Power Efficient Wireless Sensor Networks with Distributed Transmission-Induced Space Spreading

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***Abstract*— Distributed multi-transmission is proposed for power-efficient and fault-tolerant multi-hop wireless sensor networks where a signal can be received and transmitted by multiple sensors. Multi-transmission with scrambling has advantages of both space-spreading and diversity. Efficient and robust blind equalization algorithms are developed. Network power efficiency can be greatly enhanced. Fault-tolerance is studied under constraints of limited system resources.**

I. Introduction

Wireless sensor networks contain a large number of densely deployed sensors which form a dynamic multi-hop network. Each transmission by a sensor results in simultaneous reception by multiple other sensors in the network. It is therefore possible for the data packet to be re-transmitted by multiple nodes (sensors) during each hop. In most existing protocols, although multiple standby sensors constantly listen to or receive every transmission, only one sensor is usually selected to perform transmission to the next hop [2], [3]. This single-transmission scheme may not be the best one in sensor networks where bandwidth efficiency becomes of secondary importance relative to power efficiency. A more serious concern is with the compromise of network efficiency by inadequate reliability of a single sensor. Single-transmission may waste rather than reserve resources because of the need to detect transmission failure and arrange for retransmission.

The fact that energy may not be replenished in a sensor network makes power efficiency a dominating design criterion. Since wireless transceivers consume a major portion of battery power, it is desirable to improve their power efficiency. In particular, power-efficient channel identification/equalization and diversity techniques become necessary in harsh communication environment with severe multipath, deep fading as well as high sensor failure rate. This is the case, for example, when signals transmitted by sensors near ground experience more rapid attenuation and severe fading [1].

In this paper, we show how a new scheme of multi-transmission can successfully tackle the above problems. In this scheme, each data packet is transmitted in a distributed manner by multiple sensors. Since bandwidth is usually not a limiting factor in wireless sensor networks, we will attempt to maximize the network power efficiency and reliability under the constraint of bandwidth.

A sensor may be in one of the four states: sleep, standby, receiving and transmission. Existing studies suggest that powers used in standby state and in receiving state are similar [4]. Therefore, asking more standby nodes to receive data may not reduce power efficiency. On the other hand, if the same received data packet is transmitted by multiple sensors, a multi-transmission diversity is effectively created, where transmitting power required for each data packet can be much less than that for a single transmission.

Another problem considered in this paper is blind equalization in sensor networks. Obviously, training methods waste much power because of the need for repeated training. Unfortunately, most of the existing blind methods may not be suitable for sensor networks [8]. The most severe problem is that most of them fail on ill-conditioned channels [5]. In contrast, during multi-transmission, the receiving node obtains signals from multiple sensors. This property can be utilized to develop efficient and robust blind equalization algorithms.

The third benefit is that fault-tolerance can be naturally supported. Multi-hop network with single-transmission suffers greatly from sensor failures. With the multi-transmission scheme, we will show that the system reliability can be much improved.

The organization of this paper is as follows. In Section II, we introduce the multi-transmission system model. In Section III, we develop blind algorithms. In Section IV, we analyze the power efficiency. In Section V, we study the fault tolerance. Simulations are shown in Section VI and conclusions are in Section VII.

II. Multi-transmission in wireless sensor networks

We consider the wireless sensor network illustrated in Fig. 1, where a sensor needs to transmit data packets to the remote receiver through a multi-hop wireless network. During intermediate hop i, data packets from the sensors are received by multiple nodes, e.g., Nodes $j = 1, \cdots, J$. Then all these nodes can re-transmit the data packets to the next hop. Each data packet will be transmitted J times during this hop, once per node.

Consider the hop i. The baseband signal received by a receiver in the cluster $i+1$ from the transmitter j in the cluster

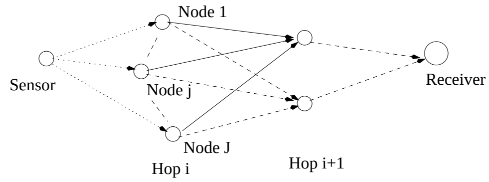

Fig. 1. System model of wireless sensor networks.

i is

$$x_j(n) = \sum_{\ell=0}^{L_h} \alpha_j h_j(\ell) s_j(n-\ell) + v_j(n), \quad j = 1, \cdots, J \quad (1)$$

where $s_j(n)$ is the transmitted symbol by node j, $v_j(n)$ is AWGN, and $h_j(\ell)$ denotes the baseband FIR channel coefficient. For convenience, we assume $\sum_{\ell=0}^{L_h} |h_j(\ell)|^2 = 1$, and the power of the received signal is represented by $\alpha_j \geq 0$.

We stack $N+1$ received samples together as sample vectors $\mathbf{x}_j(n)$. Then

$$\mathbf{x}_j(n) = \alpha_j \mathcal{H}_j \mathbf{s}_j(n) + \mathbf{v}_j(n) \quad (2)$$

where the $(N+1) \times (N+L_h+1)$ channel matrix is

$$\mathcal{H}_j = \begin{bmatrix} h_j(0) & \cdots & h_j(L_h) & & \\ & \ddots & & \ddots & \\ & & h_j(0) & \cdots & h_j(L_h) \end{bmatrix}. \quad (3)$$

III. Blind symbol estimation

We propose to scramble the transmitted signals of each node. Assume all nodes $j = 1, \cdots, J$ need transmit the same signal $s(n)$. Instead of transmitting $s(n)$ directly, each node j transmits a scrambled signal

$$s_j(n) = s(n) c_j(n), \quad 1 \leq j \leq J \quad (4)$$

where $\{c_j(n)\}$ is a pseudo-noise (PN) sequence. We require that $E[c_j(n) c_i^*(m)] = \delta(j-i)\delta(n-m)$.

Note that this scheme is similar to direct-sequence spread-spectrum (DSSS). However, in our case, the spreading is performed in space with a distributed manner.

A. Blind channel estimation

From (2) and (4), we define the cross-correlation matrix between Nodes i and j as

$$\mathbf{R}_{ji} = E[\mathbf{x}_j(n) c_j^*(n-d) \mathbf{x}_i^H(n) c_i(n-d)], \quad (5)$$

where the parameter d satisfies

$$L_h \leq d \leq N. \quad (6)$$

Because the PN sequences, symbols and noises are independent from each other, we have

$$\mathbf{R}_{ji} \quad = \quad \alpha_j \alpha_i \mathbf{h}_j(d) \mathbf{h}_i^H(d) \sigma_s^2, \quad (7)$$

where $(\cdot)^H$ denotes Hermitian, $\mathbf{h}_j(d)$ and $\mathbf{h}_i(d)$ are the $(d+1)^{\text{th}}$ columns of $\mathcal{H}_j$ and $\mathcal{H}_i$, respectively. Specifically,

$$\mathbf{h}_j(d) = [\mathbf{0}_{d-L_h}, h_j(L_h), \cdots, h_j(0), \mathbf{0}_{N-d}]^T, \quad (8)$$

where $\mathbf{0}_m$ is an m dimensional zero vector, and $(\cdot)^T$ denotes transpose.

Consider estimating the channel of Node j with signals from all J nodes. From (5) we obtain an $(N+1) \times [(J-1)(N+1)]$ matrix

$$\mathbf{R}_j = [\mathbf{R}_{j1}, \cdots, \mathbf{R}_{j,j-1}, \mathbf{R}_{j,j+1}, \cdots, \mathbf{R}_{jJ}]. \quad (9)$$

Since from (7) each column in $\mathbf{R}_j$ is simply a weighted version of the column $\mathbf{h}_j(d)$, the matrix is with rank 1. We can use the following two ways to estimate channels efficiently from (7) and (9).

The first way is to simply use a column in the matrix $\mathbf{R}_j$ with sufficiently large magnitude as channel estimation. The second way is to combine all the columns in $\mathbf{R}_j$ together recursively. To begin, we initialize with any non-zero column from $\mathbf{R}_j$, which can in fact be determined by the first way. Let such a column be $\mathbf{R}_j(:,m)$, where we use the MATLAB notation to denote the m^{th} column. Then we can estimate $\mathbf{h}_j(d)$ recursively as

$$\begin{aligned} \hat{\mathbf{h}}_j^{(0)} &= \mathbf{R}_j(:,m) \|\mathbf{R}_j(:,m)\|, \quad \text{if } \mathbf{R}_j(:,m) \neq \mathbf{0}, \\ \hat{\mathbf{h}}_j^{(k)} &= \begin{cases} \hat{\mathbf{h}}_j^{(k-1)} + \frac{\mathbf{R}_j(:,k) \mathbf{R}_j^H(:,k) \hat{\mathbf{h}}_j^{(k-1)}}{\|\hat{\mathbf{h}}_j^{(k-1)}\|}, & k \neq m. \\ \hat{\mathbf{h}}_j^{(k-1)}, & k = m. \end{cases} \end{aligned} \quad (10)$$

Proposition 1. The procedure (10) converges to $\hat{\mathbf{h}}_j = \mathbf{h}_j(d) e^{j\theta} \alpha_j^2 \sigma_s^2 \sum_{1 \leq i \leq J,\ i \neq j} \alpha_i^2$.

Proof: See [8].

B. Blind equalization

Once channels are estimated blindly, we can estimate linear filter equalizer $\mathbf{f}_j$ from the constrained optimization

$$\arg\min_{\mathbf{f}_j} \ \|\mathbf{f}_j^H \mathbf{x}_j(n)\|^2, \quad s.t., \quad \mathbf{f}_j^H \hat{\mathbf{h}}_j = 1, \quad (11)$$

where $\hat{\mathbf{h}}_j$ is assumed normalized. It is well known that (11) converges to the MMSE equalizer

$$\mathbf{f}_j = \mathbf{R}_{jj}^{-1} \hat{\mathbf{h}}_j (\hat{\mathbf{h}}_j^H \mathbf{R}_{jj}^{-1} \hat{\mathbf{h}}_j)^{-1}, \quad (12)$$

where $\mathbf{R}_{jj} = E[\mathbf{x}_j(n) \mathbf{x}_j^H(n)]$.

Symbol $s(n)$ can be estimated with information from all J nodes. For signals from node j, the equalizer output is

$$y_j(n) = \mathbf{f}_j^H \mathbf{x}_j(n) = \alpha_j s_j(n-d) + \mathbf{f}_j^H \mathbf{v}_j(n) + u_j(n), \quad (13)$$

where $u_j(n)$ is the residual inter-symbol interference (ISI)

$$u_j(n) = \alpha_j \mathbf{f}_j^H \mathcal{H}_j \mathbf{s}_j(n) - \alpha_j s_j(n-d). \quad (14)$$

From (4) and (13) we can estimate the symbol $s(n-d)$ from

$$y(n) = \sum_{j=1}^{J} y_j(n) c_j^*(n-d) = \sum_{j=1}^{J} \alpha_j s(n-d) + w(n) + u(n), \quad (15)$$

where the noise and ISI parts are

$$\begin{cases} w(n) &= \sum_{j=1}^{J} c_j^*(n-d) \mathbf{f}_j^H \mathbf{v}_j(n) \\ u(n) &= \sum_{j=1}^{J} c_j^*(n-d) u_j(n). \end{cases} \quad (16)$$

If α_j is known or estimated (from the received signal energy $E[|x_j(n)|^2] = \alpha_j^2\sigma_s^2 + \sigma_v^2$), then we can modify (15) to $y(n) = \sum_{j=1}^{J} \alpha_j y_j(n) c_j^*(n-d)$.

If the number of samples is limited or channels vary relatively fast, we can use batch processing to take better utilization of available samples. From (9), (10), (12) and (15), the batch algorithm is obtained with complexity $O(N^2)$.

On the other hand, if the sample amount is sufficient, we can use the extremely efficient adaptive implementation. First, to avoid correlation matrix estimation, we use the first way for channel estimation, i.e., estimate only one column of the correlation matrix [*c.f.* (5), (7)]

$$\hat{\mathbf{h}}_j^{(n)} = \mu_h \hat{\mathbf{h}}_j^{(n-1)} + \mathbf{x}_j(n) x_i^*(n-q) c_j^*(n-d) c_i(n-d), \quad (17)$$

where μ_h is used to track time-variation, and we need choose i and $q \in [0, L_h]$ online so that $\|\hat{\mathbf{h}}_j^{(n)}\|$ is sufficiently large. Second, with the temporarily estimated channel, we adaptively implement (11) for equalizer estimation by the Frost's Algorithm [8]

$$\mathbf{f}_j^{(n+1)} = \hat{\mathbf{h}}_j^{(n)} + [\mathbf{I} - \hat{\mathbf{h}}_j^{(n)} (\hat{\mathbf{h}}_j^{(n)})^H][\mathbf{f}_j^{(n)} - \mu_f \mathbf{x}_j(n) \mathbf{x}_j^H(n) \mathbf{f}_j^{(n)}], \quad (18)$$

where $\mathbf{I}$ is an identity matrix and μ_f is used to adjust convergence.

The computational complexity of the adaptive algorithm is $O(N)$. In addition, the new algorithms are robust to ill channel conditions, as can be easily seen from (7) and (12).

IV. Power efficiency of multi-transmission

To compare the power efficiency of multi-transmission against single-transmission, we consider the signal-to-interference-and-noise ratio (SINR) during symbol detection (15)-(16). The noise part $w(n)$ is with zero mean and variance

$$\sigma_w^2 = E[w(n)w^*(n)] = \sum_{j=1}^{J} \|\mathbf{f}_j\|^2 \sigma_v^2, \quad (19)$$

whereas the ISI part is with zero mean and variance

$$\sigma_u^2 = E[u(n)u^*(n)] = \sum_{j=1}^{J} \alpha_j^2 (\mathbf{f}_j^H \mathcal{H}_j \mathcal{H}_j^H \mathbf{f}_j - 1)\sigma_s^2. \quad (20)$$

Note that α_j is assumed constant or slowly time-varying for each node j so that channel estimation is feasible but random across sensors. Then the SINR is

$$r = \frac{(\sum_{j=1}^{J} \alpha_j)^2 \sigma_s^2}{\sigma_w^2 + \sigma_u^2}. \quad (21)$$

The SINR of single-transmission is simply the case with $J = 1$. To simplify the problem, we consider noise and ISI separately.

First, we analyze signal-to-noise-ratio (SNR) with the assumption of zero ISI and normalized equalizer, i.e., $\mathbf{f}_j^H \mathbf{f}_j = 1$. The SNR at the receiver is

$$r|_{\sigma_u=0} = \frac{\sigma_s^2}{J\sigma_v^2} \left(\sum_{j=1}^{J} \alpha_j \right)^2. \quad (22)$$

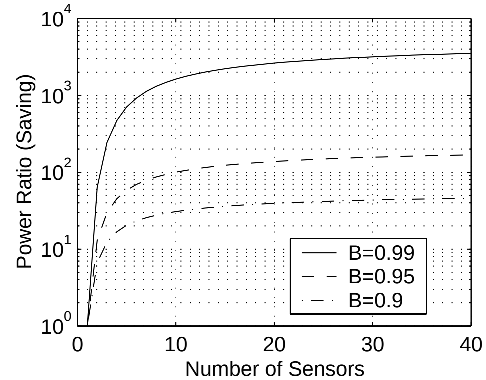

Fig. 2. Power ratio of single-transmission to multi-transmission ($\tilde{\beta}/\beta_J$) to achieve 15 dB SNR with probability B.

The key point that makes multi-transmission more power efficient than single-transmission is that the total transmission power increases linearly with J, whereas SER decreases inversely according to the J^{th} power of average SNR thanks to the multi-transmission-induced diversity.

Proposition 2. Let the total power be $JE[\alpha_j^2]\sigma_s^2$ and the power of each sensor in multi-transmission be $E[\alpha_j^2]\sigma_s^2$. If $E[\alpha_j^2]\sigma_s^2/\sigma_v^2 \gg 1$, then multi-transmission has much less SER than single-transmission, or can use much less power to achieve the same SER as the other.

Proof. See [8].

For reliable performance, the SNR $r|_{\sigma_u=0}$ should be above some threshold value with a high probability. According to (22), we need choose carefully the power $\beta_J = E[\sum_{j=1}^{J} \alpha_j^2]\sigma_s^2$ such that

$$P[\sum_{j=1}^{J} \alpha_j^2 > A] = B, \quad (23)$$

where A is determined by the required SNR for low SER. Since $\sum_{j=1}^{J} \alpha_j^2$ is Chi-square distributed with J degrees of freedom, we have $0 < A \ll \beta_J/\sigma_s^2$ for high probability $B \to 1$.

Proposition 3. Let $\tilde{\beta} = E[\tilde{\alpha}^2]\sigma_s^2$ be the power of single-transmission. For multi-transmission, there exists $\beta_J < \tilde{\beta}$ such that $P[\sum_{j=1}^{J} \alpha_j^2 > A] = P[\tilde{\alpha}^2 > A]$.

Proof. See [8].

For example, assume $\tilde{\beta} = 1$, $\tilde{\sigma}^2 = 1$, and $\sigma_v^2/\sigma_s^2 = 0.01$. To achieve 15 dB SNR with probabilities $B = 0.99$, 0.95, and 0.9, power reduction compared to single-transmission is shown in Fig. 2, which verifies that multi-transmission is more power efficient than single-transmission in fading environment.

Next, we consider the benefits of multi-transmission on residual ISI reduction. With the absence of noise, SINR (21) becomes SIR

$$r|_{\sigma_v=0} = \frac{(\sum_{j=1}^{J} \alpha_j)^2}{\sum_{j=1}^{J} \alpha_j^2 (\mathbf{f}_j^H \mathcal{H}_j \mathcal{H}_j^H \mathbf{f}_j - 1)}. \quad (24)$$

Hence, increasing transmission power does not change SIR. Assume that coefficients of $\mathbf{f}_j^H \mathcal{H}_j$ are Gaussian distributed.

Residual ISI can be modeled with Chi-square distribution. Then similarly as the SNR case, multi-transmission reduces average ISI, or reduce the outage probability resulted from heavy residual ISI in ill-conditioned channels.

Finally, because multi-transmission with scrambling can be considered as spreading in space, it is interesting to compare it with traditional direct-sequence spread-spectrum (DSSS) techniques. They have the same transmission power when J equals DSSS processing gain. However, for small J, space-spreading may be better because DSSS suffers greatly from the loss of orthogonality in multipath fading environment. In addition, DSSS with single-transmission suffers more from random power loss (α_j^2) and sensor failure.

V. Fault-tolerance

In this section, we analyze the fault tolerance property of multi-hop sensor networks with multi-transmissions. Based on the result of the analysis, we determine, for each hop, the number of active sensors that participate in every packet transmission in a K-cluster sensor network. Our goal is to maximize the signal availability for the overall network.

Assume that during the useful life of a sensor, the number of failures per packet transmission, or failure rate, remains at a constant level λ. Then the failure probability density function, and respectively, the reliability for the sensor, can be shown to be exponential [6], i.e.,

$$f^{Snsr}(t) = \lambda e^{-\lambda t}, \quad R^{Snsr}(t) = e^{-\lambda t}. \tag{25}$$

The general notion of current age t of a sensor is now specialized to the number of packet transmissions the sensor has carried out so far.

Consider a wireless sensor network of which a design life T_D is expected. A *design life* is defined as the time at which a prescribed network failure probability P^F is reached, i.e., $F^F(t)|_{t=T_D} = P^F$ where $F^F(t)$ is the cumulative distribution function of the network failure probability. The network reliability, or the probability that the network has no failure within the time interval $(0,t)$, is given by $R(t) = 1 - F^F(t)$. The K-hop network composite failure probability is given by

$$F^F(t) = 1 - \prod_{i=1}^{K}(1 - F_i^F(t)), \tag{26}$$

where $F_i^F(t)$ is the cumulative distribution function of the i-th hop failure probability.

Suppose at least k sensors must survive to guarantee a sufficient receiving signal power by the sensors of the next hop. With the involvement of J_i out of I_i sensors in every packet transmission, the cluster failure probability can be shown to be [6]

$$F_i^F(t) = \sum_{r=0}^{k-1} \binom{J_i}{r} [R^{Snsr}(t)]^r [1 - R^{Snsr}(t)]^{J_i - r}, \tag{27}$$

where $R^{Snsr}(t)$ is given in (25).

Let us first discuss the effect of duty cycle J_i/I_i on the cluster failure probability with I_i fixed. It can be observed

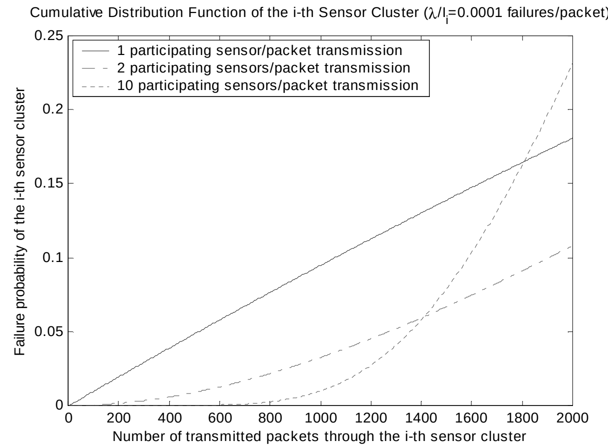

Fig. 3. Cluster failure time distribution with varying number of participating sensors.

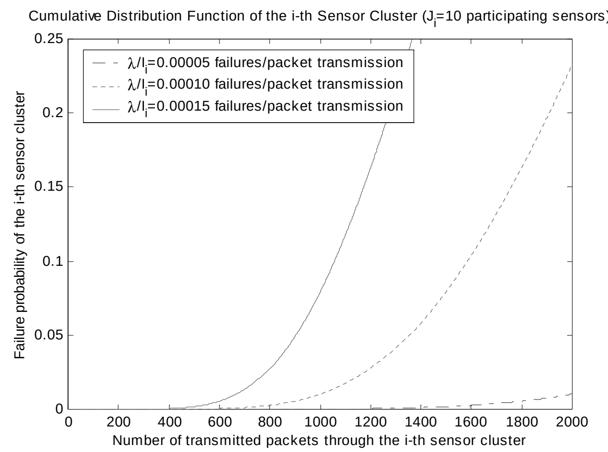

Fig. 4. Cluster failure time distribution with varying effective sensor failure rate.

from Fig. 3 that the cluster reliability benefits from the participation of a larger number of redundant "young" sensors. As the cluster ages, however, the cluster reliability suffers from the more rapid aging of its sensors due to their highly stressful lives as the result of the larger duty cycle.

We next examine the effect of sensor number I_i in a cluster with both J_i and λ fixed. As shown in Fig. 4, at a specified design life T_D, the larger the number of sensors, the more reliable is the sensor cluster. Or equivalently, to achieve the same cluster reliability, a larger I_i implies a longer design life T_D. This is the direct consequence of a reduced effective failure rate λ/I_i.

A reliability-centric design problem for wireless sensor networks can now be formulated. This problem can be classified into the general class of resource allocation problem under constraints.

Problem. For each given I_i, $i = 1, \cdots, K$, select the number of participating sensors $J_i \in [J_{i,min}, J_{i,max}]$, such that each cluster achieves the highest reliability at a specified T_D.

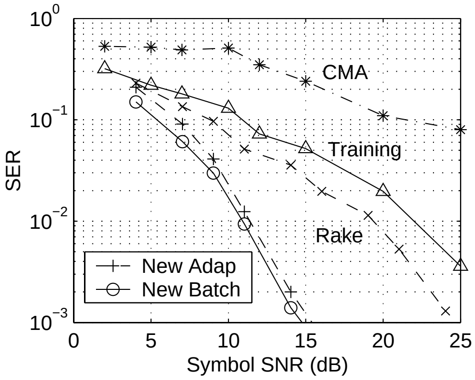

Fig. 5. SER vs. symbol SNR. Random α_j per run per sensor. 8 sensors and 500 symbols for the new methods.

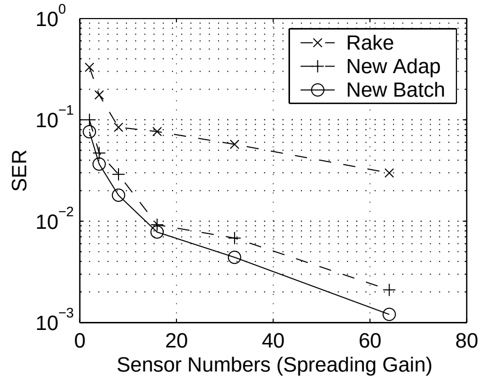

Fig. 6. SER vs. number of sensors J. 500 symbols. Symbol SNR 10 dB.

Solution. Determine the value of J_i that has the smallest failure probability $F_i^F(t)$ at T_D as per (27). Use (26) to obtain the composite failure probability of the network.

In reference to Fig. 3, for example, if $J_{i,min}$ and $J_{i,max}$ have been determined to be 1 and 10, respectively, for a design life of 2000 packet transmissions, the obvious solution for cluster i is $J_i = 2$ at which a cluster reliability of 0.89 is achieved. If it is required that the cluster reliability must exceed 0.99, one must either be content with a shorter design life at 1000 packet transmissions with $J_i = 10$, or find a way, such as network re-organization, to boost I_i for this cluster to 150% of the original number as shown in Fig. 4.

When contention exists among clusters, the network reliability maximization must be tackled as a whole. One way to avoid the situation of a combinatorial explosion in search for optimal numbers of participating sensors is to follow the operational approach described in [7] by which optimal redundancy configuration at each hop can be determined using constrained dynamic programming.

VI. Simulations

We compared our new algorithms (denoted as *New Batch* and *New Adap*) with training-based algorithm (*Training*) [5], blind CMA, and DSSS with Rake receiver.

QPSK was used. $L_h = 5$. Channels for each sensor were randomly generated. The equalizer length was 18. Symbol-error-rate (SER) was used as performance measure. α_j was randomly generated during each run according to Rayleigh distribution with unit mean and variance 0.2733. We used 500 symbols and 8 sensors for our new algorithms. Similarly, Rake used 500 symbols and processing gain 8. However, 4000 symbols were used in Training and CMA. As shown in Fig. 5, the new algorithms both outperformed the others.

We also compared the new methods and Rake when various number of sensors or processing gain was applied. As shown in Fig. 6, DSSS with Rake clearly suffered from random fading and multipath channels. In contrast, our new algorithms could take the advantage of increased diversity of multi-transmissions.

In summary, the new algorithms have robust and superior performance. Lower SER indicated in Fig. 5 can be utilized to save transmission power. To achieve the same SER 0.01, the new algorithms need less transmission power, which is shown in Table. I. For example, compared with training-based single-transmission, multi-transmission reduced power consumption, and hence prolong sensor lifetime, by 14.1 times.

	New (Batch)	New (Adap)	Training	CMA	DSSS (Rake)
Power	1	1.12	14.1	>89	7.1

TABLE I

POWER (NORMALIZED TO THAT OF NEW BATCH ALGORITHM) REQUIRED FOR SER 0.01.

VII. Conclusions

In this paper, we propose to use distributed multi-transmission in wireless sensor networks to achieve space-spreading and diversity. Transmission power can be greatly reduced in multipath fading environment. Simplified and robust blind channel equalization algorithms are developed. Fault tolerance of wireless sensor networks is also analyzed.

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