

Over-the-Air Computation Systems: Optimization, Analysis and Scaling Laws

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Outline

- Motivation
- AirComp and Federated Learning
- Computational-optimal AirComp
- Scaling Performance and conclusion

Motivation



Over-the-air consensus



Wireless distributed machine learning

Motivation – Over-the-air Consensus

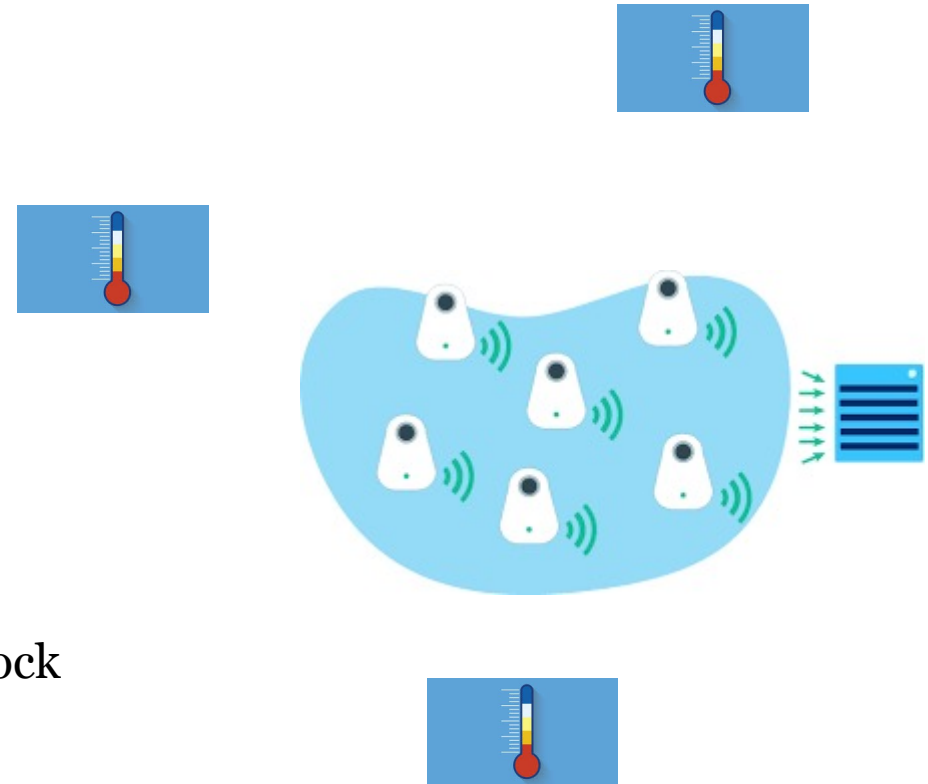
“Only the summary of data is of interest...”

- Average
- Sum
- Min or Max
- ...

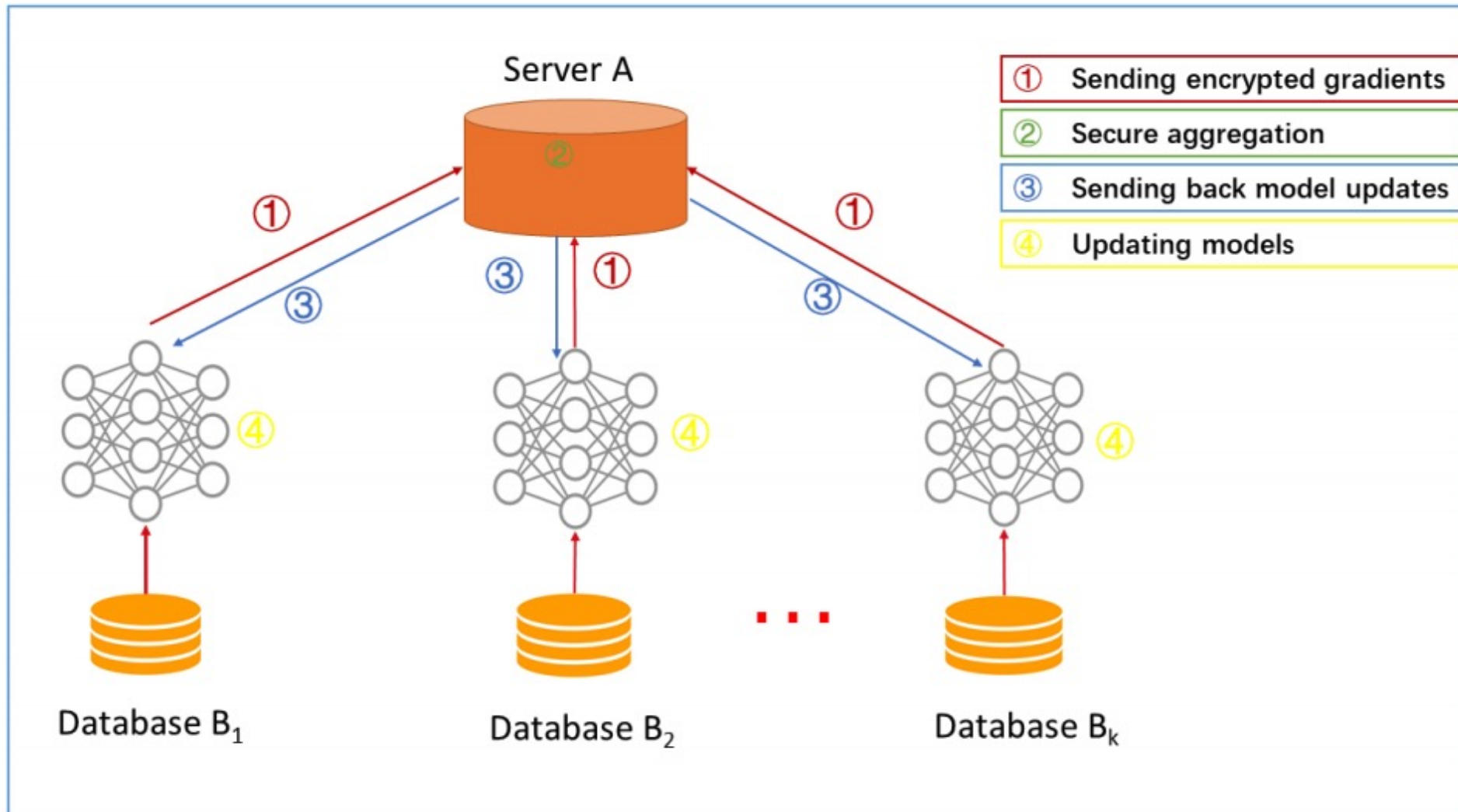
Abari, O., Rahul, H., & Katabi, D. (2016). *Over-the-air Function Computation in Sensor Networks*. <http://arxiv.org/abs/1612.02307>

Option 1: transmit all the data to the cluster head

Option 2: Jointly transmit using the same time-frequency block



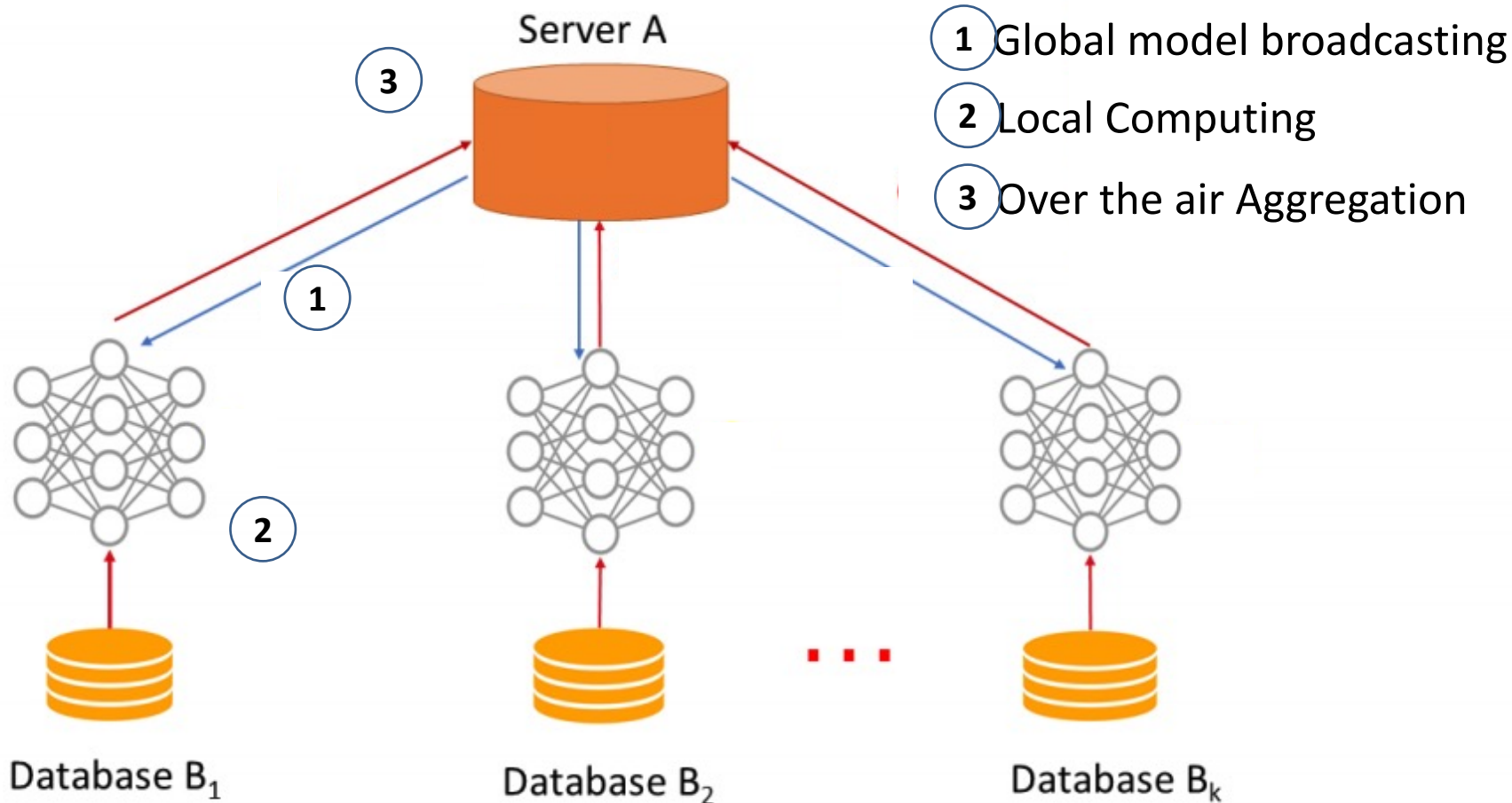
Motivation – Over-the-air Federated Learning



Communication Bottleneck:

limited radio resources

Motivation – Over-the-air Federated Learning



Aggregate the gradients over the air can dramatically reduce the required resources

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AirComp and FL – Communication model

OFDM modulation

- Bandwidth B into M orthogonal sub-channels
- Fixed digital constellation is employed by all the devices
- Map each gradient element to one digital symbol

Channel Input Vector

$$\tilde{\mathbf{g}}_k = [\tilde{g}_{k,1}, \dots, \tilde{g}_{k,q}]^T$$

Device index

The size of the model

Zhu, Guangxu, et al. "One-bit over-the-air aggregation for communication-efficient federated edge learning: Design and convergence analysis." *IEEE Transactions on Wireless Communications* 20.3 (2020): 2120-2135.

AirComp and FL – Communication model

Channel Input Vector

$$\tilde{\mathbf{g}}_k = [\tilde{g}_{k,1}, \dots, \tilde{g}_{k,q}]^T$$

We require

$$N_s = \frac{q}{M} \text{ OFDM symbols}$$

Over the Air Process

i-th aggregated gradient parameter, received at the **m-th** sub-carrier and **t-th** OFDM symbol is given by:

$$\tilde{g}_i = \sum_{k=1}^K h_k[t, m] p_k[t, m] \tilde{g}_{k,i} + z[t, m], \quad \forall i,$$



Channel
coefficients

Power Control
policy

AWGN

AirComp and FL – Communication model

Transmitter Design

one-bit quantization of local gradient estimates

$$\text{(One-bit quantization)} \quad \tilde{g}_{k,i} = \text{sign}(g_{k,i}), \quad \forall k, i.$$

Each gradient parameters is modulated into one binary phase shift keying (BPSK) symbol.

Channel Inversion

We adopt the **power control** to invert the sub-channels so that gradient transmitted by different devices are received with **identical amplitudes**

$$\tilde{g}_i = \sum_{k=1}^K h_k[t, m] p_k[t, m] \tilde{g}_{k,i} + z[t, m], \quad \forall i,$$

AirComp and FL – Communication model

Receiver Design

(Over-the-air aggregation) $\tilde{\mathbf{g}}[t] = \sum_{k=1}^K \sqrt{\rho_0} \tilde{\mathbf{g}}_k^{(\text{Tr})}[t] + \mathbf{z}[t]$

Vector with M
elements

Truncated
gradients

$$\tilde{\mathbf{g}} = [\tilde{\mathbf{g}}[1]^T, \tilde{\mathbf{g}}[2]^T, \dots, \tilde{\mathbf{g}}[N_s]^T]^T$$

(Majority-vote based decoder) $\mathbf{v} = \text{sign}(\tilde{\mathbf{g}})$

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Computational Optimal AirComp

Related works

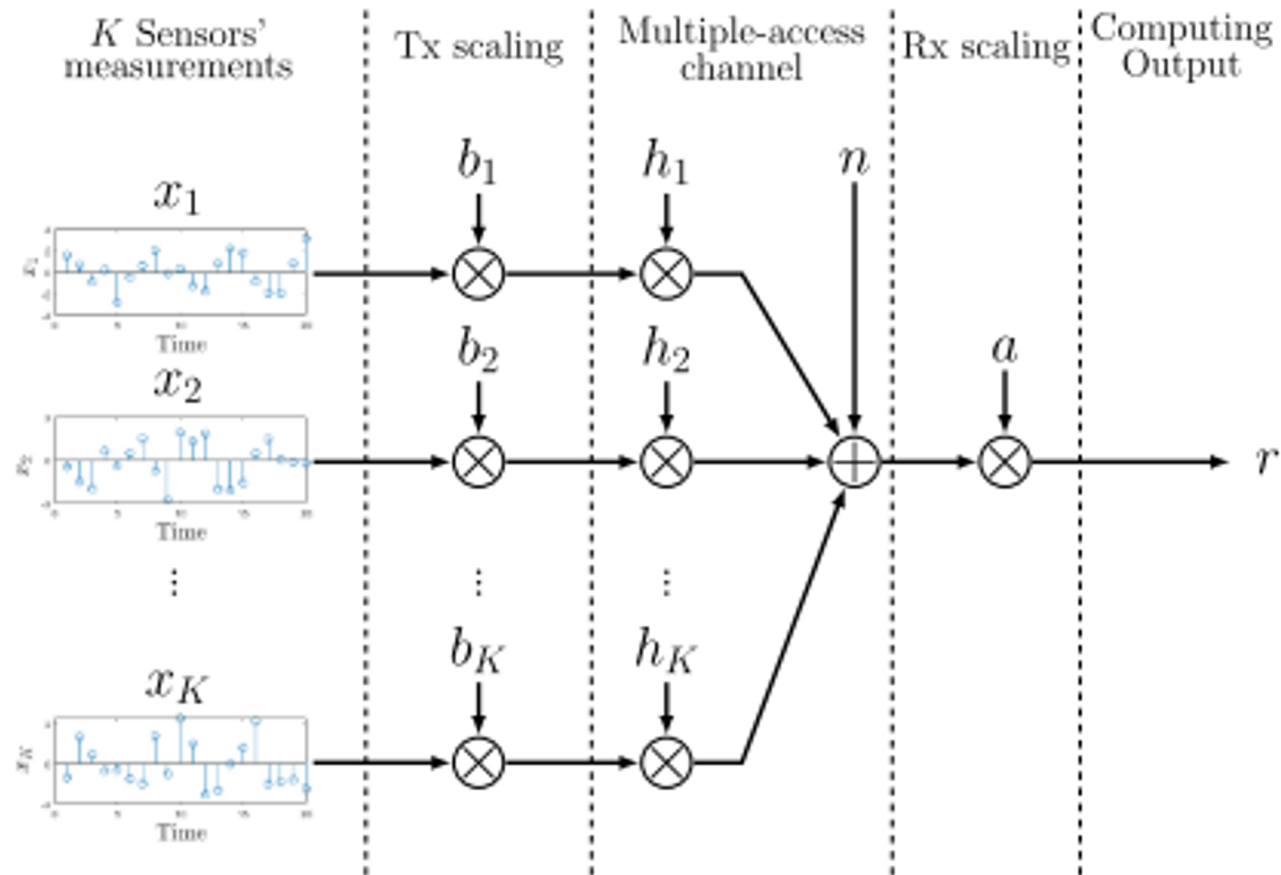
- Processing functions design

Compute a given function, ideal channel

- Performance analysis on practical wireless MAC

Compute the sum, non-ideal channel

Computational Optimal AirComp – System Model



Function

$$r = a \left(\sum_{k=1}^K h_k b_k x_k + n \right),$$

Distortion

$$\text{MSE} = \sum_{k=1}^K |a h_k b_k - 1|^2 + \sigma^2 |a|^2.$$

Power consumption (bound)

$$\text{PW} \triangleq \sum_{k=1}^K |b_k|^2.$$

Computational Optimal AirComp

“Computational-optimal: minimize MSE under power constraint”

Tx-scaling devotes power to improve SNR, while Rx-scaling (post-processing) amplifies noise without sacrificing power.

Assume the channel coefficients are known by both the transmitters and receiver.

Pre-processed signals are assumed to have zero mean and unit variance, and be independent.

Computational Optimal AirComp

Solve the problem

$$\begin{aligned} \min_{a, \{b_k\}} \quad & \text{MSE} \\ \text{subject to} \quad & |b_k|^2 \leq P, \quad \forall k. \end{aligned}$$

$$\text{MSE} = \sum_{k=1}^K |ah_k b_k - 1|^2 + \sigma^2 |a|^2.$$

Step 1: sort the channel coefficient ascendingly, and fix a

$$0 \triangleq h_0 < h_1 \leq h_2 \leq \dots$$

$$\mathcal{S}_k \triangleq \begin{cases} \left(\frac{1}{h_1 \sqrt{P}}, \infty \right), & k = 0, \\ \left(\frac{1}{h_{k+1} \sqrt{P}}, \frac{1}{h_k \sqrt{P}} \right], & k = 1, \dots, K-1, \\ \left[0, \frac{1}{h_K \sqrt{P}} \right], & k = K. \end{cases}$$

$$b_k = \begin{cases} \sqrt{P}, & 1 \leq k \leq i \\ \frac{1}{ah_k}, & i < k \leq K. \end{cases}$$

Full power transfer

Channel inversion

Computational Optimal AirComp

Step 2: solve optimal $\{a\}$, or equivalently, the critical number i

$$\text{MSE} = \sum_{k=1}^i \left| ah_k \sqrt{P} - 1 \right|^2 + \sigma^2 |a|^2, \quad a \in \mathcal{S}_i,$$

$$g_i \triangleq \begin{cases} 0, & i = 0 \\ \frac{\sqrt{P} \sum_{k=1}^i h_k}{\sigma^2 + P \sum_{k=1}^i h_k^2}, & i = 1, \dots, K. \end{cases}$$

$$i^* = \arg \max_{1 \leq i \leq K} g_i.$$

Minimal MSE and its power consumption

$$\text{MSE}^* = \sum_{k=1}^{i^*} \left(a_{i^*} h_k \sqrt{P} - 1 \right)^2 + \sigma^2 (a_{i^*})^2.$$

$$\text{PW} = \sum_{k=1}^K b_k^{*2} = P i^* + \frac{1}{(a_{i^*})^2} \sum_{k=i^*+1}^K \frac{1}{h_k^2}.$$

Full power transfer

Channel inversion

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Scaling Performance – Benchmark Policies

Channel-Inversion Policy: set the critical number $i = 1$ (i.e., force to channel inversion)

Energy-Greedy Policy: set the critical number $i = K$ (i.e., force to full power)

Scaling Performance – a Suboptimal Policy

Define:

Policy is computation-effective iff

$$\lim_{K \rightarrow \infty} \frac{E[\text{MSE}]}{K} = 0.$$

Policy is energy-efficient iff

$$\lim_{K \rightarrow \infty} \frac{E[\text{PW}]}{K} = 0.$$

Definition 6 (First- ι Policy): A Tx-Rx scaling policy of the AirComp system is a first- ι policy if it satisfies:

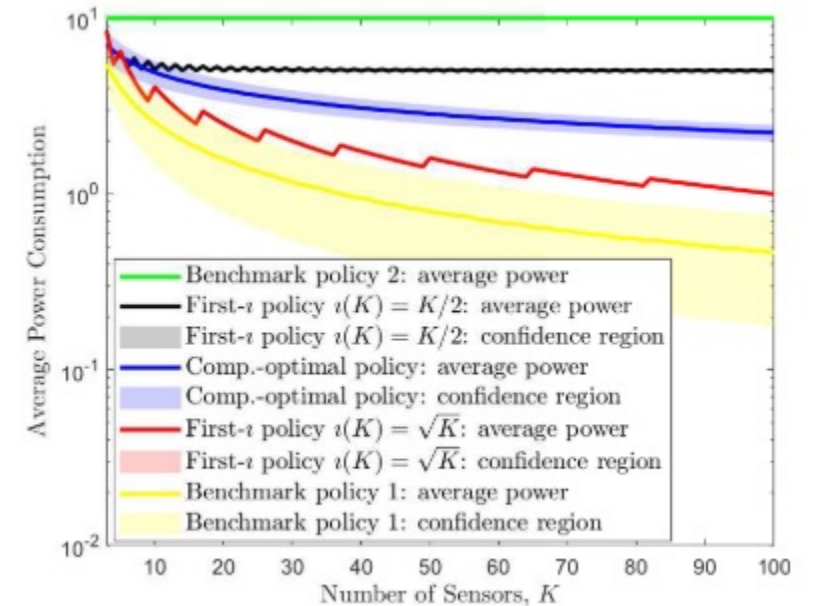
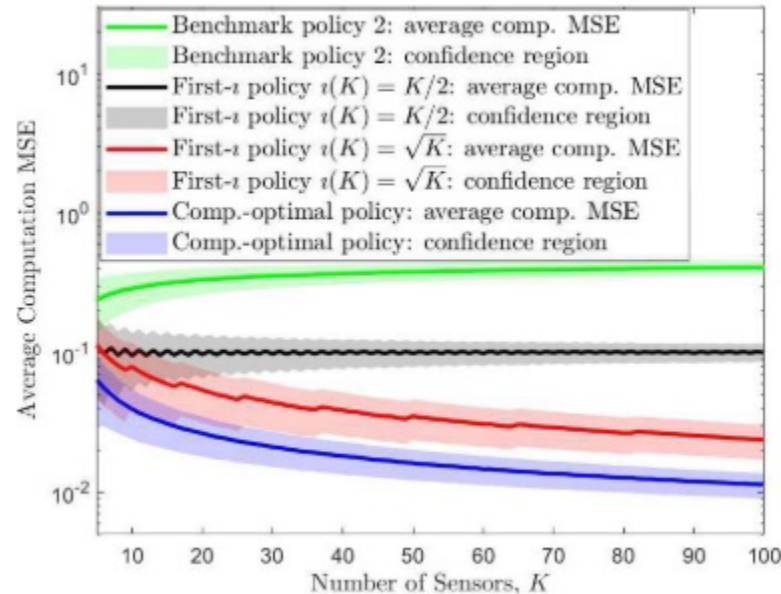
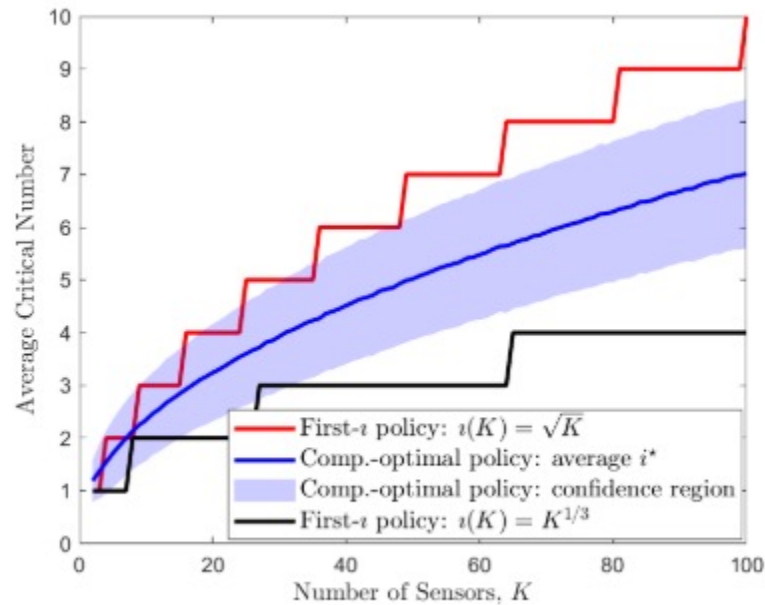
- i) the critical number is determined by a function, i.e., $\iota = \iota(K)$, where $\iota : \mathbb{N} \rightarrow \mathbb{N}$ and $\iota(K) \leq K$,
- ii) the Rx-scaling factor $a \in \mathcal{S}_i$, and
- iii) the Tx-scaling factor b_k is given by (8), $\forall k \in \{1, \dots, K\}$.

Does not depend on channel realizations!

Numerical Result

Simulation parameters

Transmission power = 10
Receiving noise power = 1
Channel coefficients: i.i.d. Rayleigh fading with unit variance



Conclusion

COMPUTATION EFFECTIVENESS AND ENERGY EFFICIENCY OF AIRCOMP POLICIES

	Computation-Effective Policy	Energy-Efficient Policy
Benchmark Policy 1 [12, 13]	✗	✓
Benchmark Policy 2	✗	✗
Computation-Optimal Policy	✓	✓
First- ι Policy with $\iota(K) = \sqrt{K}$	✓	✓
First- ι Policy with $\iota(K) = K/2$	✗	✗

Computation-optimal policy has a vanishing average MSE and a vanishing average power consumption with the increasing number of sensors

First- ι policy (square root) reveals the tradeoff between computation effectiveness and energy efficiency, which is important in practical AirComp system design

An aerial photograph of the University of Houston campus at dusk. The foreground shows several large, modern university buildings with flat roofs and some with glass facades. A central green lawn with winding paths and trees is visible. In the background, the Houston city skyline is visible against a twilight sky with soft orange and blue hues. A large, solid red rectangular banner is positioned at the top of the image, containing the text 'THANK YOU' in white, bold, sans-serif capital letters.

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