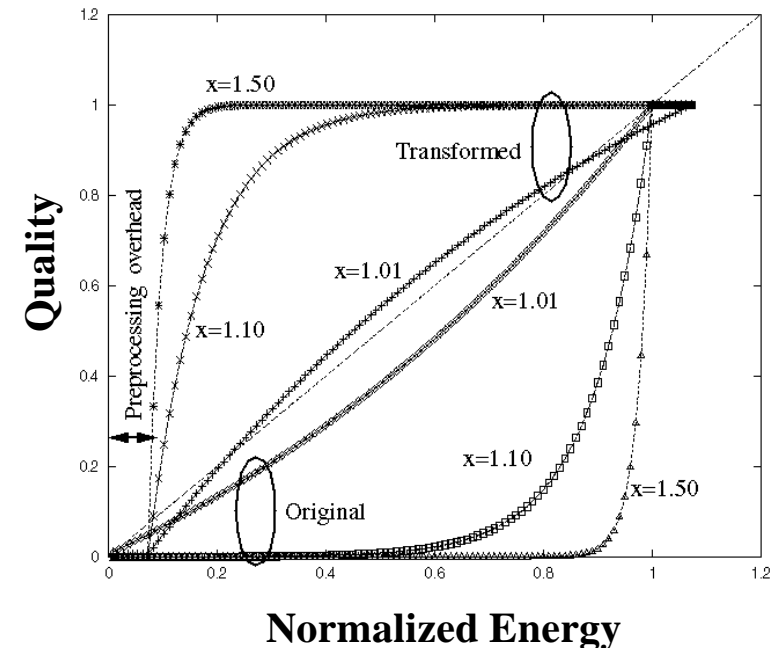


- Maximize quality for given energy availability
- **Energy Quality** (E-Q) graph maximally concave

# Simple Example

$$y = f(x) = 1 + k_1x + k_2x^2 + \dots + k_Nx^N$$

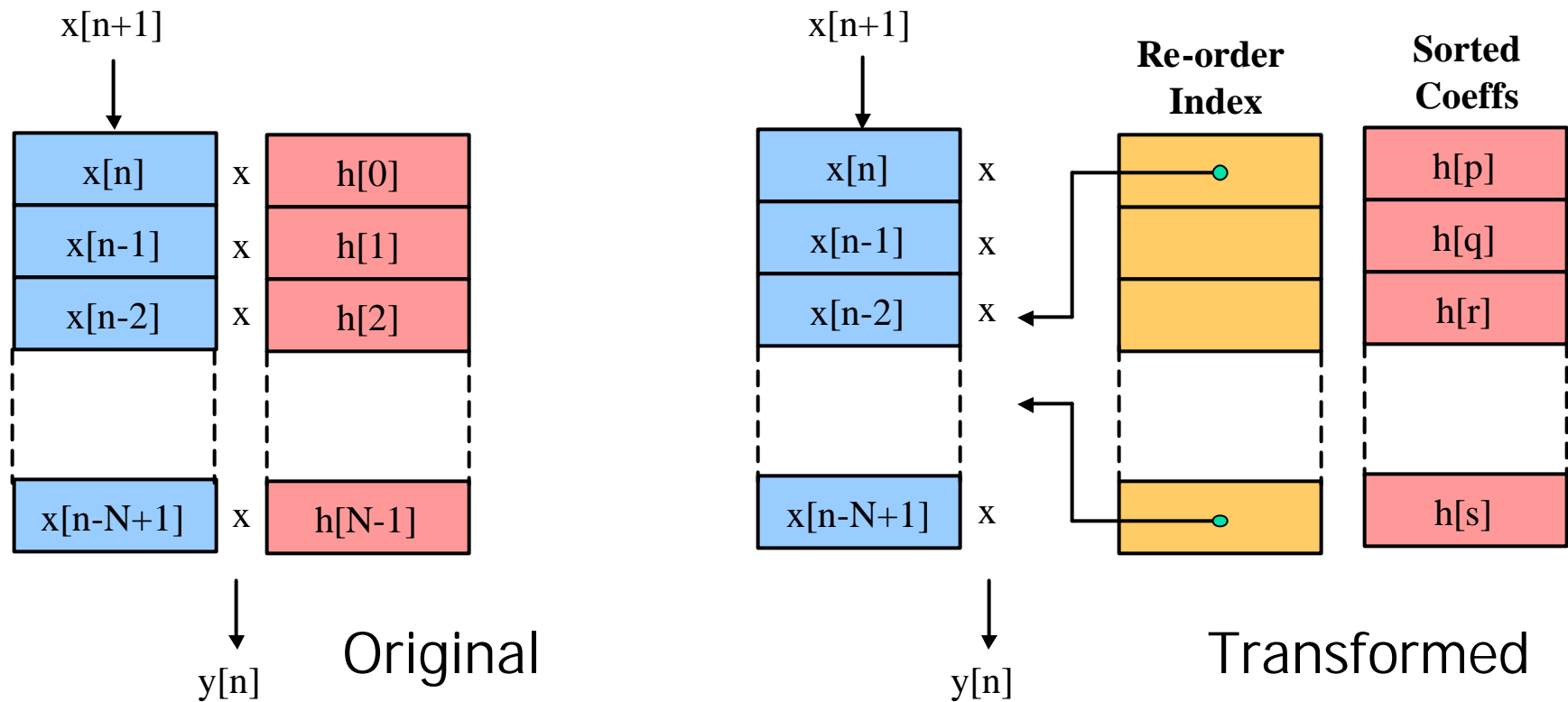
| Original  | Scalable  |
|---|---|
| <pre>xpowi = 1.0; y = 1.0; for(i=1; i&lt;N; i++) {   xpowi *= x;   y += xpowi*k[i]; }</pre> | <pre>if(x &gt; 1.0) {   xpowi = pow(x,N);   y = k[N]*xpowi+1;   for(i=N-1; i&gt;0; i--) {     xpowi /= x;     y += xpowi*k[i]; } } else { //original algo }</pre> |



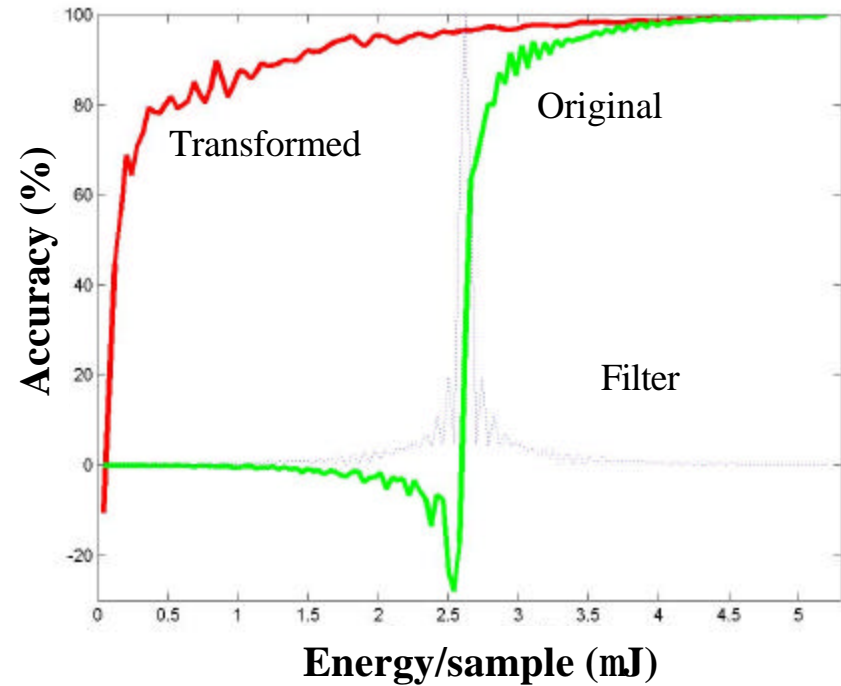
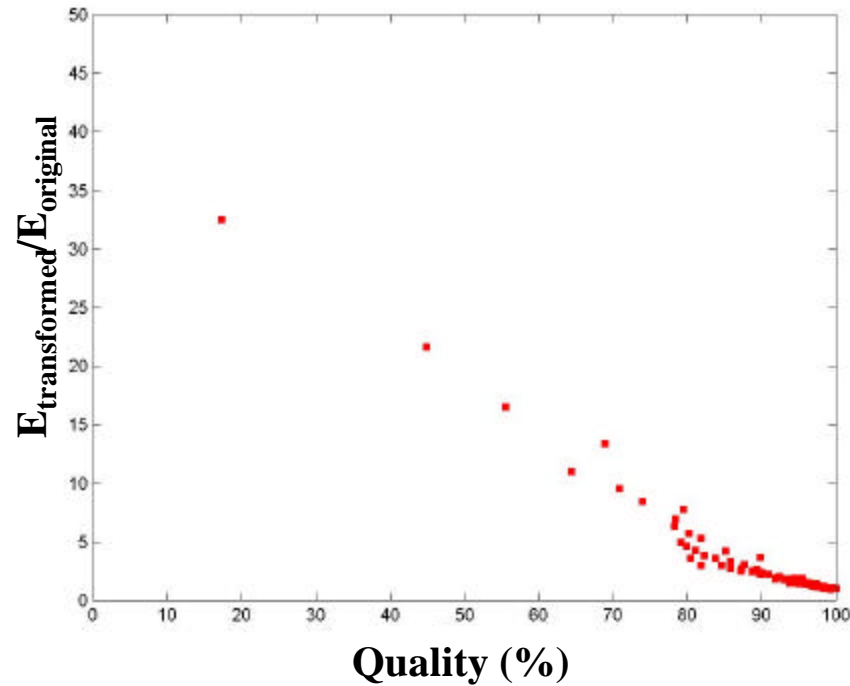
- Incremental refinement
- Most-significant-first approach

# Scalable Filtering

$$y[n] = \sum_{k=0}^{N-1} h[k]x[n-k]$$



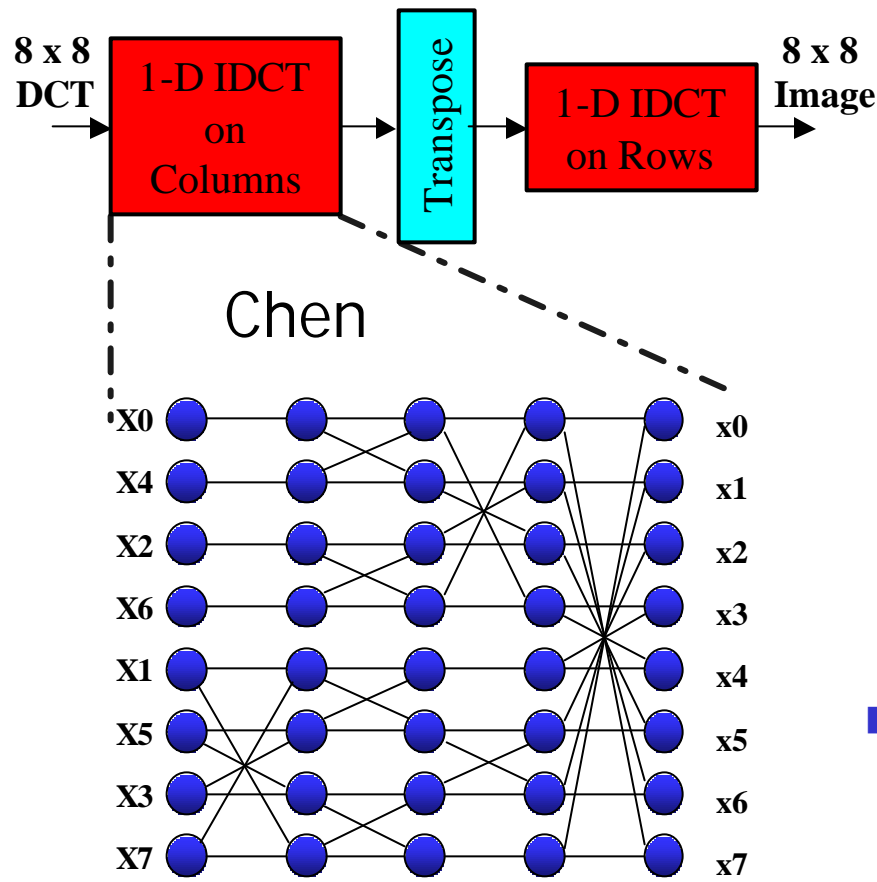
# Scalable Filtering E-Q



- 128 Tap FIR filtering on speech data
- StrongARM measurements
  - $5.12\mu\text{J}$  per sample
  - $0.21\mu\text{J}$  per sample overhead (4%)

# Scalable Image Decoding: IDCT

$$x[i, j] = \frac{1}{4} \sum_{u=0}^7 \sum_{v=0}^7 c[u]c[v]X[u, v] \cos\left(\frac{(2i+1)u\pi}{16}\right) \cos\left(\frac{(2j+1)v\pi}{16}\right)$$



$$\begin{bmatrix} x_{0,0} \\ x_{0,1} \\ x_{0,2} \\ \vdots \\ \vdots \\ x_{7,7} \end{bmatrix} = X_{0,0} \begin{bmatrix} c_0^{0,0} \\ c_1^{0,0} \\ c_2^{0,0} \\ \vdots \\ \vdots \\ c_{63}^{0,0} \end{bmatrix} + X_{0,1} \begin{bmatrix} c_0^{0,1} \\ c_1^{0,1} \\ c_2^{0,1} \\ \vdots \\ \vdots \\ c_{63}^{0,1} \end{bmatrix} + \dots + X_{7,7} \begin{bmatrix} c_0^{7,7} \\ c_1^{7,7} \\ c_2^{7,7} \\ \vdots \\ \vdots \\ c_{63}^{7,7} \end{bmatrix}$$

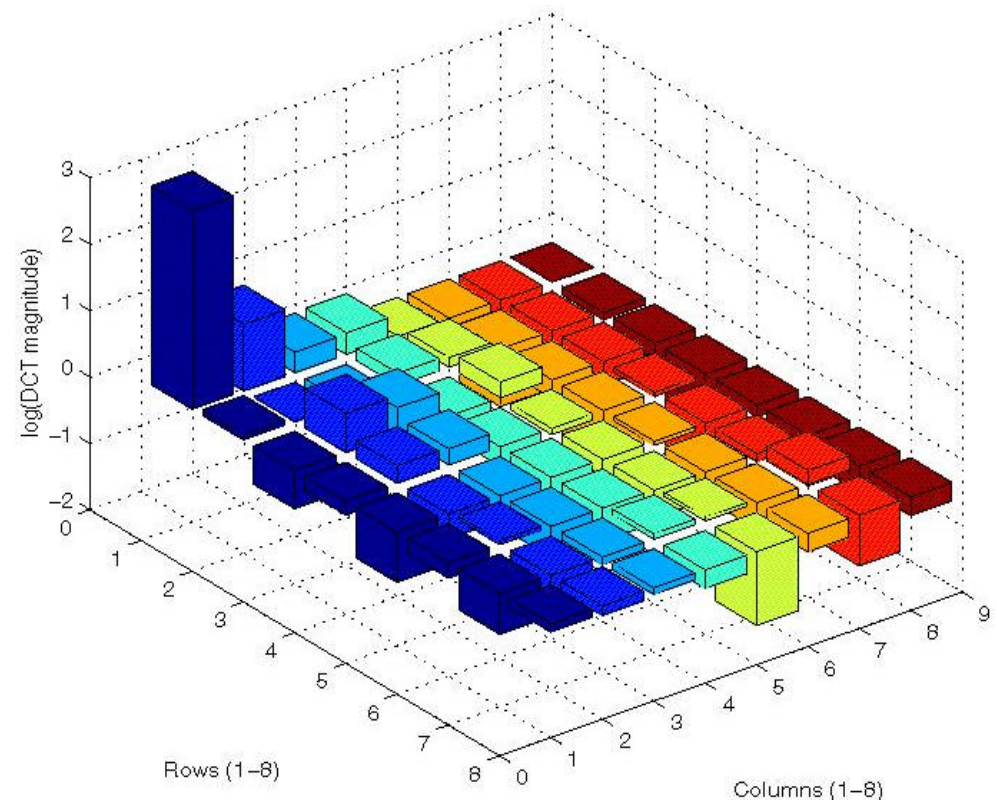
FM-IDCT

- Scalability at the cost of slightly more operations

# Most Significant DCT Coefficients



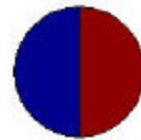
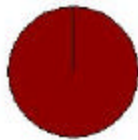
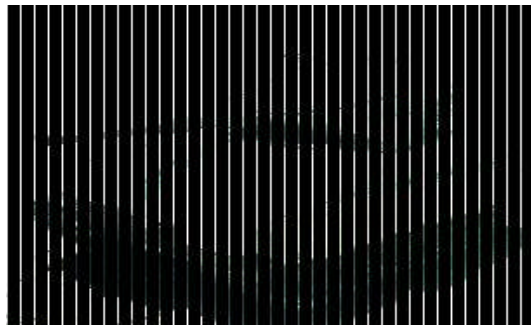
8x8 DCT



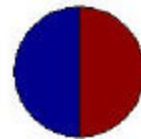
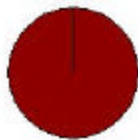
- Most energy concentrated in lower coefficients
- Accumulate lower frequency components first

# Scalable vs Non-Scalable IDCT

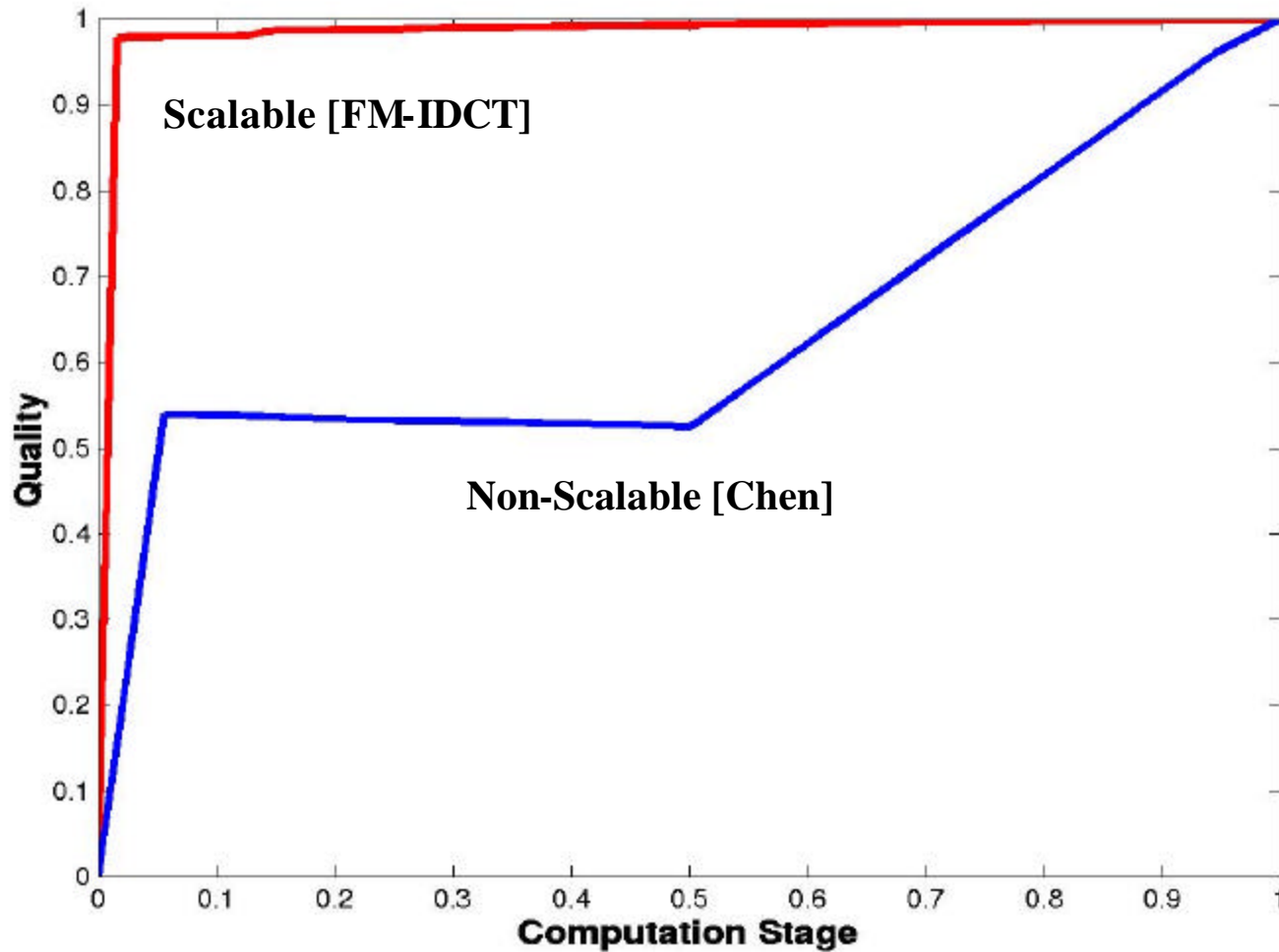
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FM-IDCT



# IDCT E-Q





# Conclusions

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- Power Management in Sensor Networks using
  - OS directed smart hierarchical shutdown
  - Scalable Algorithms
- Power Aware Sensor Node and Network
  - Power and transition overheads
  - Energy gain idle thresholds
- Energy-Quality Scalability
  - Missed events vs. Energy
  - Algorithmic transformations for scalability