

# RF Power Source and Estimation Diversity in Distributed Sensing with Passive Wireless Communications

*A. Ozan Bicen* and *Ozgur B. Akan*

Next-generation Wireless Communications Laboratory,  
Department of Electrical and Electronics Engineering,  
Koc University, Istanbul, 34450, Turkey.  
Email: {abicen, akan}@ku.edu.tr

## Abstract

Sensor nodes constitute a distributed wireless sensing architecture, such that, multiple sensors report their observations. However, sensor networks are comprised of energy-constrained nodes. Therefore, there have been many efforts to devise energy-efficient communication algorithms for sensor networks to achieve reliable and energy-efficient distributed wireless sensing. Recently, to mitigate battery depletion problem and extend network lifetime, wireless passive sensor networks (WPSN) have become a new field of interest. Modulated backscattering is an important communication technique in WPSN to alleviate reaching unlimited lifetime for sensor nodes. In this paper, we theoretically analyze event distortion in WPSN that is employing modulated backscattering for communication. First, we model backscattered power by sensor nodes at RF sources using log-normal channel model. Then, using the backscattered power gain of sensor nodes, the mean square error of estimated signal is analyzed for various number of RF sources and power levels in WPSN. The objective of this work is to reveal the impact of RF source diversity on event estimation distortion in WPSN.

## 1 Introduction

Wireless sensor networks (WSN) are characterized by their low-cost, low-power, and collaborative sensing nature. Due to limited-sizes, price-constraints, and random deployment, it is not generally feasible to deploy sensor nodes with large batteries and perform maintenance of individual batteries. Since power consumption of sensor nodes is dominated by its communication capabilities, wireless passive sensor networks (WPSN) [1] have been proposed to benefit from power radiated by RF sources to overwhelm depletion of energy sources of sensor nodes.

Power radiated by RF sources can be used either for charging batteries or modulated backscattering by sensor nodes [1]. As long as 100mV of voltage is induced on the receiving antenna, RF-to-DC converter could provide DC power [2] which can be used to operate sensor node or charge battery to be used later. With modulated backscattering communication technique, a WPSN node can modulate the incident wave from RF source by changing its antenna impedance [3]. Since the communication power consumption is higher than other units' for sensor nodes, modulated backscattering can help to resolve the lifetime constraint of traditional WSN. RF sources can gather the wave backscattered by sensor nodes, and either they can participate in distributed estimation of event signal or send the gathered information to an information collection center.

Estimation distortion in WPSN is closely coupled by the number and power of RF sources, i.e., RF source diversity, since modulated backscattering employing sensor nodes use the intercepted power from RF sources to transmit their observations. In this work, we analyze the estimation diversity based on RF source diversity in WPSN. We develop an analytical model for estimation distortion which incorporates power radiated by RF sources. Backscattered power by WPSN nodes at RF source via modulated backscattering in WPSN is derived in Section 2, and then, the mean square error for the best linear unbiased estimator is provided in Section 3. Based on theoretical analysis, simulation results for RF source and estimation diversity in WPSN are presented in Section 4. The outcomes of this work constitute a strong theoretical background that can be used in the design of reliable and efficient communication techniques for WPSN. Finally, the concluding remarks are given in Section 5.

## 2 Backscattered Power in WPSN

Here, we model the backscattered power by WPSN nodes at RF sources. Since WPSN nodes communicate via modulated backscattering, they use received power from RF sources to transmit their observations. Therefore, we started our analysis with modeling of the power of the delivered observations to RF sources. We have used log-normal channel model [4] for our backscattered power calculations. Path-loss for power intercepted by sensor node  $k$  from RF source  $l$ , can be calculated as

$$\left( \frac{P_{k,l}^i}{P_l^{RF}} \right)_{dB} = 10 \log_{10} K_{k,l}^i - 10 \gamma \log_{10} \left( \frac{d_{k,l}}{d_0} \right) - \psi_{dB} \quad (1)$$

where  $d_0$  is the reference distance,  $d_{k,l}$  is the distance between sensor node  $k$  and RF source  $l$ ,  $K_{k,l}^i$  is the intercepted power from RF source  $l$  by sensor node  $k$  at distance  $d_0$ ,  $\gamma$  is the path-loss exponent, and  $\psi_{dB}$  is a Gaussian random variable with zero mean and  $\sigma_{\psi_{dB}}^2$  variance. Reference path loss for power radiated by RF source  $l$ , i.e., path loss for intercepted power by sensor node  $k$  at distance  $d_0$  from RF source  $l$ , can be calculated according to Friis model [5] as  $K_{k,l}^i = \frac{P_{d_0}^i}{P_l^{RF}} = \left( \frac{G_l^{RF}}{4\pi d_0^2} \right) \cdot \sigma_k$ , where  $G_l^{RF}$  is the antenna gain of RF source  $l$ ,  $\sigma_k$  is the radar cross section (RCS) area for sensor node  $k$ . Path loss for received power at RF source  $m$  from sensor node  $k$  can be calculated as

$$\left( \frac{P_{k,m}^r}{P_{k,l}^i} \right)_{dB} = 10 \log_{10} K_{k,m}^r - 10 \gamma \log_{10} \left( \frac{d_{k,m}}{d_0} \right) - \psi_{dB} \quad (2)$$

where  $K_{k,m}^r = \frac{P_{d_0}^r}{P_{k,l}^i} = \frac{G_m^{RF}}{4\pi d_0^2} \cdot A_{em}$ , and  $A_{em}$  is the antenna effective area for RF source  $m$ , i.e.,  $A_{em} = \frac{G_m^{RF} \lambda_k^2}{4\pi}$ , for  $\lambda_k$  is the wavelength of the transmitted wave by sensor  $k$ . Finally, backscattered power via modulated backscattering by sensor  $k$  at RF source  $m$  in WPSN can be found as

$$\begin{aligned} P_{k,m}^r &= \sum_{l=1}^L P_{k,l}^i_{dB} + \left( \frac{P_{k,m}^r}{\sum_{l=1}^L P_{k,l}^i} \right)_{dB} = \sum_{l=1}^L \left( P_l^{RF}{}_{dBm} + \left( \frac{P_{k,l}^i}{P_l^{RF}} \right)_{dB} \right) + \left( \frac{P_{k,m}^r}{\sum_{l=1}^L P_{k,l}^i} \right)_{dB} \\ &= \sum_{l=1}^L \left( P_l^{RF}{}_{dBm} + 10 \log_{10} K_{k,l}^i - 10 \gamma \log_{10} \left( \frac{d_{k,l}}{d_0} \right) - \psi_{l,dB} \right) + 10 \log_{10} K_{k,m}^r - 10 \gamma \log_{10} \left( \frac{d_{k,m}}{d_0} \right) - \psi_{dB} \quad (3) \end{aligned}$$

$P_{k,m}^r$  shows the received power level at RF source  $m$ , as a function of power radiated by RF source  $l$ , distances of sensor nodes to the power radiating RF source  $d_{k,l}$  and information receiving RF source  $d_{k,m}$ , path-loss exponent  $\gamma$ , and shadowing variance  $\psi$ . Based on the received power  $P_{k,m}^r$ , we derive the event estimation distortion in the next section.

## 3 Best Linear Unbiased Estimation in WPSN

We employ the best linear unbiased estimator (BLUE) [6] at RF sources, since we do not assume any specific distribution for sensed signal and noise. Observation  $s_k(t)$  is the distorted version of random signal  $\theta(t)$  by observation noise  $n_k^s(t)$ , i.e.,  $s_k(t) = \theta(t) + n_k^s(t)$ , at sensor  $k$  and time  $t$ . We also assume that both  $\theta(t)$  and  $n_k^s(t)$  are i.i.d. over time. Each sensor broadcast the signal  $s_k(t)$  to RF sources, where  $\theta(t)$  is estimated from the received version of  $s_k(t)$ . We also assume that  $\theta(t)$  and  $n_k^s(t)$  have zero mean and has a power of  $\sigma_\theta^2$  and  $\sigma_k^2$ , respectively. We assume RF sources communicate with sensors over single hop via  $k$  orthogonal channels that experience independent shadowing ( $\psi$ ) and zero-mean AWGN ( $n_k^c$ ). We also assume that synchronization is achieved between each sensor and RF power source, and hence, effect of phase is eliminated. Motivated by the results in [7], each sensor employs analog amplify and forward uncoded transmission. Under independence over time assumption, time indices are ignored for all variables. Power gain  $\delta_{k,m}$  for the sensed signal  $s_k$  by sensor  $k$  that is received at RF source  $m$  can be determined as

$$\delta_{k,m} = \sqrt{\frac{P_{k,m}^r}{\sigma_\theta^2 + \sigma_k^2}} \quad (4)$$

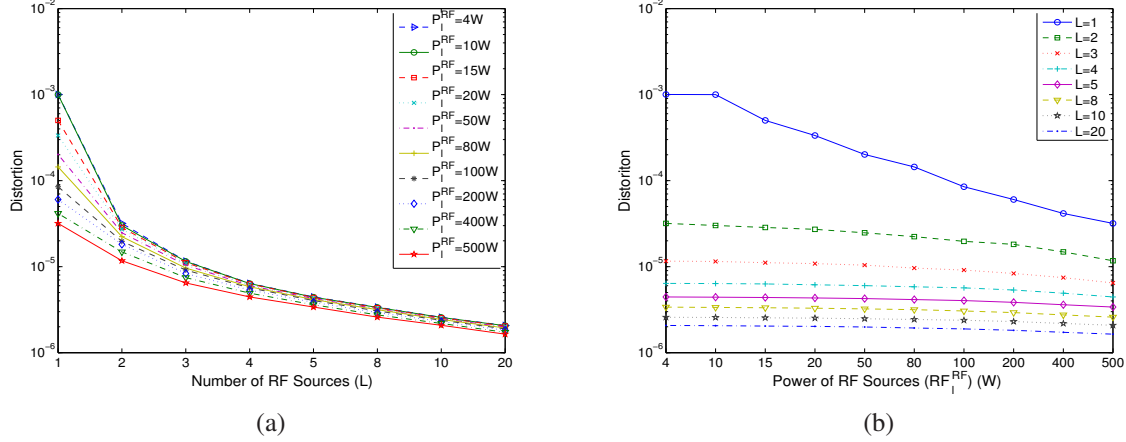


Figure 1: Estimation distortion vs number of RF sources (a) and power levels (b) in WPSN.

Received sample vector at RF source  $m$ , i.e.,  $\mathbf{r}_m$ , is as  $\mathbf{r}_m = \mathbf{h}_m\theta + \mathbf{n}_m$ , where  $\mathbf{r}_m = [r_{1,m}, \dots, r_{K,m}]^T$ ,  $\mathbf{h}_m = [\delta_{1,m}, \dots, \delta_{K,m}]^T$ , and  $\mathbf{n}_m = [\delta_{1,m}n_1^s + n_1^c, \dots, \delta_{K,m}n_K^s + n_K^c]^T$ . Noise covariance matrix  $\mathbf{R}_m$  for received samples at RF source  $m$  is a  $K$  dimensional rectangular diagonal matrix whose diagonal entries are  $\delta_{k,m}^2\sigma_k^2 + \eta_k^2$  for  $k = 1 \dots K$ , and other entries are 0. Hence, the mean square error for BLUE can be determined as [6]

$$Var[\hat{\theta}_m] = [\mathbf{h}_m^T \mathbf{R}_m^{-1} \mathbf{h}_m]^{-1} = \left( \sum_{k=1}^K \frac{1}{\sigma_k^2 + \eta_k^2 / \delta_{k,m}^2} \right)^{-1} \quad (5)$$

It is deduced from (5) that the estimation distortion decreases with increasing  $\delta_{k,m}$ . Distortion in the event estimation indicates how reliably event features can be extracted from sensor observations. In Section 4, we analyze the distortion function in (5) to quantitatively explore the effects of RF source and estimation diversity in WPSN.

## 4 Analysis and Results

We placed 10000 passive sensor nodes in a 1000x1000 m area with a grid topology. BLUE employing RF sources are randomly distributed inside this field with a varying number from 1 to 20. Simulations are repeated 10 times and results are averaged.  $P_l^{RF}$  is kept constant for all  $l$ , and varied from 4 W to 500 W.  $\gamma$  and  $\psi_{dB}$  are kept constant as 3 and 3.8, respectively.  $d_0$  is taken as 100 m. It is assumed that at least 100 mW must be intercepted by sensor node to operate [2], and received signal power level at RF sources must be greater than  $-90$  dBm due to typical receiver sensitivity levels [5].  $\sigma_\theta^2$  and  $\sigma_k^2$  are assumed to be 1 and 0.01, respectively. Antenna gains  $G_l^{RF}$  are neglected, i.e., set equal to 1, for all  $l$ . AWGN variance ( $\eta_k^2$ ) is set to  $-90$  dBm for all  $k$ . Simulation results are presented in Fig. 1.

In Fig. 1 (a), with the increasing number of RF sources for a fixed power level, estimation distortion decreases with increasing number of reporting sensors, i.e., estimation diversity, since the number of activated sensor nodes increases with the number of RF sources. Similarly, in Fig. 1 (b) estimation distortion decreases with increasing power level of RF sources for a fixed number, since power gain of active sensors and number of activated sensors increase with the power level of RF sources. We call this decrease in the distortion due to estimation diversity and increasing power level as RF source diversity gain for reliable event estimation in WPSN.

On the other hand, it is observed in Fig. 1 (a) and Fig. 1 (b) that achieved event estimation distortion cannot be further reduced after a certain number of RF sources or power level, respectively. Thus, considerable amount of energy can be saved via joint consideration of the required number of RF sources and power level for reliable event estimation. Moreover, in Fig. 1, it can be observed that event estimation distortion can be more effectively decreased via increasing

the number of RF sources than increasing the power level of RF sources. However, bad channel characteristics may require higher power radiation by RF sources to achieve reliability, while increasing number of reporting source nodes may cause higher contention delays in cases where orthogonal channels cannot be reserved for sensors. Sufficient number of RF sources and their desired power levels for reliable event estimation may change based on varying channel characteristics and number of activated sensor nodes. Thus, adaptive RF source activation and power level adjustment can be employed. RF sources may be mobilized and circulate collaboratively the passive sensor field for event estimation at required reliability level.

## 5 Conclusion

In this work, we presented an analysis of event distortion in WPSN with respect to RF source diversity. We modeled the intercepted power by sensor nodes and backscattered power at RF sources in WPSN. Then, we presented event estimation distortion analysis for BLUE. Simulation results reveal that via increasing number of RF sources or power radiated by RF sources, estimation distortion can be decreased, i.e., RF source diversity can be benefited in WPSN to achieve reliable event estimation. Future work includes development of efficient RF source deployment and power adjustment algorithms to improve distributed estimation performance in WPSN.

## 6 Acknowledgments

This work was supported in part by the Turkish Scientific and Technical Research Council under grant #110E249 and by the Turkish National Academy of Sciences Distinguished Young Scientist Award Program (TUBA-GEBIP).

## 7 References

1. O. B. Akan, M. T. Isik, and B. Baykal, "Wireless Passive Sensor Networks," *IEEE Communications Magazine*, vol. 47, no. 8, pp. 92-99, August 2009.
2. F. Kocer, P. M. Walsh, and M. P. Flynn, "Wireless, remotely powered telemetry in 0.25 $\mu$ m CMOS," in *Proc. IEEE Radio Frequency Integrated Circuits Symposium (RFIC)*, pp. 339-342, June 2004.
3. M. Kossel, H. R. Benedickter, R. Peter, and W. Bachtold, "Microwave backscatter modulation systems," *2000 IEEE MTT-S Digest*, vol. 3, pp. 1427-1430, June 2000.
4. M. Zuniga and B. Krishnamachari, "Analyzing the transitional region in low power wireless links," in *Proc. IEEE SECON'04*, Oct. 2004, pp. 517-526.
5. C. A. Balanis, *Antenna Theory: Analysis and Design*, 2nd ed. John Wiley and Sons Inc., 1997.
6. J. M. Mendel, *Lessons in Estimation Theory for Signal Processing, Communications, and Control*, Englewood Cliffs, NJ: Prentice-Hall, 1995.
7. M. Gastpar, B. Rimoldi, and M. Vetterli, "To code, or not to code: lossy source-channel communication revisited," *IEEE Trans. Inf. Theory*, vol. 49, pp. 1147-1158, May 2003.