



# A Statistical Framework for Designing On-chip Thermal Sensing Infrastructure

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# Outline

- Motivation/overview
- Fusion center design
- Sensor design/compression
  - Noisy sensor behavior
  - Exploiting the correlation
- Sensor placement
- Overall flow and interplay
- Results and conclusion

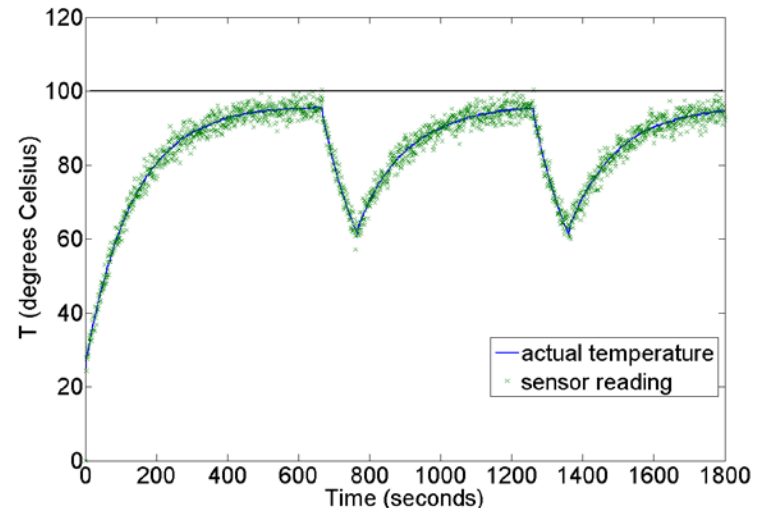
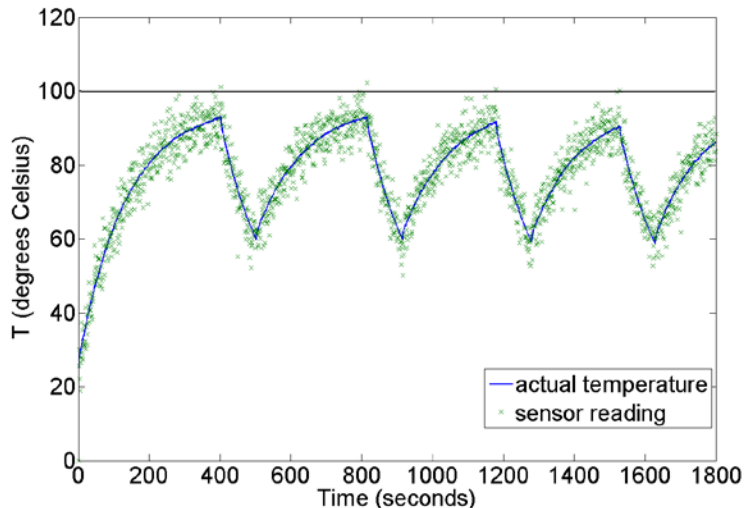
# Motivation

## ■ Thermal/power stress

- Heavy task execution
- Increasing chip density
- Leakage power

## ■ Dynamic thermal management (DTM)

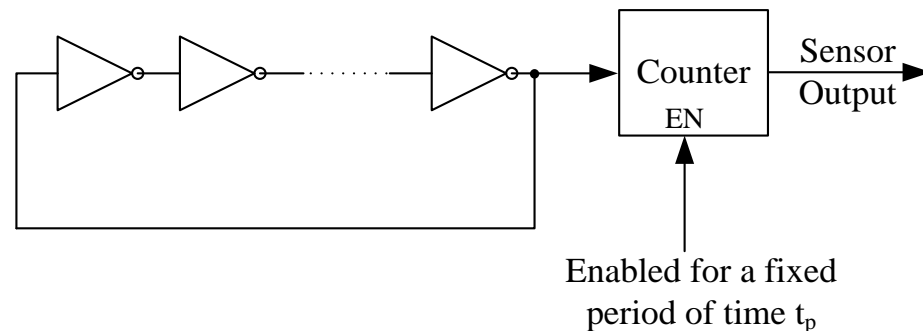
- Essentially sacrificing performance for lower temperature
- Need accurate runtime thermal information



# Motivation

- Need sensors to provide accurate runtime thermal input
- On-chip thermal sensors
  - On-chip sensors can sample the thermal state of the chip during runtime

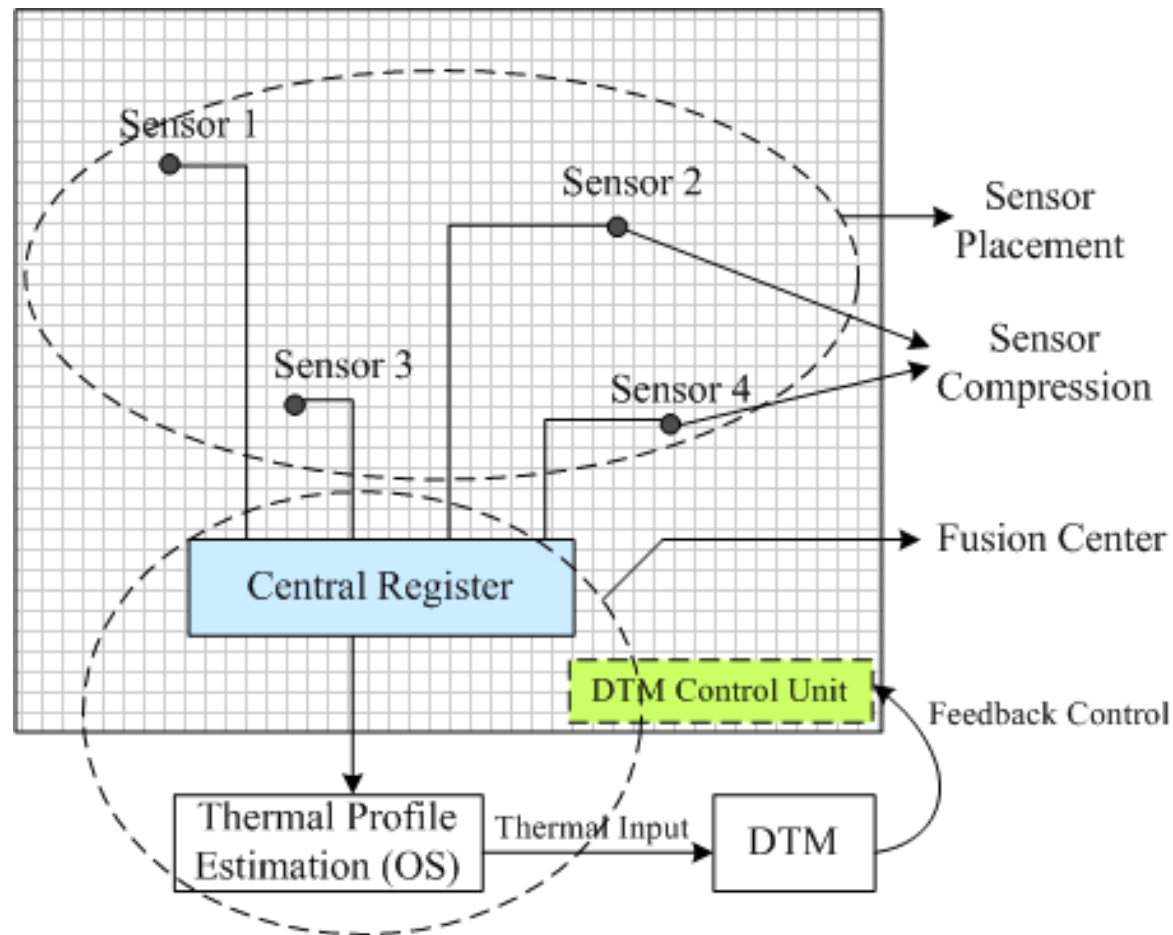
A simple ring oscillator-based thermal sensor



# Motivation

- Several problems for a naïve thermal sensing scheme.
  - Sensors cannot go everywhere
  - Sensors are subject to noise
  - Resource is limited
- Our goal --- a complete thermal sensing infrastructure that includes:
  - Sensor design/compression
  - Sensor placement
  - Data fusion

# Overall structure



# Fusion Center Design

- Central register (**finite size  $M$** )

- Could be a single or multiple actual registers

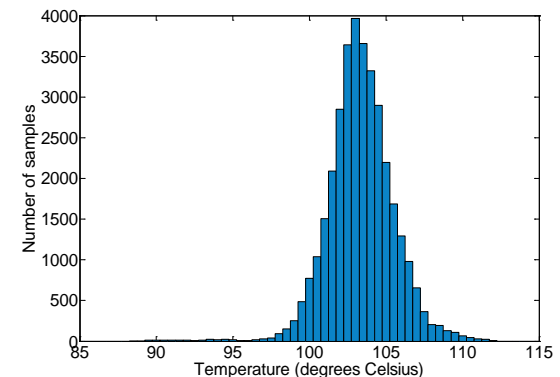
- Fusion algorithm

- Model the thermal profile as a random vector  $\mathbf{T}$
- Predict ( $\mathbf{T}$ ) given the sensor obs vector ( $\mathbf{T}_S$ )
- Exploit statistical information (mean, var, correlation etc.)

- Bayesian Estimation Philosophy

Scalar case: 
$$E(T | T_S) = \mu_T + \frac{\rho_{TS} \sigma_T}{\sigma_S} (T_S - \mu_S)$$

Vector case: 
$$E(\vec{T} | \vec{T}_S) = \vec{\mu}_T + \Sigma_{TS} \Sigma_{SS}^{-1} (\vec{T}_S - \vec{\mu}_S)$$



# Fusion Center Design

- Given sensor input, the variance of  $T$  is reduced to:

$$\begin{aligned}\hat{\Sigma}_{TT} &= E\left((T - E(T | T_s)) \cdot (T - E(T | T_s))^T\right) \\ &= \Sigma_{TT} - \Sigma_{TS} \Sigma_{SS}^{-1} \Sigma_{ST}\end{aligned}$$

- Diagonal elements – variance of the thermal estimates.
- Reflects the fundamental uncertainty of our estimation.  
(how far away our estimates are from the real temperature)
- Used to drive sensor placement.
- A better metric to drive sensor placement?
  - Sensors are not like cameras
  - Generate the probability of capturing all hotspots



# Sensor Design

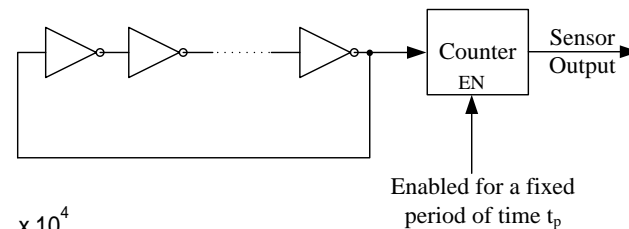
- Noisy sensor behavior (Monte Carlo Simulation)

$$f = \frac{1}{P} = \frac{1}{N(t_{PHL} + t_{PLH})}$$

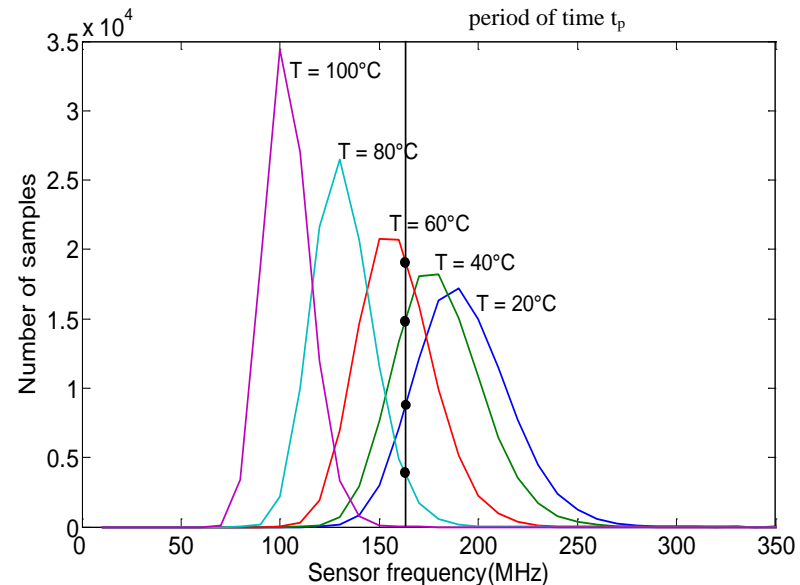
$$t_{PHL} = \frac{2C}{\mu_n C_{ox} (W/L)_n (V_{DD} - V_t)} \left[ \frac{V_t}{V_{DD} - V_t} + \frac{1}{2} \ln \left( \frac{3V_{DD} - 4V_t}{V_{DD}} \right) \right]$$

$$\mu_{n/p} = \mu_0 (T / T_0)^{-1.5}$$

$$V_t = V_{t0} + 0.002(T - T_0)$$



- Sensor readings are compressed as well due to center register size constraint
- Hypothesis testing



# Sensor Design

- Target: minimize the expected prediction error:

$$\begin{aligned} \text{Cost} &= E(|T_{pred} - T_{real}| | T_{obs}) \\ &= \sum_{i=1}^n |T_{pred} - H_i| \cdot \frac{\text{prob}(T_{real} = H_i | T_{obs})}{\text{prob}(T_{obs})} \\ &\quad \xrightarrow{\text{Bayes rule}} \frac{\text{prob}(T_{obs} | T_{real} = H_i) \cdot P_i}{\text{prob}(T_{obs})} \\ &= \frac{\text{prob}(T_{obs} | T_{real} = H_i) \cdot P_i}{\sum_{j=1}^n \text{prob}(T_{obs} | T_{real} = H_j) \cdot P_j} \end{aligned}$$

- Optimal decision rule:

$$T_{pred} = \delta(T_{obs}) = \arg \min_{T_{pred} = H_1 \dots H_n} E(|T_{pred} - T_{real}| | T_{obs})$$

- Implement as an encoder at the sensor output

# Sensor and fusion center co-design

## ■ How do we compress sensors so that...

- They fit into the central register
- Collectively they provide better accuracy
  - more compressed sensors vs fewer non-compressed ones

## ■ Bit allocation problem:

- Decide how to allocate a total of  $M$  bits to  $n$  sensors so that the overall expected estimation error is minimum:

(suppose  $s_i$  is the number of bits allocated to sensor  $i$ )

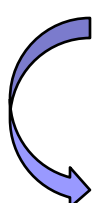
Minimize  $E(\text{error}(s_1, s_2, \dots, s_n))$

Subject to 
$$\begin{cases} 0 \leq s_i \leq b_i \\ \sum_i s_i = M \end{cases}$$

# Sensor Compression

- Target: to reduce the overall expected error caused by sensor compression.

$$TotalCost = E(\text{error}(s_1, s_2, \dots, s_n))$$

$$\begin{aligned} E(T_i | \vec{T}_s) &= E\left(\sum_{\forall grids:i} |E(T_i | \vec{T}_s^c) - E(T_i | \vec{T}_s^a)|\right) \\ &= \mu_{T_i} + \Sigma_{TS} \Sigma_{SS}^{-1} (\vec{T}_s - \vec{\mu}_s) \end{aligned}$$

$$= E\left(\sum_{\forall rows} |\Sigma_{TS} \Sigma_{SS}^{-1} (\vec{T}_s^c - \vec{T}_s^a)|\right)$$

- Different compression scheme leads to different overall error.
- Can be formulated as a optimization problem (see details in our paper).

# Sensor Placement

- Let “**S**” and “**T**” represent the set of sensor locations and all chip locations, respectively.
- Problem formulation:

*choose  $S \subset T$  with  $|S| = n$*

*such that  $\text{trace}(\hat{\Sigma}_{TT})$  is minimized*

- As mentioned earlier  $\hat{\Sigma}_{TT}$  represents the fundamental uncertainty/variance associated with our thermal estimates

$$\hat{\Sigma}_{TT} = \Sigma_{TT} - \Sigma_{TS} \Sigma_{SS}^{-1} \Sigma_{ST}$$

# Sensor Placement Algorithm

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**Algorithm**    <Sensor Placement>

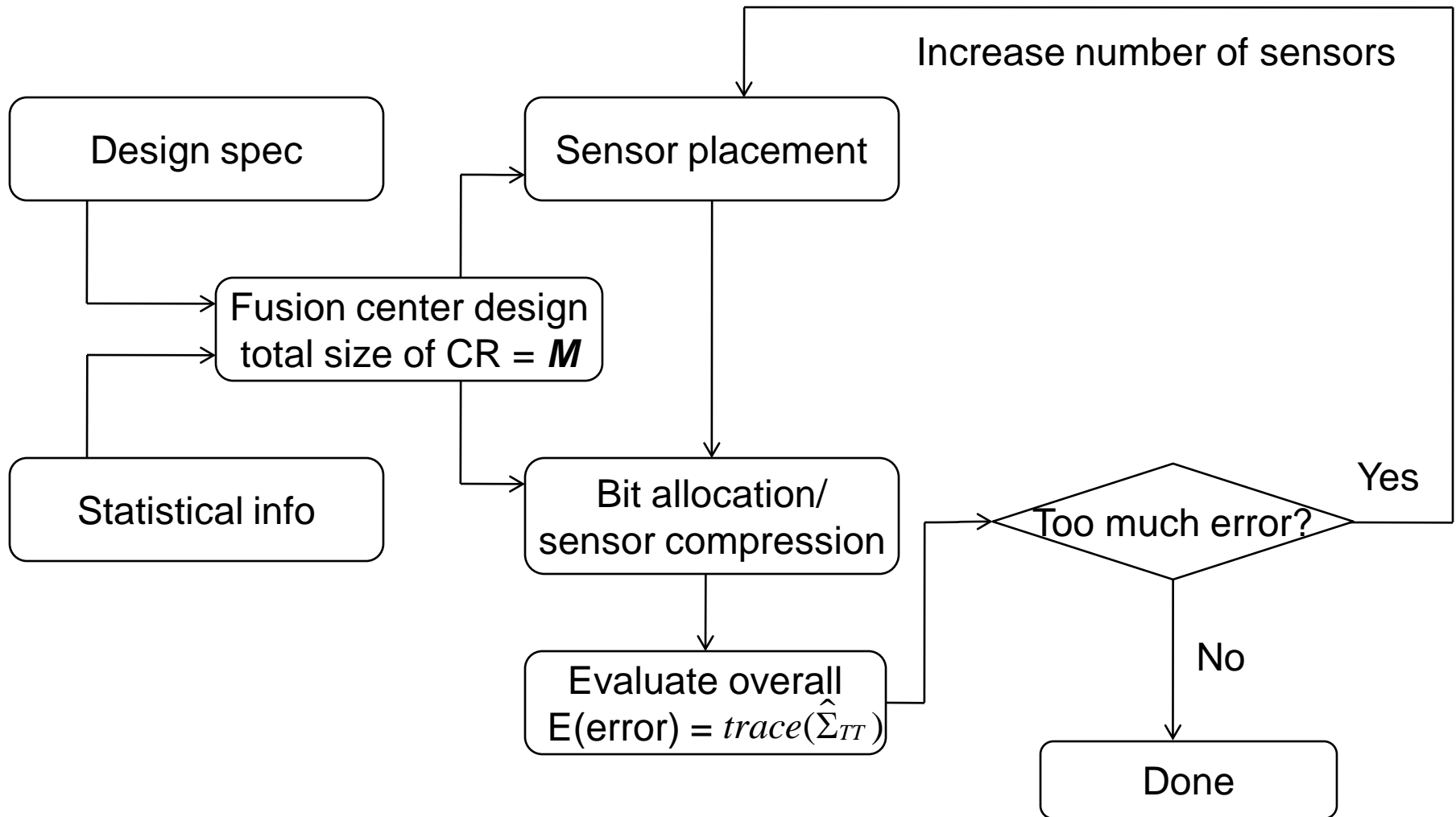
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**Input:** Desired number of sensors  $n$ , all grid location set  $T$

**Output:** Sensor location set  $S$  with  $|S| = n$

- 1:  $S \leftarrow \emptyset$
  - 2: **while**  $|S| < n$  **do**
  - 3:    **for all**  $i \in T \setminus S$  **do**
  - 4:      $S_{new} \leftarrow S \cup i$
  - 5:     Calculate the new  $\hat{\Sigma}_{TT}$  using  $S_{new}$
  - 6:    **end for**
  - 7:    Select  $i_{min}$  which results in the minimum trace( $\hat{\Sigma}_{TT}$ )  
    among all  $i$
  - 8:     $S \leftarrow S \cup i_{min}$
  - 9: **end while**
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# Overall flow and interplay



# Experimental Results

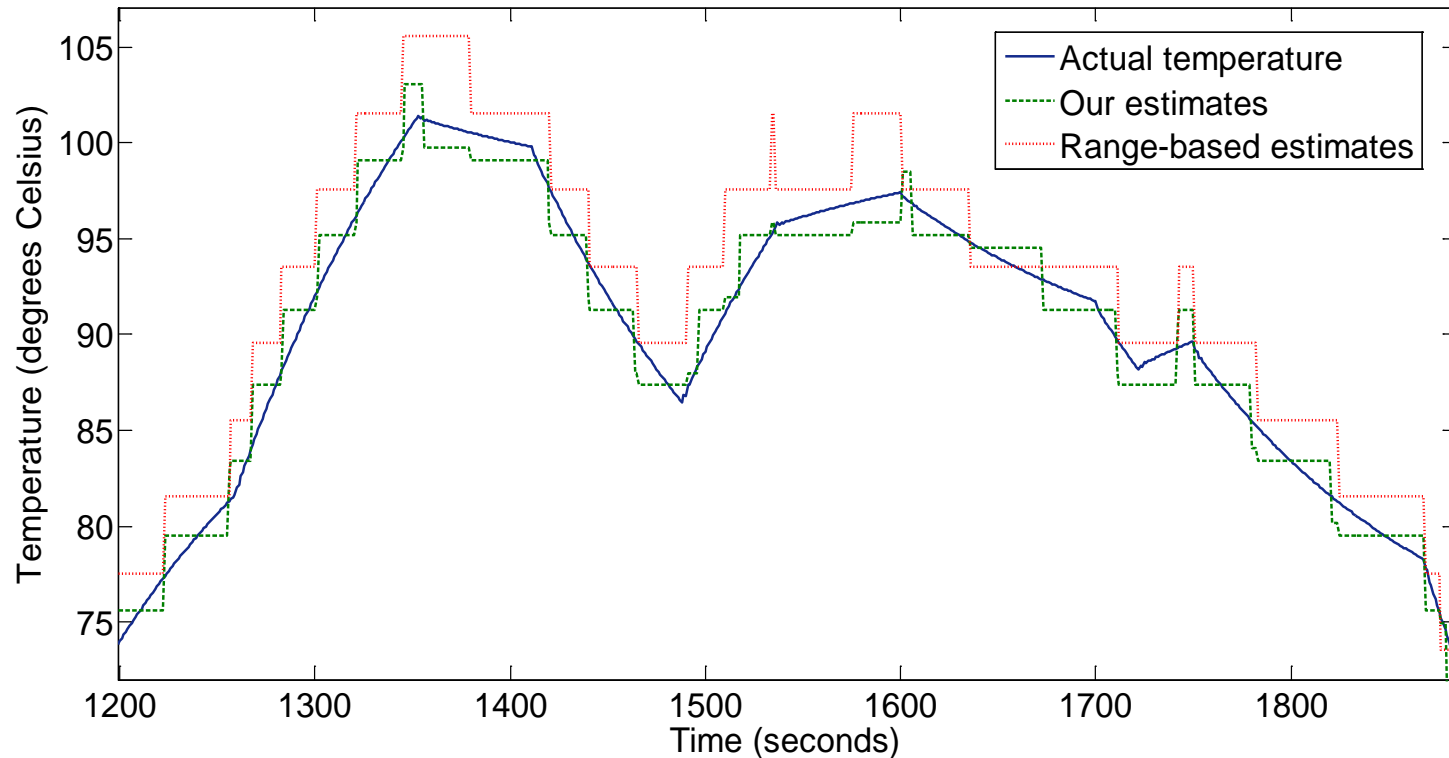


Fig. 1 Dynamic temperature tracking curves



# Experimental Results

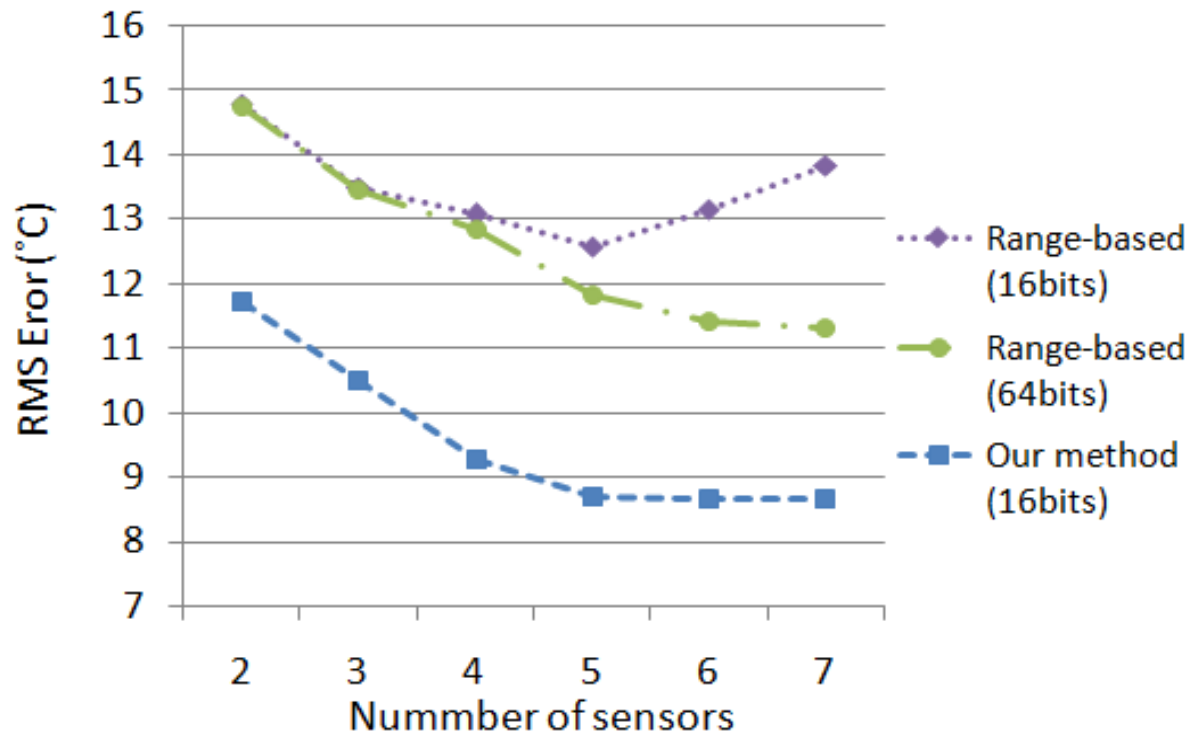


Fig. 2 RMS error comparison when increasing the number of sensors

# Conclusion

- We presented a unified statistical framework for designing a complete thermal sensing infrastructure.
- Significant improvement in thermal sensing accuracy can be achieved with very small overhead
- Our methodology has the capability of trading off complexity for accuracy at will. It also takes into account various design considerations such as sensor noise and area constraints.



Thank you!