Optimal Wireless Power Transfer and Harvested Power Allocation for Diffusion LMS in Wireless Sensor Networks

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Outline

Distributed Estimation in WSNs

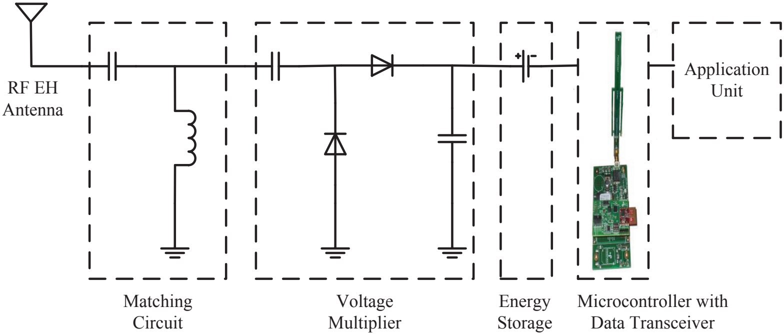
- Why distributed estimation in WSN:
  - Absence of a centralized processor
  - Limited power and communication range for sensors
- How to perform distributed estimation:
  - Each sensor collect measurements.
  - Each sensor perform inference by exchanging information only with its neighbors iteratively [1, 2].
- Typical distributed estimation strategies: consensus [3, 4] and diffusion [5, 6].
  - Diffusion is scalable and robust, and thus preferable [2].

RF-based Wireless Power Transfer (WPT)

- Why RF-based WPT:
  - Advantages: Longer distance, convenient, robust, low cost, etc.
  - Applications: sensor network, consumer electronics, etc.
- Harvested signal power: $P_r = P_t \times G_a \times d^{-\alpha} \times \eta$
  - α: path loss factor; η: energy conversion efficiency $(0.2 - 0.9)$
  - High-efficiency WPT via beamforming

RF-based WPT and Motivation

- Example: sensor planform powered by RF-energy harvesting (RF-EH)
- RF-EH module: “Rectenna” (antenna + rectifying circuit) [7]



- Motivation: by capacitating some nodes to perform WPT to their neighbours, to increase the accuracy of measurement collection and information exchange, and hence decrease the network mean-square-deviation (MSD)

Outline

System Description

- A WSN that performs diffusion least mean-squares (LMS) strategy.
- Each super nodes (SN) with L antennas performs beamforming to neighboring CNs. Assume the neighborhoods of any two SNs do not overlap.
- Some single-antenna common node (CN) can harvest RF-energy from a SN.

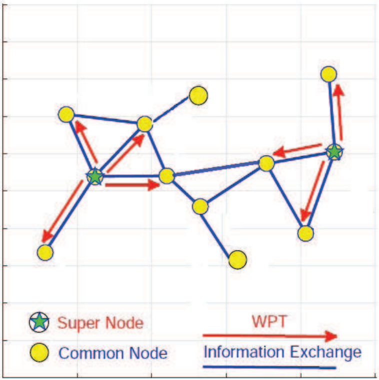


Figure: Example of Network topology

Set Notations

- Sets of all sensors, SNs and CNs are denoted by $\mathbb{N}$, $\mathbb{N}^{\mathsf{s}}$ and $\mathbb{N}^{\mathsf{c}}$, resp..
- Neighborhood of node k including itself: $\mathbb{N}_k$ with cardinality n_k
- Set of near-tier CNs (each being within the neighborhood of a SN): $\mathbb{N}^{\mathsf{c}}_{\mathsf{n}}$
- Set of far-tier CNs (each being not within the neighborhood of a SN): $\mathbb{N}^{\mathsf{c}}_{\mathsf{f}}$

Distributed estimation via least mean-squares (LMS)

- Parameter of interest: an unknown $M \times 1$ vector $\mathbf{w}^o$

- Measurement collected by sensor k in iteration i:

$$d_k(i) = \mathbf{u}_{k,i}\mathbf{w}^o + v_k(i), \tag{1}$$

  where $\mathbf{u}_{k,i}$ is $1 \times M$ random regression vector, $v_k(i)$ is measurement noise.

- Objective of WSN: to compute an estimate $\mathbf{w}$ of $\mathbf{w}^o$ in a distributed manner by solving LMS problem:

$$\min_{\mathbf{w}} \quad \sum_{k=1}^{N} E\left[|\mathbf{d}_k(i) - \mathbf{u}_{k,i}\mathbf{w}|^2\right]. \tag{2}$$

Adapt-then-combine (ATC) diffusion

- Each node k performs the following update equations [8]

$$\boldsymbol{\psi}_{k,i} = \mathbf{w}_{k,i-1} + \mu_k \mathbf{u}_{k,i}^* \left[d_k(i) - \mathbf{u}_{k,i}\mathbf{w}_{k,i-1} \right], \quad \text{(adapt)} \tag{3a}$$

$$\mathbf{w}_{k,i} = \sum_{l \in \mathbb{N}_k} a_{lk} \boldsymbol{\psi}_{l,i} + \widetilde{\mathbf{v}}_{k,i}, \quad \text{(combine)} \tag{3b}$$

  where μ_k is step-size, a_{lk} are (fixed) combination weights, and $\widetilde{\mathbf{v}}_{k,i}$ is the aggregate noise $\widetilde{\mathbf{v}}_{k,i} \triangleq \sum_{l \in \mathbb{N}_k \setminus \{k\}} a_{lk} \widetilde{\mathbf{v}}_{lk,i}$, with $\widetilde{\mathbf{v}}_{lk,i}$ being the noise vector for link from node $l \in \mathbb{N}_k$ to node k. Denote the matrix of a_{lk} by $\mathbf{A}$.
- Assume that elements of $\mathbf{u}_{k,i}$ are zero-mean and i.i.d.. Define $\mathbf{R}_k \triangleq E\left[\mathbf{u}_{k,i}^* \mathbf{u}_{k,i}\right]$ and $\mathcal{R} \triangleq \mathrm{diag}\left(\mathbf{R}_1, \cdots, \mathbf{R}_N\right)$.
- Both measurement noise $v_k(i)$ and link noise $\widetilde{\mathbf{v}}_{lk,i}$ are i.i.d., zero-mean, with variance σ_k^2 and $\widetilde{\sigma}_{lk}^2$, respectively. Aggregate noise $\widetilde{\mathbf{v}}_{k,i}$ is zero-mean, and has covariance matrix

$$\widetilde{\mathbf{R}}_k = \sum_{l \in \mathbb{N}_k \setminus \{k\}} a_{lk}^2 \widetilde{\sigma}_{lk}^2 \mathbf{I}_M. \tag{4}$$

(Steady-state) Network MSD

- Definition of network MSD

$$\text{MSD} \triangleq \lim_{i\to\infty} \frac{1}{N} \sum_{k=1}^{N} \mathbb{E}\left[\left\|\mathbf{w}^o - \mathbf{w}_{k,i}\right\|^2\right]. \quad (5)$$

- Give the following notations:

$$\mathcal{A} \triangleq \mathbf{A} \otimes \mathbf{I}_M,\ \mathcal{B} \triangleq \mathcal{A}^T \left(\mathbf{I}_{NM} - \mathcal{M}\mathcal{R}\right),\ \mathcal{F} \triangleq \mathcal{B} \otimes \mathcal{B}^* \quad (6)$$

$$\mathcal{M} \triangleq \text{diag}\left(\mu_1 \mathbf{I}_M,\ \cdots,\ \mu_N \mathbf{I}_M\right) \quad (7)$$

$$\mathcal{S} \triangleq \text{diag}\left(\sigma_1^2 \mathbf{R}_1,\ \cdots,\ \sigma_N^2 \mathbf{R}_N\right) \quad (8)$$

$$\widetilde{\mathcal{R}} \triangleq \text{diag}\left(\widetilde{\mathbf{R}}_1,\ \cdots,\widetilde{\mathbf{R}}_N\right), \quad (9)$$

where $\otimes$ is the Kronecker product.

Network MSD (cont.)

Lemma ([8])

Assuming the step-sizes $\{\mu_k\}$ is sufficiently small, the network MSD is given by

$$\text{MSD} = \frac{1}{N}\left[\text{vec}\left(\mathcal{A}^T\mathcal{M}\mathcal{S}\mathcal{M}\mathcal{A} + \widetilde{\mathcal{R}}\right)\right]^T \cdot (\mathbf{I}_{N^2M^2} - \mathcal{F})^{-1} \cdot \text{vec}(\mathbf{I}_{NM}). \tag{10}$$

Moreover, the MSD in (10) is upper bounded as follows

$$\text{MSD} \leq \frac{c^2}{N} \cdot \frac{\text{Tr}\left(\mathcal{A}^T\mathcal{M}\mathcal{S}\mathcal{M}\mathcal{A} + \widetilde{\mathcal{R}}\right)}{1 - [\rho(\mathbf{I}_{NM} - \mathcal{M}\mathcal{R})]^2}, \tag{11}$$

where c is some positive scalar.

- From (8), (9) and (4), the upper bound (11) depends on the the measurement-noise power $\{\sigma_k^2\}$ and the link-noise power $\{\widetilde{\sigma}_{lk}^2\}$. Hence, overall MSD can thus be reduced, if both the measurement-noise power and link-noise power are reduced.

Simultaneous Wireless Information and Power Transfer (SWIPT) from SNs

- Assume indep. Rayleigh fading, i.e., $\mathbf{h}_{lk,i} \sim \mathcal{CN}(\mathbf{0}_M, \beta_{lk}\mathbf{I}_L)$ with path loss β_{lk}.
- Beamformer for SWIPT from SN m

$$\mathbf{z}_{m,i} = \sum_{t \in \mathbb{N}_m} \sqrt{\xi_{mt}} \frac{\mathbf{h}^*_{mt,i}}{\|\mathbf{h}_{mt,i}\|}, \tag{12}$$

  where $\sum_{t \in \mathcal{N}_m} \xi_{mt} = 1$. Then, transmitted signal $\mathbf{y}_{m,i} = \sqrt{p_m} s_{m,i}\mathbf{z}_{m,i}$, with transmit power p_m.

- Power splitting at CN k, i.e., the streams $\sqrt{\rho_k}\acute{r}_{k,i}$ for RF-energy harvesting (EH) and $\sqrt{1-\rho_k}\acute{r}_{k,i}$ for information decoding (ID).

SWIPT from SNs (cont.)

- (Average) Harvested power by CN k

$$p_k^{\text{har}}(\xi_{mk}) = E_{\mathbf{z}_{m,i},\mathbf{h}_{mk,i}}\left[\left|\sqrt{p_m\rho_k}\mathbf{z}_{m,i}^T\mathbf{h}_{mk,i}x_{m,i}\right|^2\right]$$
$$= p_m\rho_k\beta_{mk}\big((L-1)\xi_{mk}+1\big). \quad (13)$$

- For ID, the recovered information vector $\boldsymbol{\psi}_{mk,i} = \boldsymbol{\psi}_{m,i} + \widetilde{\mathbf{v}}_{mk,i}$, where the power of link noise $\widetilde{\mathbf{v}}_{mk,i}$ is assumed to be proportional to the SINR, i.e.,

$$\widehat{\sigma}_{mk}^2(\xi_{kq}) = \frac{\alpha p_m\beta_{mk}(1-\rho_k)L\xi_{mk}}{p_m\beta_{mk}(1-\rho_k)\left(1-\xi_{mk}\right)+\grave{\sigma}_{mk}^2}, \quad (14)$$

  where $\grave{\sigma}_{mk}^2$ is the power of baseband noise $\grave{n}_{mk,i}$ for ID, constant α depends on the digital modulation order, quantization order, etc..

Harvested Power Allocation and Noise Reduction

- Default power for CN to perform sensing and transmission are b_l^{sen} and b_l^{tr}, resp.
- Near-tier CN k uses p_k^{sen} and p_k^{tr} as additional power for measurement sensing and information transmission, resp..
- Using higher power to sense more samples and taking the sample mean as the measurement, the measurement-noise power

$$\widehat{\sigma}_k^2 = \begin{cases} \widehat{\sigma}_k^2(p_k^{\mathsf{sen}}) = \frac{b_k^{\mathsf{sen}}\sigma_k^2}{b_k^{\mathsf{sen}}+p_k^{\mathsf{sen}}}, & \text{if } k \in \mathbb{N}_{\mathsf{n}}^{\mathsf{c}} \\ \sigma_k^2, & \text{if } k \in \mathbb{N}_{\mathsf{f}}^{\mathsf{c}} \cup \mathbb{N}^{\mathsf{s}} \end{cases} \tag{15}$$

- Since higher transmission power decreases the link-noise, the link-noise power for node q

$$\widehat{\sigma}_{kq}^2 = \begin{cases} \frac{b_k^{\mathsf{tr}}\widetilde{\sigma}_{kq}^2}{b_k^{\mathsf{tr}}+p_m\rho_k\beta_{mk}((L-1)\xi_{mk}+1)-p_k^{\mathsf{sen}}}, & \text{if } k \in \mathbb{N}_{\mathsf{n}}^{\mathsf{c}},\ q \neq k \\ \frac{\alpha p_k\beta_{kq}(1-\rho_q)L\xi_{kq}}{p_k\beta_{kq}(1-\rho_q)\left(1-\xi_{kq}\right)+\grave{\sigma}_{kq}^2}, & \text{if } k \in \mathbb{N}^{\mathsf{s}},\ q \in \mathbb{N}_{\mathsf{n}}^{\mathsf{c}} \\ \widetilde{\sigma}_{kq}^2, & \text{if } k \in \mathbb{N}_{\mathsf{f}}^{\mathsf{c}} \end{cases} \tag{16}$$

Problem Formulation

- Objective: minimize the upper-bound of network MSD in (11)
- *Variables*: beamforming parameters $\{\boldsymbol{\xi}_m = [\xi_{m1}\ \xi_{m2} \cdots \xi_{mn_m}]^T\}$, and the power $\mathbf{p}_m^{\text{sen}} = [p_{k_1}^{\text{sen}} p_{k_2}^{\text{sen}} \cdots p_{k_{n_m}}^{\text{sen}}]^T$ allocated to local sensing
- MSD minimization problem:

$$(\text{P1}) \min_{\{\boldsymbol{\xi}_m\},\ \{\mathbf{p}_m^{\text{sen}}\}} \quad f_m(\mathbf{p}_m^{\text{sen}}, \boldsymbol{\xi}_m) \triangleq \sum_{k\in\mathbb{N}_{\text{n}}^{\text{c}}} \left[\frac{c_{1k}}{b_k^{\text{sen}} + p_k^{\text{sen}}} + \frac{c_{2k}}{c_{3k}(\xi_{m,k}) - p_k^{\text{sen}}} + c_{4k}(\xi_{mk}) \right] \tag{17a}$$

$$\text{s. t.} \quad 0 \le p_k^{\text{sen}} \le c_{3k}(\xi_{mk}) - b_k^{\text{tr}} \tag{17b}$$

$$\sum_{k\in\mathbb{N}_m\setminus\{m\}} \xi_{mk} = 1, \quad \forall\, m \in \mathbb{N}^{\text{s}} \tag{17c}$$

$$0 \le \xi_{mk} < 1, \quad \forall m \in \mathbb{N}^{\text{s}}, \forall\, k \in \mathbb{N}_{\text{n}}^{\text{c}} \tag{17d}$$

where c_{1k} and c_{2k} are constants depending on k, and the quantities

$$c_{3k}(\xi_{mk}) = b_k^{\text{tr}} + p_m \rho_k \beta_{mk}\big((L-1)\xi_{mk} + 1\big), \tag{18}$$

$$c_{4k}(\xi_{mk}) = \frac{\alpha p_m \beta_{mk}(1-\rho_k) L \xi_{mk} M a_{mk}^2}{p_m \beta_{mk}(1-\rho_k)(1-\xi_{mk}) + \dot{\sigma}_{mk}^2}. \tag{19}$$

Outline

Primal Decomposition

- Lower-level subproblems: for each near-tier CN k, to optimize local harvested power allocation p_k^{sen} for given $\boldsymbol{\xi}_m$, i.e.,

$$\begin{aligned}(\text{P2}) \min_{p_k^{\text{sen}}} \quad & g_k(p_k^{\text{sen}}, \xi_{mk}) \triangleq \frac{c_{1k}}{b_k^{\text{sen}} + p_k^{\text{sen}}} \\ & + \frac{c_{2k}}{c_{3k}(\xi_{mk}) - p_k^{\text{sen}}} + c_{4k}(\xi_{mk}) && \text{(20a)} \\ \text{s. t.} \quad & 0 \le p_k^{\text{sen}} \le c_{3k}(\xi_{mk}) - b_k^{\text{tr}}. && \text{(20b)}\end{aligned}$$

- Higher-level master problems: for each SN m, to update the beamforming parameters (i.e., coupling variables) $\boldsymbol{\xi}_m$, i.e.,

$$\begin{aligned}(\text{P3}) \min_{\boldsymbol{\xi}_m} \sum_{k \in \mathbb{N}_{\text{m}}} & \left[\frac{c_{1k}}{b_k^{\text{sen}} + p_k^{\text{sen}\star}} + \frac{c_{2k}}{c_{3k}(\xi_{mk}) - p_k^{\text{sen}\star}} + c_{4k}(\xi_{mk})\right] && \text{(21a)} \\ \text{s. t.} \quad & \sum_{k \in \mathbb{N}_m \setminus \{m\}} \xi_{mk} = 1, && \text{(21b)} \\ & 0 \le \xi_{mk} < 1, \quad \forall\, k \in \mathbb{N}_{\text{m}}^{\text{s}} \setminus \{m\} && \text{(21c)}\end{aligned}$$

  where $p_k^{\text{sen}\star}(\xi_{mk})$ is the optimal solution to (P2) for given ξ_{mk}.

- The set defined by (21b) and (21c) is denoted by $\boldsymbol{\Xi}$.

Solution to (P2) and subgradient

- Closed-form solution of subproblem (P2):

$$p_k^{\mathsf{sen}\star} = \max\left\{\min\left\{\frac{c_{3k}(\xi_{m,k})-\sqrt{c_{2k}/c_{1k}}b_k^{\mathsf{tr}}}{1+\sqrt{c_{2k}/c_{1k}}}, c_{3k}(\xi_{m,k})-b_k^{\mathsf{tr}}\right\}, 0\right\}$$

- Subgradient of subproblem (20):

$$s_k(p_k^{\mathsf{sen}\star}, \xi_{mk}) = \partial g_k(p_k^{\mathsf{sen}\star}, \xi_{mk}) - \lambda^\star(\xi_{mk}), \tag{22}$$

  where $\lambda^\star(\xi_{mk})$ is the optimal Lagrange multiplier w.r.t constraint (20b).
- Let $\mathbf{s}_m = [s_{k_1}(p_k^{\mathsf{sen}\star}, \xi_{mk}) \cdots s_{k_{n_m}}(p_k^{\mathsf{sen}\star}, \xi_{mk})]^T$.

Subgradient-based Algorithm

- To find the optimal solutions for each SN m and its neighboring CNs:

Algorithm 1 Subgradient-based Algorhtim:

Initialization: a proper step-size θ, small positive constants ε, iteration index $t = 0$, some feasible $\boldsymbol{\xi}_m(0) \in \Xi$.
repeat
  SN m sends $\xi_{mk}(t)$ to each neighboring CN $k \in \mathbb{N}_m$.
  Each CN k finds the optimal power for sensing $p_k^{\mathsf{sen}\star}(t)$ and the subgradient $s_k(p_k^{\mathsf{sen}\star}(t), \xi_{mk}(t))$, and sends them back to SN m.
  SN m updates $\boldsymbol{\xi}_m$ by using the subgradient method

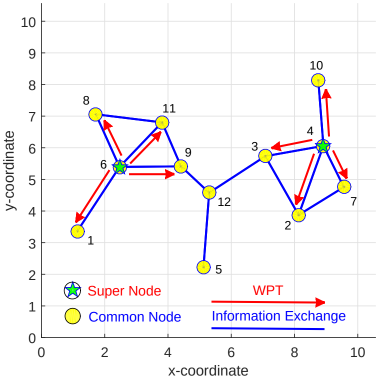
$$\boldsymbol{\xi}_m(t+1) = [\boldsymbol{\xi}_m(t) - \theta \mathbf{s}_m(t)]_{\Xi},$$

  where $[\cdot]_{\Xi}$ is the projection onto the feasible set Ξ.
  $t = t + 1$.
until $|\boldsymbol{\xi}_m(t) - \boldsymbol{\xi}_m(t-1)| > \varepsilon$
return $\boldsymbol{\xi}_m^\star = \boldsymbol{\xi}_m(t)$, $\mathbf{p}_m^{\mathsf{sen}\star} = \mathbf{p}_m^{\mathsf{sen}\star}(t)$.

Outline

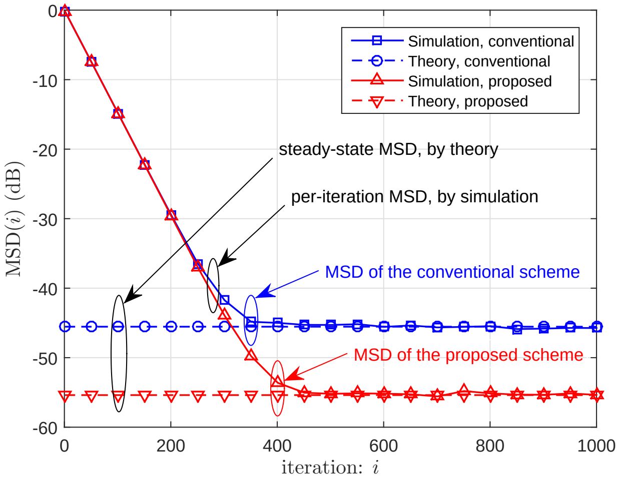
Simulation parameters

- Measure.-noise power for CNs and SNs: uniform in $[-25, -10], [-35, -25]$dB
- Link-noise power for all nodes: uniform in $[-70, -60]$ dB
- Uniform combination [5], i.e., $a_{lk} = \frac{1}{n_k}$, if $l \in \mathbb{N}_k$, and zero otherwise
- $M = 2, L = 4, p_4 = p_6 = 1$ W, $b_k^{\text{sen}} = 10^{-4}$ W, $b_k^{\text{tr}} = 10^{-3}$ W, $\mu_k = 0.01$, $\mathbf{R}_k = 1.6862 \times \mathbf{I}_2$; Path loss: $\beta_{lk} = 10^{-2} d_{lk}^{-2}$ (Note: d_{lk} with unit of meter)



Network MSD performance

- Achieve 9.85 dB lower MSD than that of the conventional scheme without WPT
- Steady-state MSD matches theoretical results (10)



Outline

Conclusion

1. For a hybrid WSN performing adapt-then-combine diffusion strategy, optimal wireless power transfer and harvested power allocation are obtained, to minimize the network-wide MSD.
2. Numerical results show that the MSD is significantly reduced compared to the conventional diffusion strategy without WPT, since the proposed scheme decreases the CNs' measurement-noise power and increases their transmission power.

Q&A

Thanks for your attendance!

Questions?

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