Application-Specific Node Clustering of IR-UWB Sensor Networks with Two Classes of Nodes

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Abstract— **Energy efficiency and low cost hardware are prerequisites for a successful deployment of wireless sensor networks. Many applications of wireless sensor networks require a transmission from sensor nodes to a common sink. A formation of node clusters and a hierarchical transmission scheme can be employed to increase the area that can be covered by the sensor network, which is limited by the transmission range of the nodes. Algorithms for node clustering usually assume that each sensor node potentially can take over the role of a cluster head. In this paper, it is assumed that only a pre-determined subset of all nodes is capable of becoming cluster head, resulting in decreased system complexity. A node clustering algorithm that accounts for this restriction is presented and the performance of a clustered sensor network for distributed detection is analyzed depending on the fraction of potential cluster head nodes.**

I. Introduction

Wireless sensor networks have a wide range of applications like detection of events or monitoring and tracking of objects in a region of interest. They consist of a large number of locally dispersed sensor nodes, which are usually powered by batteries with limited energy. To realize a sensor network with low cost and maximum lifetime it is crucial to employ low complexity hardware as well as power-aware communication algorithms and protocols. Low complexity transceiver circuitry can be accomplished by impulse radio ultra-wideband (IR-UWB). Moreover, IR-UWB requires only low transmission power, has a high system capacity and is resilient against multi-path fading and is therefore assumed to be an enabling technology for wireless sensor networks. For many sensing applications, possibly pre-processed observations of the sensor nodes have to be conveyed to a central point for further processing. The exemplary application considered in this paper is the detection of events in a region of interest, which is often the initial task in an overall sensing application. In distributed detection, the sensor nodes process their observations locally and make preliminary decisions about state of the observed environment, e.g., absence or presence of a target. The local decisions are transmitted to a fusion center and combined to obtain a final detection result with high reliability [1]. The primary performance metric for a sensor network for this application should be the minimization of the global probability of detection error [2].

If the nodes transmit their local decisions directly to the fusion center, the nodes' limited transmission range restricts the area that can be covered by the sensor network. This problem can be addressed by the formation of node clusters and a hierarchical transmission of the decisions to the fusion center via cluster heads. For the generation of such a hierarchical network topology several algorithms have been suggested (e.g., [3], [4], [5]). The algorithms differ in their objectives, their complexity and the assumptions for the multiple access scheme. Most node clustering algorithms premise that every node in the network is capable of becoming cluster head. This guarantees the greatest space of possible topology configurations, among which the one that maximizes the performance metric should be chosen. On the other hand, this flexibility comes with a higher hardware complexity for the sensor network since the additional administrative tasks of a cluster head increase the hardware complexity. Moreover, a cluster head might need more energy provided by a larger battery than an ordinary node for its operation. As only a small fraction of all nodes really becomes a cluster head, this additional complexity of the remaining nodes is useless once the topology is set up. In this paper, we therefore assume two classes of sensor nodes. While the more complex and expensive nodes from the first class are capable of becoming cluster head, the nodes from the second class can only act as leaf nodes. In the context of standard IEEE 802.15.4 similar node classes are referred to as full function devices (FFDs) and reduced function devices (RFDs), respectively. This notation will be used in the remainder of the paper. To account for these two node classes special node clustering algorithms are required. We extend a node clustering algorithm from [6], which is tailored for distributed detection, such that it can deal with two node classes. We analyze the performance degradation dependent on the fraction of FFDs among all nodes and point out how it can be compensated by an increased total transmission power of the network.

The remainder of the paper is organized as follows. In Section II, the system model is introduced. The considered detection application is described in Section III. The node clustering algorithm is stated in Section IV and finally, in Section V we present and discuss numerical results.

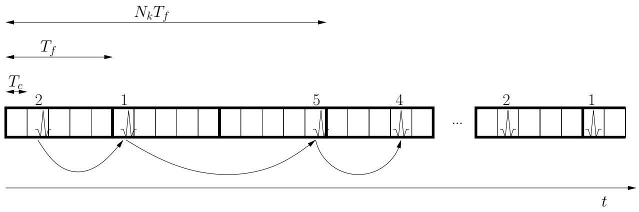

Fig. 1. Illustration of parameters used in the system model. In the example $c^{(k)} = (2,1,5,4)$, $d_1^{(k)} = 1$, $d_2^{(k)} = 0$, and $N_k = 3$.

II. System Model

A. Network model

We consider a clustered sensor network with a set $\mathcal{N} = \{S_1, \ldots, S_N\}$ of sensor nodes. Among these nodes is a subset $\mathcal{F} \subseteq \mathcal{N}$ of full function devices (FFDs) which are capable of becoming cluster head. The nodes of the non-empty subset $\mathcal{M} \subseteq \mathcal{F}$ act as cluster heads after the node clustering procedure is performed. The remaining nodes $\mathcal{L} = \mathcal{N} \setminus \mathcal{M}$ act as leaf nodes. Each leaf node is associated to exactly one cluster head by the mapping

$$c \colon \mathcal{L} \to \mathcal{M}. \tag{1}$$

The set of nodes that transmit to the same cluster head $S_m \in \mathcal{M}$ is denoted by $\mathcal{C}_m$.

B. Impulse Radio Ultra-Wideband (IR-UWB)

We assume IR-UWB as transmission scheme of the sensor nodes [7]. The transmitted IR-UWB signal $s_j(t)$ of sensor node S_j can be written as

$$s_j(t) = A_j \sum_{i=-\infty}^{\infty} w(t - iT_f - c_i^{(j)} T_c - \alpha d_{\lfloor i/N_j \rfloor}^{(j)}). \tag{2}$$

where $d^{(j)}$ are the data bits, which are transmitted by a number of N_j subsequent equally modulated impulses of amplitude A_j and shape $w(t)$. In each frame of length T_f one impulse is transmitted resulting in an ultra-wide occupancy of the frequency spectrum. Data bits are assumed to be coded by binary pulse position modulation (PPM) with modulation index α. Multiple access to the channel is realized by pseudo random time hopping codes c_i which reduce the probability of repeated collisions of pulses from two transmitters at a receiver position. Inside a frame, the pulse is delayed by an integer multiple of the chip length T_c given by the hopping code. Fig. 1 illustrates the transmission scheme. The resulting signal-to-interference and noise ratio (SINR) γ_j of the link between node S_j and the corresponding receiver S_{m_j} reads as

$$\gamma_j = N_j \frac{g_{jm_j} p_j}{\varsigma^2 \sum_{k \neq j} g_{km_j} p_k + \frac{\eta_{m_j}}{T_f}}, \tag{3}$$

where η_{m_j} is the energy of the additional noise at the receiver. A vector $\boldsymbol{p}$ with minimum transmission power levels of the nodes, that realizes given SINR requirements $\gamma_1, \ldots, \gamma_N$ can be computed by

$$\boldsymbol{p} = [\boldsymbol{I} - \boldsymbol{\Gamma} \boldsymbol{N}^{-1} \boldsymbol{B}]^{-1} \boldsymbol{\tau}. \tag{4}$$

The diagonal matrices $\boldsymbol{\Gamma}$ and $\boldsymbol{N}$ contain the SINR requirement γ_j and the number of pulse repetitions for one data bit N_j of node S_j as the jth entry. The entries b_{ij} of matrix $\boldsymbol{B}$ read as

$$b_{ij} = \begin{cases} \sigma^2 g_{jm_i} / g_{im_i}, & i \neq j \\ 0, & i = j \end{cases}.$$

The elements τ_j of the positive vector $\boldsymbol{\tau}$ are

$$\tau_j = \frac{\eta_{m_j} \gamma_j}{T_f N_j g_{jm_j}}.$$

More details and different possibilities of an efficient implementation of the power control procedure can be found in [5].

III. Distributed Detection in Tree Networks

The considered application for the sensor network is distributed detection of signal sources in a region of interest. The problem of distributed detection in tree networks under consideration of noisy communication channels is shortly described in the following. A more comprehensive description can be found, e.g., in [6]. We consider a binary hypothesis testing problem with hypotheses H_0, H_1 indicating the state of the observed environment (e.g., absence or presence of a target) and associated prior probabilities $\pi_0 = P(H_0)$, $\pi_1 = P(H_1)$. In order to detect the true state of nature, sensors $S_1, \ldots, S_N$ collect an array of random observations $(X_1, \ldots, X_N) \in \mathcal{X}_1 \times \cdots \times \mathcal{X}_N$ which is generated according to either H_0 or H_1. The random observations $X_1, \ldots, X_N$ are assumed to be conditionally independent across sensors given the underlying hypothesis and distributed according to

$$H_0 \colon X_j \sim \mathcal{N}(0, \sigma_j^2), \quad H_1 \colon X_j \sim \mathcal{N}(\mu_j, \sigma_j^2), \tag{5}$$

for all S_j. The variance σ_j^2 describes Gaussian background noise and the mean μ_j indicates the deterministic signal component under hypothesis H_1 at sensor S_j. The local observation signal-to-noise ratio (SNR) at sensor S_j is given by

$$\mathrm{SNR}_j = 10 \log_{10} \left(\frac{\mu_j^2}{\sigma_j^2} \right) \quad [\mathrm{dB}]. \tag{6}$$

A. Leaf node decision rules

The leaf nodes $S_j \in \mathcal{L}$ process their respective observations X_j independently by forming local decisions

$$U_j = \delta_j(X_j), \quad S_j \in \mathcal{L}. \tag{7}$$

In the case of binary quantization, the leaf node decision rules are mappings $\delta_j \colon \mathcal{X}_j \to \{0, 1\}$. Each local decision U_j is characterized by the following local false alarm and miss probabilities

$$P_{f_j} = P(U_j = 1 | H_0), \tag{8}$$
$$P_{m_j} = P(U_j = 0 | H_1). \tag{9}$$

B. Transmission of local decisions

Each leaf node $S_j \in \mathcal{L}$ transmits its decision U_j to its associated cluster head $S_{m_j} \in \mathcal{M}$ and each cluster head $S_m \in \mathcal{M}$ transmits its decision U_m to the fusion center. Due to noisy channels, the received decisions $\widetilde{U}_j$ and $\widetilde{U}_m$ are potentially corrupted. We model the communication channels $C_1, \ldots, C_N$ of both the leaf nodes and the cluster heads by binary symmetric channels with bit-error probabilities $\varepsilon_1, \ldots, \varepsilon_N$, i.e.

$$\varepsilon_j = P(\widetilde{U}_j = 1|U_j = 0) = P(\widetilde{U}_j = 0|U_j = 1) \tag{10}$$

for $S_j \in \mathcal{N}$. Modified detection error probabilities $\widetilde{P}_{f_j} = P(\widetilde{U}_j = 1|H_0)$ and $\widetilde{P}_{m_j} = P(\widetilde{U}_j = 0|H_1)$ including errors from the communication channels are then given as

$$\begin{aligned} \widetilde{P}_{f_j} &= P_{f_j} + \varepsilon_j(1 - 2P_{f_j}), \\ \widetilde{P}_{m_j} &= P_{m_j} + \varepsilon_j(1 - 2P_{m_j}). \end{aligned} \tag{11}$$

Physically, the bit-error probability ε_j results from distortions caused by noise and multi-user interference. For the IR-UWB system considered in Section II, ε_j is related to the SINR γ_j by

$$\varepsilon_j = \frac{1}{2}\text{erfc}(\sqrt{\gamma_j}), \quad S_j \in \mathcal{N}. \tag{12}$$

Using the power assignment algorithm (4), SINR values of all links can be controlled. We determine SINR requirements $\gamma_1, \ldots, \gamma_N$ by a cross-layer approach described in [8]. This approach aims to maximize the global detection performance given a maximum total transmission power p_{tot}. According to the strategy SINR requirement γ_j of node S_j is determined by

$$\gamma_j = \left(\frac{g_{jm_j}}{g_{\max}}\right) \cdot \left(\frac{\partial \widetilde{\lambda}_j}{\partial \gamma_j}\right)^{-1}(\varrho), \tag{13}$$

where g_{jm_j} is the path gain between S_j and its receiver normalized by the maximum path gain $g_{\max}$ and $\widetilde{\lambda}_j$ is the effective sensor weight of sensor S_j, which is defined as

$$\widetilde{\lambda}_j = \log\left(\frac{(1 - \widetilde{P}_{f_j})(1 - \widetilde{P}_{m_j})}{\widetilde{P}_{f_j}\widetilde{P}_{m_j}}\right), \quad S_j \in \mathcal{N}. \tag{14}$$

The total transmission power p_{tot} can be controlled by the trade-off parameter ϱ (see [8]).

C. Cluster head decision rules

Each cluster head $S_m \in \mathcal{M}$ processes its observation X_m with respect to the received local decisions from the leaf nodes. E.g., if the cluster head S_m receives the subset $\widetilde{U}_1, \ldots, \widetilde{U}_k$ of local decisions from the leaf nodes of its cluster $\mathcal{C}_m$, it makes a decision

$$U_m = \delta_m(X_m, \widetilde{U}_1, \ldots, \widetilde{U}_k), \tag{15}$$

where the cluster head decision rule δ_m is a mapping $\delta_m \colon \mathcal{X}_m \times \{0,1\}^k \to \{0,1\}$.

D. Optimal channel-aware fusion rule

At the fusion center, the received decisions $\widetilde{U}_m$ from the cluster heads $S_m \in \mathcal{M}$ are combined to yield the final decision U_0, where the fusion rule δ_0 is a Boolean function $\delta_0 \colon \{0,1\}^{|\mathcal{M}|} \to \{0,1\}$. The sensor network detection performance is measured in terms of the global probability of error $P_e = \pi_0 P_f + \pi_1 P_m$, which is a weighted sum of the global probability of false alarm $P_f = P(U_0 = 1|H_0)$ and the corresponding global probability of miss $P_m = P(U_0 = 0|H_1)$.

IV. Node Clustering for IR-UWB Sensor Networks with Two Classes of Nodes

In this section, we present an application-specific algorithm that performs the clustering of the sensor network into a tree structure as considered in the previous section. It extends the algorithm in [6] in order to deal with the described two node classes. The algorithm selects the non-empty set of cluster heads $\mathcal{M}$ among the set of all FFD nodes $\mathcal{F}$. The remaining nodes $\mathcal{L} = \mathcal{N} \setminus \mathcal{M}$ act as leaf nodes. Every leaf node is associated to exactly one cluster head according to (1). The set of nodes that transmit to the same cluster head $S_m \in \mathcal{M}$ is denoted by $\mathcal{C}_m$. A formal description of the algorithm is given in Algorithm 1. It starts with an initialization of the already introduced sets $\mathcal{M}$, $\mathcal{L}$, $\mathcal{F}$ and $\mathcal{N}$. Initially, set $\mathcal{H}$ is empty, and $\mathcal{S}$ contains all FFD nodes. Parameter d_{tr} is the maximum transmission range of the nodes. The cluster head selection is based on an application specific node metric μ. Since RFDs are not capable of becoming cluster head, the metric is only computed for FFDs. For each FFD node $S_j \in \mathcal{F}$ the metric $\mu(S_j)$ is given by

$$\mu(S_j) = \left(\left(\frac{1}{|\mathcal{T}_j|}\sum_{S_i \in \mathcal{T}_j} d_{ji}\right) \cdot d_j^{\text{FC}}\right)^{-1} \cdot \text{SNR}_j, \quad S_j \in \mathcal{F}, \tag{16}$$

Algorithm 1 Algorithm for node clustering with two classes of nodes

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Initialize:
d_ij ← sqrt((x_i − x_j)^2 + (y_i − y_j)^2);  S_i, S_j ∈ N
M ← ∅;
H ← ∅;
L ← N;
S ← F;
T_j ← {S_i ∈ N | d_ji ≤ d_tr};  S_j ∈ F
μ(S_j) ← (((1/|T_j|) Σ_{S_i ∈ T_j} d_ji) · d_j^FC)^{−1} · SNR_j;  S_j ∈ F
while S ≠ ∅ do
    S_k = arg max_{S_j ∈ S} μ(S_j);
    M ← M ∪ S_k;
    L ← L \ S_k;
    H ← {S_j ∈ S | d_kj < d_tr};
    S ← S \ H;
end while
C_m ← {S_j ∈ L | d_jm < d_jn, S_n ∈ M \ S_m};   S_m ∈ M
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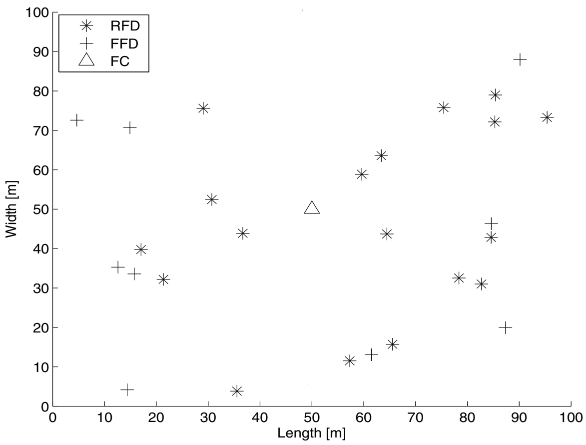

Fig. 2. Exemplary random scenario. Crosses denote FFDs which are capable of becoming cluster head, stars denote RFDs which can only act as leaf nodes and the triangle symbolizes the fusion center.

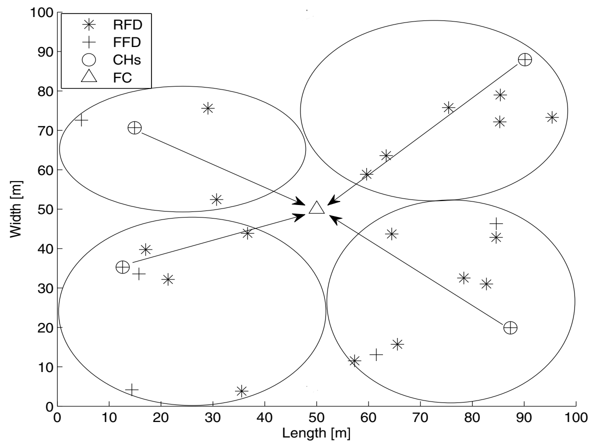

Fig. 3. Scenario after clustering. All nodes inside an ellipse form a cluster. Inside a cluster, the leaf nodes (FFDs and RFDs) transmit to their circled cluster head, which in the second step transmits to the fusion center.

where d_{ji} is the distance between nodes S_j and S_i, d_j^{FC} denotes the distance of S_j to the fusion center and SNR_j is the observation SNR of S_j according to (6). Set $\mathcal{T}_j$ includes all nodes (FFDs and RFDs) inside the maximum transmission range d_{tr} of node S_j. The metric aims to minimize the necessary transmission power by privileging cluster configurations with low distances between transmitters and receivers. Furthermore, FFD nodes with a high local observation SNR are favored to become cluster head, because it was observed in [9], that it is advantageous for hierarchical detection networks to order sensors from least reliable to most reliable detection quality.

In the main loop of the algorithm, the FFD node of $\mathcal{S}$ with the maximum value of μ is chosen as cluster head. Afterwards, all neighboring FFD nodes of the new cluster head being in $\mathcal{S}$ are deleted from $\mathcal{S}$. This means, that these FFD nodes cannot become a cluster head anymore and will act as a leaf node. If $\mathcal{S}$ is non-empty the process returns to the beginning of the loop and selects the next cluster head. When the loop is finished and all cluster heads have been selected, all remaining leaf nodes consisting in general of FFDs and RFDs are associated to the spatially nearest cluster head. Fig. 2 and Fig. 3 illustrate the clustering for an exemplary random scenario.

V. Numerical Results

In this section, we present simulation results. Special emphasis is put on the influence of the fraction of FFDs among all nodes. Table I lists the simulation parameters.

For the simulation, N sensor nodes with a varying fraction of FFDs were randomly placed in an area of size A. The local observation signal-to-noise ratios $\mathrm{SNR}_1, \ldots, \mathrm{SNR}_N$ of the nodes are assumed to be independent and identically uniformly distributed between 0 and 10 dB. After generating the tree topology with Algorithm 1, the global probability of detection error P_e is determined for a given total transmission power p_{tot}. The SINR requirements for the communication links are computed according to (13). The pathloss is assumed proportional to $d_{jm_j}^{-\beta}$, where d_{jm_j} is the distance between node S_j and its receiver S_{m_j}.

While for a decreasing fraction of FFDs among all nodes the probability of detection error increases (Fig. 4), it decreases with an increasing total transmission power p_{tot} (Fig. 5). For the network designer these facts imply, that a performance degradation caused by a decreased fraction of the more expensive FFD nodes can be compensated by an increased total transmission power of the network. In Fig. 6 the first two figures (Fig. 4 and Fig. 5) are combined in a 3D plot. On the ground plane a contour plot with isolines of equal detection error probabilities is shown. All combinations of the fraction of FFDs and the total transmission power on such a line result in the same global probability of detection error. In Fig. 7 a more detailed view on the contour plot is given. It can be observed that the slope of the curves is almost flat for higher fractions of FFDs. This implies that to maintain a given detection error probability the fraction of FFDs can be reduced substantially without spending much additional transmission power. To achieve a very low probability of detection error P_e, the fraction of FFDs cannot be chosen arbitrarily small. For a probability of detection error of, e.g., 10^{-4} the fraction

TABLE I

Parameters used in the simulation.

parameter	value
N	40
A	$100\,\mathrm{m} \times 100\,\mathrm{m}$
d_{tr}	$35\,\mathrm{m}$
β	2
ς^2	$1.9966 \cdot 10^{-3}$
N_j	10
T_c	$2\,\mathrm{ns}$
T_f	$100\,\mathrm{ns}$
η	$10^{-11}\,\mathrm{J}$

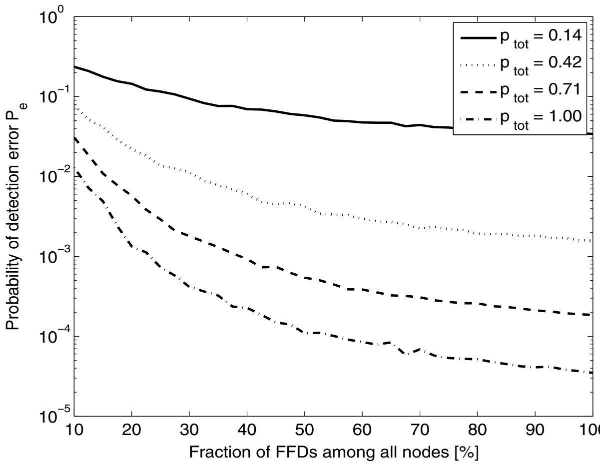

Fig. 4. Probability of detection error P_e depending on the fraction of FFDs among all nodes for different levels of total transmission power p_{tot}.

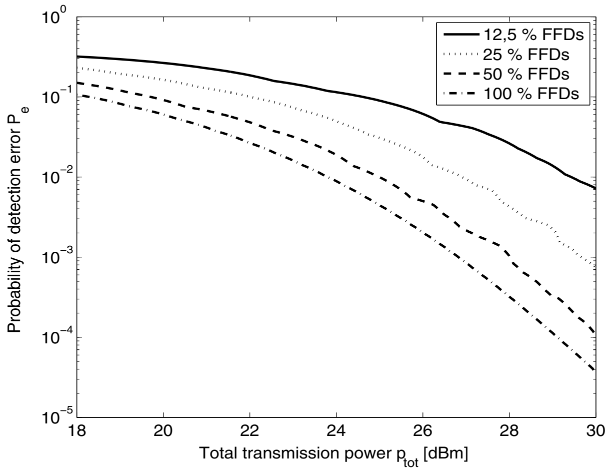

Fig. 5. Probability of detection error P_e depending on the total transmission power p_{tot} of the network for different fractions of FFDs among all nodes.

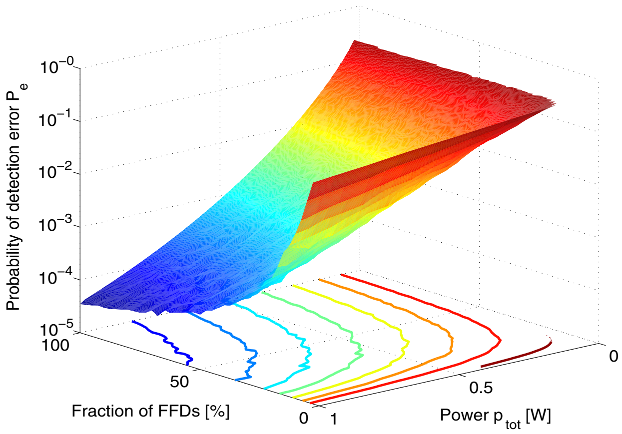

Fig. 6. Probability of detection error P_e depending on the fraction of FFDs and total transmission power p_{tot}. The contour plot on the ground shows isolines with equal detection error probabilities.

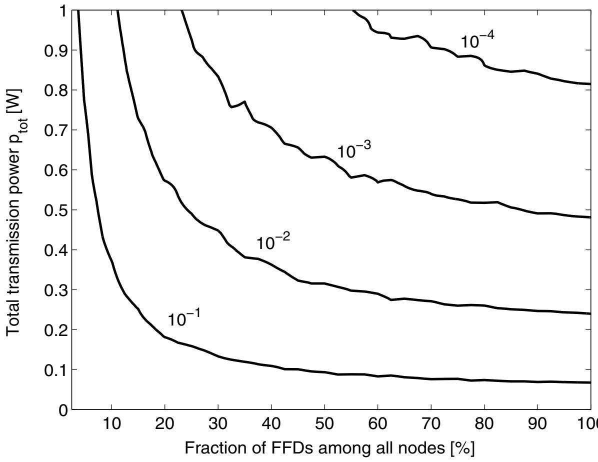

Fig. 7. The contour plot shows isolines for different detection error probabilities P_e depending on the fraction of FFDs among all nodes and total transmission power p_{tot}.

has to be larger than about 55% for the analyzed range of total transmission power levels. Yet, this means that to achieve the same global detection performance almost one half of all nodes (about 45%) can be low complexity and cheaper RFD nodes, if in trade the total transmission power p_{tot} is increased from $0.8\,\text{W}$ to $1.0\,\text{W}$.

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