Developing a mathematical model for cooperative MIMO communication at wireless sensor network

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***Abstract*—Cooperative MIMO explores the wireless communication schemes between multiple sensors emphasizing the multiple input multiple output (MIMO) structure. In this paper, an energy efficient cooperative technique is proposed for a wireless sensor network (WSN) where selected numbers of sensors at the transmitting end are used to form a MIMO structure wirelessly connected with selected numbers of sensors at the receiving end. The selection of nodes in the transmitting end is based on a selection function which is a combination of channel condition, residual energy, inter sensor distance in a cluster and geographical location whereas the selection in receiving side is performed on the basis of channel condition. Data are sent by the sensors in a cluster to a data gathering node (DGN) using a multihop transmission. We are concentrating our design on the intermediate hop where sensors in a cluster transmit their data to the sensors in another cluster with MIMO communication. In this study, a mathematical model has been developed for higher probability subset of sensors from a number of available sensors in a cluster. Simulation results show that the selected approach shows better performance in terms energy efficiency.**

***Index Terms*—Cooperative technique, probabilistic approach, selection function, MIMO, wireless sensor networks**

I. Introduction

With recent technical and technological advances in wireless sensor network (WSN), it becomes possible to envisage not only simple non real-time WSN data collections but also more complicated real-time WSN applications including surveillance, intrusion detection and environmental monitoring [1]. The size of sensors is typically small but the functions inside the sensor are complex. Recent hardware advancements allow more signal processing functionality to be integrated into a single sensor chip. RF transceiver, A/D and D/A converters, base band processors, and other application interfaces are integrated into a single device to be used as a smart wireless node. System on chip (SoC) and Network on Chip (NoC) have been developed for integrated system design of those kinds of applications. A wireless sensor network typically consists of a large number of sensor nodes distributed over a certain region. Monitoring node (MN) monitors its surrounding area, gathers application-specific information, and transmits the collected data to a data gathering node (DGN) or a gateway. Energy issues are more critical in the case of MNs rather than in the case of DGNs since MNs are remotely deployed and it is not easy to frequently change the energy sources. Therefore, the MNs have been the principal design issue for energy limited wireless sensor network design. MIMO [2], [3] is a potential candidate for energy efficient design for a targeted probability of bit error rate at the receiver. There has been a great amount of research on various MIMO techniques (including MISO and SIMO) in wireless communication systems due to its diversity and BER improvements. But the fact that MIMO techniques could require complex transceiver circuitry and signal processing leading to large power consumptions at the circuit level has precluded the application of MIMO techniques to energy limited wireless sensor networks. Moreover, physical implementation of multiple antennas at a small-size sensor node may not be feasible. The solution came in the form of cooperative MIMO [2-5]. Cooperative MIMO is a kind of MIMO technique where the multiple inputs and outputs are formed via cooperation. The concept has been proposed to achieve MIMO capability in a network of single antenna nodes. The sensors cooperate with each other to form a multiple input multiple output structure. The results in [2] show that cooperative MIMO based sensor networks may in fact lead to better energy efficiency and smaller end-to-end delay. Later this idea has been improved in [3] by Jayaweera considering channel estimation (training overhead) in the DGN side. Recently this technique is further modified in [8] by Y. Gai considering data aggregation at the cluster head. However, these cooperative techniques consider all the monitoring nodes to cooperate with each other for energy efficient communication. Since all the nodes are transmitting the data, energy is utilized inefficiently. One approach to the node selection is done by Mr. I. Ahmed in [9], [22] where the nodes are selected on the basis of geometric locations of the MNs. Another approach for node selection is taken in [5], [25] where the node selection is done on the basis of channel gain parameter.

In this paper, we propose a selection based cooperative communication for energy-limited wireless sensor networks where the multiple sensors in input and output cluster form the MIMO structure. The selection of nodes in the input cluster is based on a selection function which is a combination of channel condition, residual energy, inter sensor distance in a cluster and geographical location of the sensors whereas the nodes in the output cluster is selected on the basis of channel condition only. We derive a probabilistic model for selecting a sensor in a cluster. This probabilistic approach addresses the importance of a node to be included for selective transmission.

The remainder of this paper is organized as follows: In section 2, the proposed system model of selective approach is introduced. In section 3, probabilistic model is developed with mathematical derivations. Section 4 shows the energy model and simulation results are discussed in section 5. Section 6 concludes this paper.

II. System Model

Our system model is a centralized wireless sensor network suitable to applications like IEEE 1451.5 standard, where many clusters with several sensors are connected wirelessly with the DGN using multihop communication. We are concentrating our design on cluster to cluster communication which is an intermediate hop between the cluster to DGN data transmission. The system model is shown in Fig. 1. We assume a system with narrowband, frequency-flat Rayleigh fading channels and perfectly synchronized transmission/reception between wireless sensor nodes. We consider N_t transmitted and N_r received antennas each placed at a sensor. The received discrete-time signal is attenuated by a $N_t \times N_r$ channel matrix H of scalar fading coefficients. We assume each element in H is a zero-mean circulant symmetric complex Gaussian random variable with unit variance. The fading is assumed constant during the transmission of each frame. Unless otherwise specified, the terms node, sensor and MN are considered as synonyms to each other.

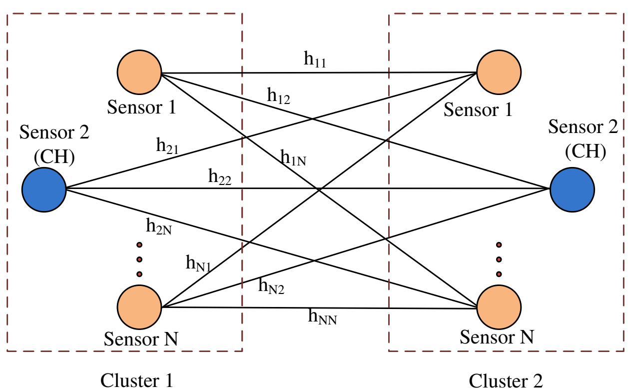

Fig. 1. System model for cluster to cluster communication in wireless sensor network

For sensor networks, maximizing the network lifetime is the main concern and it directly depends on the total energy consumption. To reduce the energy consumption, energy efficient transmission is necessary. Since MIMO can provide energy savings in fading channels [12] we can use it in the form of cooperative MIMO to transmit data from a cluster to another cluster. Energy efficient transmission is possible using cooperative transmission [2], [3] but the use of all the sensors in a cluster make the cooperative transmission inefficient. Recently researches have been done to optimize the cooperative transmission by using single parameter selection of cooperative nodes [5], [9]. But all these single parameter node selection algorithms are incomplete in a sense that they are not considering all the selection parameters which contribute to minimize energy consumption. Residual energy and inter sensor distance in a cluster are two important parameters which are not yet explored for the node selection. Probabilistic approach using these parameters is not developed. The solution for these problems is to include all the selection parameters using a selection function and develop the effect of probabilistic approach using this selection function.

A. Construction of selection function

Cooperative MIMO works with multiple sensors and it is possible to choose a number of sensors aomong the available sensors. To achieve the near optimal solution, several selection parameters need to be considered in the form of a selection function. If the cluster head can dynamically select the sensors with better selection parameters, it can help to reduce the overall energy consumption. The overall energy consumption largely varies due to several parameters: i) channel condition ii) residual energy iii) inter sensor distance in a cluster and iv) geographical location of the sensors. These parameters are the potential candidates for node selection.

In this paper we propose an idea of using selected number of sensors from available active sensors to transmit the data of all the sensors in a cluster for more energy efficiency. Channel condition parameter h is a critical issue in transmitting data to a distant receiver. The signal power drops off due to three effects: mean propagation path loss, macroscopic fading and microscopic fading. To represent the channel condition, we only use microscopic fading since the other effects can be easily minimized using controlled transmission [12]. As the cooperative MIMO is based on the distributed antennas, and the channel parameter is different from one node to another, this feature can be used to optimize the data transmission. Residual energy r_e is the amount of energy present in a sensor at a particular time. Inter sensor distance in a cluster d_m is the distance between a cluster head and the other sensors inside a cluster. The closer the sensors are the less is the energy consumption for local communication. Geographical location of the sensors, d is the distance of the sensors from the receiving cluster. Total energy consumption increases with the increase in this distance. Node selection is based on the previously explained four parameters and a sensor is selected on the basis of the following node selection function,

$$N_S = \frac{dd_m}{hr_e}. \tag{1}$$

The node selection function is chosen in a way that all the required choices of selection parameters for energy efficient transmission will lead to a smaller value of selection function. For example, higher value of h and r_e are desirable and lower value of d and dm are desirable for lower energy consumption which lead to a smaller value of proposed selection function. The parameters in the node selection function are normalized. Therefore, the idea of our proposal is to calculate this node selection function for each sensor and then select two sensors with smaller selection function values.

B. Selection procedure of sensors

The physical phenomena monitored by sensor networks, e.g. forest temperature, water contamination, usually yield sensed data that are strongly correlated. Data aggregation is the tool by which the correlated data size can be significantly reduced depending on the correlation factor. In Fig. 2, sensors at the receiving cluster continuously send training bits to all the available sensors at the transmitting end. After receiving the training bits, these sensors estimate the channel and determine the distance from the receiving cluster. Then they send the results to the cluster head along with their residual energy and information data. The cluster head then estimates the inter sensor distance d_m and selects the sensors with better selection function among the available sensors. At the same time it sends the channel estimation results to the receiving cluster head. Cluster head at the receiving side selects receiving sensors on the basis of channel estimation result performed at the transmitting end and send a command signal to remain active. This estimation procedure is performed in every frame until the completion of the data transmission from the transmitting end sensors to the receiving end sensors. After the sensors transmit their data to the cluster head, it aggregates the data [8] and sends all the data to the remaining active sensors within that cluster. It then sends a command signal to the selected sensors to start transmitting data. After receiving the data, selected sensors at the receiving cluster transmit them to their cluster head locally.

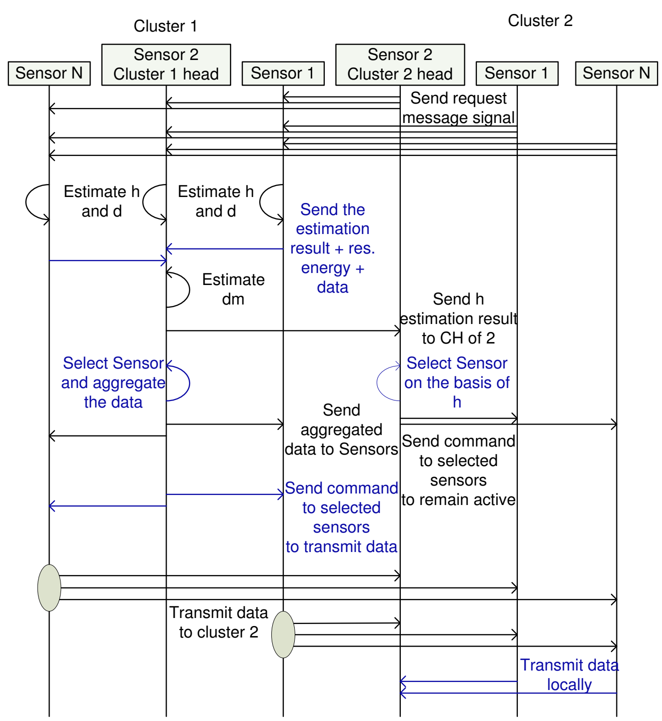

Fig. 2. Cooperative communication using selection

III. Probabilistic model

We can find a probabilistic model of this proposed node selection scheme based on the fact that the minimum value of this node selection function will have the maximum probability to be selected. We can choose a subset of sensors within a cluster which have higher probability to be selected. We assume a cluster based sensor network where the cluster head is centrally located with other sensors and they are Gaussian distributed around the cluster head. Data gathered by the sensors are correlated and sent to the cluster head for data aggregation purpose. For cooperative data transmission, sensors at the transmitting cluster are selectively chosen on the basis of four parameters. These parameters collectively form a selection function and its value is measured for all the available sensors. Sensors are selected on the basis of minimum value of this selection function. The selection function is shown in equation 1. The probability that a sensor is selected from an available number of active sensors in a cluster is given by

$$P_S = \frac{P\{d\}P\{d_m\}}{P\{h\}P\{r_e\}} \tag{2}$$

Probability distribution for longhaul distance d

Let the sensors in cluster 1 are Gaussian distributed with zero mean and variance σ_{d1}^2. Again let the sensors in cluster 2 are also Gaussian distributed with zero mean and variance σ_{d2}^2. So, the distance from a sensor located at cluster 1 to a sensor located at cluster 2 is a random variable with mean d_{avg} and variance $\sigma_{d1}^2 + \sigma_{d2}^2$ where d_{avg} is the average distance from the cluster 1 sensors to cluster 2 sensors. So, the probability distribution function for this longhaul distance is given by

$$f(d) = \frac{1}{\sqrt{2\pi(\sigma_{d1}^2+\sigma_{d2}^2)}} e^{-\frac{(d-d_{avg})^2}{2\left(\sigma_{d1}^2+\sigma_{d2}^2\right)}} \tag{3}$$

We consider a sensor to be selected if it is located at the dashed area in Fig. 3 which is closer to the receiving cluster. So, the probability that a sensor will be selected on the basis of longhaul distance is given by

$$\begin{aligned} P\{d\} &= P\{(d_{avg}-D) \le d \le d_{avg}\} \\ &= \int_{d_{avg}-D}^{d_{avg}} \frac{1}{\sqrt{2\pi(\sigma_{d1}^2+\sigma_{d2}^2)}} e^{-\frac{(d-d_{avg})^2}{2\left(\sigma_{d1}^2+\sigma_{d2}^2\right)}} dd \end{aligned} \tag{4}$$

where D is the distance shown in Fig. 3. We can finally get

$$P\{d\} = \frac{1}{2}\left[erf\left(\frac{D}{\sqrt{2\left(\sigma_{d1}^2+\sigma_{d2}^2\right)}}\right)\right] \tag{5}$$

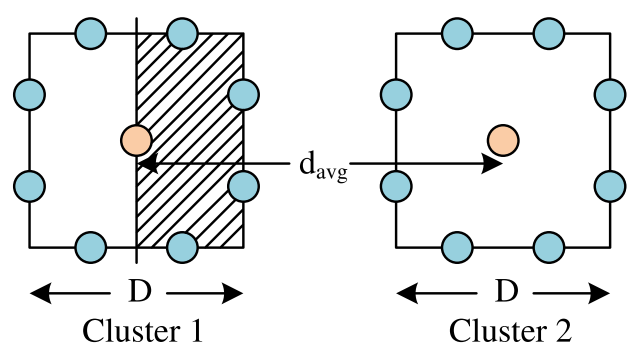

Fig. 3. Distribution for longhaul distance

Probability distribution for the distance between the sensors in a cluster d_m

As the sensors in a cluster are assumed to be Gaussian distributed, and we also assume that the cluster head is centrally located, the probability distribution function is given by

$$\begin{aligned} f(d_m) &= \frac{1}{\sqrt{2\pi}\sigma_{d1}} e^{-\frac{\left(d_m-\mu_{d_m}\right)^2}{2\sigma_{d1}^2}} \\ &= \frac{1}{\sqrt{2\pi}\sigma_{d1}} e^{-\frac{{d_m}^2}{2\sigma_{d1}^2}} \end{aligned} \quad (6)$$

The probability that a sensor will be selected on the basis of inter sensor distance is

$$\begin{aligned} P\{d_m\} &= P\{(-\sigma_{d1} < d_m < \sigma_{d1})\} \\ &= \int_{-\sigma_{d1}}^{\sigma_{d1}} \frac{1}{\sqrt{2\pi}\sigma_{d1}} e^{-\frac{{d_m}^2}{2{\sigma_{d1}}^2}}\, dd_m \\ &= erf(\frac{1}{\sqrt{2}}) \end{aligned} \quad (7)$$

Probability distribution for channel gain parameter h

Channel gain parameter is chosen to be zero mean circularly symmetric complex Gaussian distributed. So, the envelop of its distribution follows Rayleigh distribution as follows

$$f(h) = \frac{h}{{\sigma_h}^2} e^{-\frac{h^2}{2{\sigma_h}^2}} \quad (8)$$

The probability that the channel gain is above a critical value h_c is given by

$$\begin{aligned} P\{h\} = P(h > h_c) &= \int_{h_c}^{\infty} \frac{h}{{\sigma_h}^2} e^{-\frac{h^2}{2{\sigma_h}^2}}\, dh \\ &= 1 - CDF(h_c) \\ &= 1 - (1 - e^{-\frac{{h_c}^2}{2{\sigma_h}^2}}) \\ &= e^{-\frac{{h_c}^2}{2{\sigma_h}^2}} \end{aligned} \quad (9)$$

Assuming this ZMCSCG distribution follows normal distribution with unit variance, the resulted Rayleigh distribution will also be with unit variance. So, we get

$$P\{h\} = e^{-\frac{{h_c}^2}{2}} \quad (10)$$

Probability distribution for residual energy r_e

We are using the selection function at the transmitting cluster. So the calculations done here are concentrated on the transmitting cluster. Residual energy is different for different types of nodes. For normal node, the residual energy is

$$\begin{aligned} E_{re_n} &= E_{re_{n_0}} - L_r E_{trl} - N_t L_r E_{rel} \\ &\quad - N_t L_r E_{trL} \end{aligned} \quad (11)$$

and for the cluster head, the equation is written as

$$\begin{aligned} E_{re_h} &= E_{re_{h_0}} - N_t L_r [E_{rel} + E_{agg} \\ &\quad + E_{trl} + E_{trL}] \end{aligned} \quad (12)$$

Here $E_{re_{n_0}}$ and $E_{re_{h_0}}$ are residual energies in previous round for normal node and cluster head respectively, E_{trl} and E_{rel} are the energy needed per bit for local transmission and local reception for transmitting cluster whereas E_{trL} is the energy needed per bit for long haul transmission. E_{agg} is data aggregation energy per bit. N_t is the number of available sensor nodes at the transmitting cluster and L_r is the bit size in a single round. Local reception energy can be replaced by $E_{rel} = (P_{MIX} + P_{LNA} + P_{fil_r} + P_{IFA} + P_{ADC} + P_{syn})/R_b$. Local and longhaul transmitted energy can be replaced by the following equations using equations (1) - (4)

$$E_{trl} = [\{\overline{E}_b \times \frac{(4\pi)^2 {d_m}^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) + E_{cir}] \quad (13)$$

$$E_{trL} = [\{\overline{E}_b \times \frac{(4\pi)^2 d^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) + E_{cir}] \quad (14)$$

where the symbols are explained in aforementioned equations and E_{cir} represents circuit energy consumption during transmission and can be replaced by $E_{cir} = (P_{DAC} + P_{MIX} + P_{fil_t} + P_{syn})/R_b$. Now the residual energy for the normal node becomes

$$\begin{aligned} E_{re_n} &= E_{re_{n_0}} - L_r[\{\overline{E}_b \times \frac{(4\pi)^2 {d_m}^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) \\ &\quad + E_{cir}] - N_t L_r E_{rel} - N_t L_r [\{\overline{E}_b \\ &\quad \times \frac{(4\pi)^2 d^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) + E_{cir}] \end{aligned} \quad (15)$$

Again the residual energy for cluster head is

$$\begin{aligned} E_{re_h} &= E_{re_{h_0}} - N_t L_r [E_{rel} + E_{agg} + [\{\overline{E}_b \\ &\quad \times \frac{(4\pi)^2 {d_m}^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) + E_{cir}] + [\{\overline{E}_b \\ &\quad \times \frac{(4\pi)^2 d^k}{G_t G_r \lambda^2} M_l N_f\}(1+\alpha) + E_{cir}]] \end{aligned} \quad (16)$$

Putting the value of

$$L_r\{\overline{E}_b \times \{(4\pi)^2/(G_t G_r \lambda^2)\} M_l N_f\}(1+\alpha) = K$$

we get the normal node residual energy like the followings

$$\begin{aligned} E_{re_n} &= E_{re_{n_0}} - N_t L_r E_{rel} - K {d_m}^k - N_t K d^k \\ &\quad - (N_t + 1) L_r E_{cir} \\ &= \Xi - \Upsilon(X^k + N_t Y^k) \\ &= \Xi - \Upsilon(X^k + Z^k) \end{aligned} \quad (17)$$

where $\Xi = E_{re_{n_0}} - N_t L_r E_{rel} - (N_t+1) L_r E_{cir}$, $\Upsilon = K$, $X = d_m$, $Y = d$ and $Z = {N_t}^{\frac{1}{k}} Y$

Again the residual energy for the cluster head is

$$\begin{aligned} E_{re_h} &= E_{re_{h_0}} - N_t L_r E_{rel} - N_t L_r E_{agg} \\ &\quad - N_t L_r K {d_m}^k - N_t L_r K d^k - 2 N_t L_r E_{cir} \\ &= \Phi - \Psi(X^k + Y^k) \end{aligned} \quad (18)$$

where $\Phi = E_{re_{h_0}} - N_t L_r E_{rel} - N_t L_r E_{agg} - 2N_t L_r E_{cir},\ \Psi = N_t L_r K,\ X = d_m,\ and\ Y = d$. The residual energy in both cases from equation (17) and (18) are of the form of $\mathcal{Z} = \vartheta - \varrho(\mathcal{X}^k + \mathcal{Y}^k)$. Taking $k = 2$, we get

$$\begin{aligned}\mathcal{Z} &= \vartheta - \varrho(\mathcal{X}^2 + \mathcal{Y}^2)\\ &= \vartheta - \varrho\mathcal{W}\end{aligned} \tag{19}$$

where $\mathcal{W} = \mathcal{X}^2 + \mathcal{Y}^2$. Here $\mathcal{X}$ is a normal distribution with zero mean and ${\sigma_x}^2$ variance whereas $\mathcal{Y}$ is a normal distribution with μ_y mean and ${\sigma_y}^2$ variance. $\mathcal{W}$ follows the non central chi-square distribution with pdf

$$f_{\mathcal{W}}(w;k,\lambda) = \frac{1}{2}e^{-\frac{w+\lambda}{2}}\left(\frac{w}{\lambda}\right)^{\frac{k}{4}-\frac{1}{2}} I_{\frac{k}{2}-1}(\sqrt{\lambda w}) \tag{20}$$

where $I_m(n)$ is a modified Bessel function of the first kind given by $I_m(n) = \left(\frac{n}{2}\right)^m \sum_{j=0}^{\infty} \frac{\left(\frac{n^2}{4}\right)^j}{j!\Gamma(m+j+1)}$ and $\lambda = \sum_{i=1}^{k}\left(\frac{\mu_i}{\sigma_i}\right)$ and cdf

$$F(w) = \sum_{j=0}^{\infty} e^{-\frac{\lambda}{2}} \frac{(\frac{\lambda}{2})^j}{j!} \frac{\gamma(j+k/2, w/2)}{\Gamma(j+k/2)} \tag{21}$$

Putting the value of $k = 2$ and $\lambda = \frac{\mu_y^2}{\sigma_y^2}$ we get the pdf and cdf like the followings

$$\begin{aligned}f_{\mathcal{W}}(w;2,\frac{\mu_y^2}{\sigma_y^2}) &= \frac{1}{2}e^{-\frac{w+\frac{\mu_y^2}{\sigma_y^2}}{2}}\left(\frac{w\sigma_y^2}{\mu_y^2}\right)^{\frac{2}{4}-\frac{1}{2}}\\ &\quad\times I_{\frac{2}{2}-1}\left(\sqrt{\frac{\mu_y^2}{\sigma_y^2}w}\right)\\ &= \frac{1}{2}e^{-\frac{w+\frac{\mu_y^2}{\sigma_y^2}}{2}} I_0\left(\sqrt{\frac{\mu_y^2}{\sigma_y^2}w}\right)\end{aligned} \tag{22}$$

$$F(w) = \sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{(\frac{\mu_y^2}{2\sigma_y^2})^j}{j!} \frac{\gamma(j+1, w/2)}{\Gamma(j+1)} \tag{23}$$

Again we have $\mathcal{Z} = \vartheta - \varrho\mathcal{W}$. To get the cdf with variable $\mathcal{Z}$ we get

$$\begin{aligned}F_{\mathcal{Z}}(z) &= p[\mathcal{Z} \le z]\\ &= p[\vartheta - \varrho\mathcal{W} \le z]\\ &= p[\mathcal{W} \ge \frac{z-\vartheta}{\varrho}]\\ &= 1 - F_{\mathcal{W}}(\frac{z-\vartheta}{\varrho})\\ &= 1 - \sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{(\frac{\mu_y^2}{2\sigma_y^2})^j}{j!} \frac{\gamma(j+1, \frac{z-\vartheta}{2\varrho})}{\Gamma(j+1)}\end{aligned} \tag{24}$$

Probability that the residual energy will be greater than r_m is given by

$$\begin{aligned}P\{\acute{r}_e\} &= P(\acute{r}_e > r_m)\\ &= 1 - F_{\mathcal{Z}}(r_m)\\ &= \sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{(\frac{\mu_y^2}{2\sigma_y^2})^j}{j!} \frac{\gamma(j+1, \frac{r_m-\vartheta}{2\varrho})}{\Gamma(j+1)}\end{aligned} \tag{25}$$

Considering both the normal node and cluster head we find the revised probability for residual energy

$$\begin{aligned}P\{r_e\} &= \frac{N_t-1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{(\frac{\mu_y^2}{2\sigma_y^2})^j}{j!} \frac{\gamma(j+1, \frac{r_m-\Xi}{2\Upsilon})}{\Gamma(j+1)}\\ &\quad+[\frac{1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{(\frac{\mu_y^2}{2\sigma_y^2})^j}{j!}\\ &\quad\times\frac{\gamma(j+1, \frac{r_m-\Phi}{2\Psi})}{\Gamma(j+1)}]\end{aligned} \tag{26}$$

The probability that a node in a cluster will be selected is given by

$$\begin{aligned}P_S &= \frac{P\{d\}P\{d_m\}}{P\{h\}P\{r_e\}}\\ &= \frac{\frac{1}{2}\left[erf\left(\frac{D}{\sqrt{2(\sigma_{d1}^2+\sigma_{d2}^2)}}\right)\right] erf\left(\frac{1}{\sqrt{2}}\right)}{\begin{aligned}&e^{-\frac{{h_c}^2}{2}}[\frac{N_t-1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!}\\ &\times\frac{\gamma\left(j+1, \frac{r_m-\Xi}{2\Upsilon}\right)}{\Gamma(j+1)}\\ &+\frac{1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}}\\ &\times\frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!}\frac{\gamma\left(j+1, \frac{r_m-\Phi}{2\Psi}\right)}{\Gamma(j+1)}]\end{aligned}}\end{aligned} \tag{27}$$

In this probability model, a sensor in a cluster is selected as a member of higher probability subset when it's distance d from the sensors at the receiving cluster is within $(d_{avg} - D \le d \le d_{avg}$ where D is the diameter of a cluster and d_{avg} is the average distance between the transmitting end sensors and receiving end sensors, the inter sensor distance d_m is within $-\sigma_{d1} < d_m < \sigma_{d1}$, the channel gain parameter $h > h_c$ and the residual energy $r_e > r_m$ where h_c and r_m are the critical values for channel gain and residual energy respectively.

Theorem: 1 *The probability that a sensor in a cluster is included in a higher probability subset is given by*

$$P_S = \frac{\frac{1}{2}\left[erf\left(\frac{D}{\sqrt{2(\sigma_{d1}^2+\sigma_{d2}^2)}}\right)\right] erf\left(\frac{1}{\sqrt{2}}\right)}{e^{-\frac{h_c{}^2}{2}}[\frac{N_t-1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!} \times\frac{\gamma\left(j+1,\frac{r_m-\Xi}{2\Upsilon}\right)}{\Gamma(j+1)} + \frac{1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \times\frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!}\frac{\gamma\left(j+1,\frac{r_m-\Phi}{2\Psi}\right)}{\Gamma(j+1)}]} \quad (28)$$

If the sensors in a cluster are at an equal distance from the cluster head, we can ignore the effect of d_m on the selection function. Again if the cluster is at a long distance from the receiving cluster, we can ignore the effect of longhaul distance, d. Considering these two special cases, the selection function reduces to

$$N_S = \frac{1}{hr_e}. \quad (29)$$

Corollary: 1 *Sensors located at equal distance from the cluster head in a cluster and at a long distance from receiving cluster is included in a higher probability subset for cooperative transmission with the following probability*

$$P_S = \frac{e^{\frac{h_c{}^2}{2}}}{[\frac{N_t-1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!} \times\frac{\gamma\left(j+1,\frac{r_m-\Xi}{2\Upsilon}\right)}{\Gamma(j+1)} + \frac{1}{N_t}\sum_{j=0}^{\infty} e^{-\frac{\mu_y^2}{2\sigma_y^2}} \times\frac{\left(\frac{\mu_y^2}{2\sigma_y^2}\right)^j}{j!}\frac{\gamma\left(j+1,\frac{r_m-\Phi}{2\Psi}\right)}{\Gamma(j+1)}]} \quad (30)$$

IV. Energy model

The energy model is based on the system model shown in Fig. 1. We state our problem from the receiver point of view, therefore a loss model is used to estimate the received energy. To estimate the total energy consumption, both circuit and transmitter powers are taken into consideration. We use the same transmitter and receiver block shown in [2], [6], and [7]. Source coding, pulse shaping, modulation and error correction coding blocks are omitted for simplicity. The total power consumption for a single node consists of two main parts, namely, the power consumption of all the power amplifiers P_{PA} which is a function of transmission power P_{out}, and the power consumption of all other circuit blocks P_C

$$P_T = P_{PA} + P_C. \quad (31)$$

The amplifier power can be calculated using the following equation

$$P_{PA} = (1+\alpha)P_{out}, \quad (32)$$

where $\alpha = (\frac{\xi}{\eta} - 1)$, where η is the drain efficiency [10] and ξ is the peak to average ratio [7]. When the channel only experiences a k^{th} power path loss with additive white Gaussian noise (AWGN), P_{out} can be calculated using the link budget relationship [17] as follows.

$$P_{out} = \overline{E}_b R_b \times \frac{(4\pi)^2 d^k}{G_t G_r \lambda^2} M_l N_f, \quad (33)$$

where $\overline{E}_b$ is the average energy per bit required for a given bit error rate (BER) specification, R_b is the transmission bit rate, d is the transmission distance, G_t and G_r are the transmitter and receiver antenna gains respectively, λ is the carrier wavelength, M_l is the link margin compensating the hardware process variations and other background noise, N_f is the receiver noise figure defined as $N_f = \frac{N_r}{N_0}$ where N_r is the power spectral density (PSD) of the total effective noise at the receiver input and N_0 is the single-sided thermal noise PSD at the room temperature.

The circuit power includes transmitter and receiver circuit power P_{ct} and P_{cr} respectively. This power consumption is due to several power blocks such as P_{mix}, P_{syn}, P_{filt}, P_{filr}, P_{LNA}, P_{IFA}, P_{DAC}, and P_{ADC} which are the power consumption values of the mixer, the frequency synthesizer, the active filters at the transmitter and at the receiver side, the low noise amplifier, the intermediate frequency amplifier, the D/A and A/D converter, respectively. The total energy consumption per bit can be written as

$$E_{bt} = \frac{(P_{PA} + P_C)}{R_b}, \quad (34)$$

where R_b is the actual bit rate and can be replaced by $R_b^{eff} = \frac{F - pN_T}{F} R_b$ when pN_T training symbols are inserted in each block to estimate the channel at the receiving cluster or DGN side. The block size is equal to F symbols and can be obtained by setting $F = \lfloor T_C R_S \rfloor$, where R_S is the symbol rate and T_C is the fading coherence time. The fading coherence time can be estimated from $T_C = \frac{3}{4 f_m \sqrt{\pi}}$ where the maximum Doppler shift f_m is given by $f_m = \frac{v}{\lambda}$ with v being the velocity and λ being the carrier wavelength [11]. The total energy consumption is estimated by multiplying E_{bt} by the number of bits L to be transmitted. Now we develop the mathematical model where we estimate total energy consumption for cooperative communication. Channel estimation is performed in every data frame and energy per bit is multiplied by the total data size to get the total energy consumption. Therefore, the total energy consumption in cooperative case for this scheme is

$$\begin{aligned} E_{CO}^{C-C} &= \sum_{i=1}^{N_t} \frac{L_i}{F} E_{ch} + L_{ch} \sum_{i=1}^{N_t-1} \frac{L_i}{F} E_i^t \\ &+ L_{ch} \frac{L_i}{F} E_S^l + \sum_{i=1}^{N_t-1} L_i E_i^t + E_{da} \sum_{i=1}^{N_t} L_i \\ &+ (N_t - 1) E_i^{t0} \sum_{i=1}^{N_t} L_i \gamma_i + L_c p_s \frac{L_i}{F} \sum_{i=1}^{x} E_i^{t0} \\ &+ E_M^l \sum_{i=1}^{N_t} L_i \gamma_i + \frac{1}{b_{mimo}} \sum_{i=1}^{N_t} L_i \sum_{i=1}^{y} b_{l_r} E_j^t, \end{aligned} \quad (35)$$

TABLE I
OPTIMIZED CONSTELLATION SIZE FOR CLUSTER TO CLUSTER DATA TRANSMISSION AT N_t = 4 & N_r = 4

d(m)	1	5	10	15	20	40	70	100
$b_{4\times4}$	18	13	10	9	8	6	4	3
$b_{2\times4}$	18	11	9	8	7	4	3	2
$b_{1\times4}$	14	9	6	5	4	2	1	1

where E_{ch} is the channel estimation energy and is using 28 μJ/bit/signals in our simulation experiment [13]. Data size L_i is divided by the frame size F to find out the number of channel estimations required for the transmitted data size L_i as channel estimation is performed once in a frame duration. The second term is due to the transfer of channel estimation result to their own cluster head. E_i^t is the energy per bit required to transmit the channel estimation result from a sensor to the cluster head. L_{ch} is the number of bits needed to transmit the channel estimation result. $L_{ch}\frac{L_i}{F}E_S^l$ is the term required to transmit the channel estimation result to the receiving cluster head due to channel estimation purpose. The same energy per bit E_i^t is needed to transmit the data from sensors to the cluster head. E_{da} is the energy dissipation per bit required in the cluster head for data aggregation. It depends on the algorithm complexity[16].

$$E_{da}(L) = \begin{cases} C_0 + C_1 \times L + C_2 \times L^2 & \text{for } O(n^2) \\ C_0 + C_1 \times L & \text{for } O(n) \end{cases}, \quad (36)$$

where L is the number of transmission bits and C_0, C_1 and C_2 are coefficients depending on the software and CPU parameters. In our model, we use beam forming algorithm and 5 nJ/bit/signals in simulation experiments [8]. E_i^{t0} denotes the local transmission energy cost per bit for transferring the aggregated data to the remaining active sensors, γ is the percentage of remaining data after aggregation and it reflects the correlation between data amongst different sensors. The same energy per bit E_i^{t0} is needed to transmit a command signal from the cluster head to the selected sensors. L_c denotes the bit length of a command signal and $x = N_{Bt} - 1$ for the cluster head being a selected sensor and $x = N_{Bt}$ otherwise where N_{Bt} denotes number of selected sensors at the transmission end. p_s is the probability that a selected sensor is changed in the next frame and is chosen as $\frac{1}{N_t}$. After receiving all the bits, the selected nodes encode the transmission sequence according to some diversity scheme, such as the STBC. E_M^l denotes the energy cost per bit for the long-haul MIMO transmission [2]. $\sum_{i=1}^{N_t} L_i$ is divided by the optimal bit size of the longhaul transmission b_{mimo} to find the number of symbols present in the received signal. The number of symbols is then multiplied by the optimal bit size of the local transmission b_{l_r} to find the total bit length. E_j^t is the energy per bit required to transmit the data from a sensor to the cluster head at the receiver side. $y = N_{Br} - 1$ is used for the cluster head being a selected sensor and $x = N_{Br}$ otherwise where N_{Br} denotes number of selected sensors at the receiving end.

For the SISO approach, sensors will transmit their data to the cluster head and as there is no burden for channel estimation, the cluster head will transmit all the aggregated data directly to the destination node without any cooperation. So the total energy consumption becomes

$$E_{SISO}^{C-C} = \sum_{i=1}^{N_t-1} L_i E_i^t + E_{da}\sum_{i=1}^{N_t} L_i + E_{S_{C-C}}^l \sum_{i=1}^{N_t} L_i\gamma_i, \quad (37)$$

where $E_{S_{C-C}}^l$ denotes the SISO long haul transmission and can be calculated as a special case of MIMO transmission with $N_{Bt} = 1$ and $N_{Br} = 1$ where N_{Bt} and N_{Br} are the selected number of antennas at the transmitting and receiving end respectively. In both SISO and MIMO case, optimized constellation size is used according to the different communication distance so that at any given distance, the communication energy consumption is minimized under its constellation size. In Table I, the optimized constellation sizes are shown for different combination of selected sensors (N_{Bt}) and receiving number of sensors (N_r) for cluster to cluster data transfer.

V. SIMULATION RESULTS AND DISCUSSION

In order to get the total communication energy consumption, the average energy per bit required for a given BER P_b, $\overline{E}_b$ need to be determined. In our approach we get the value of $\overline{E}_b$ by using a numerical search. we have taken ten thousand randomly generated channel samples and averaged to find the desired bit error rate at each transmission distance. The value of the constellation size is optimized for each transmission distance. For the long haul communication, SISO is taken as a special case of MIMO structure. The channel matrix of a MIMO system can be written as

$$\mathbf{H} = \begin{pmatrix} h_{11} & h_{12} & \dots & h_{1N_{Br}} \\ h_{21} & h_{22} & \dots & h_{2N_{Br}} \\ \vdots & \vdots & \vdots & \vdots \\ h_{N_{Bt}1} & h_{N_{Bt}2} & \dots & h_{N_{Bt}N_{Br}} \end{pmatrix}$$

Out of N_t available sensors, N_{Bt} number of sensors will be selected to transmit the data of all the active sensors. In the receiving side, N_{Br} number of sensors are selected to receive the data in the case of receiving cluster out of N_r available sensors. A list of system parameters used in our simulation is shown in Table II where the power consumption values of various circuit blocks are quoted from [10], [18]-[20].

TABLE II
SYSTEM PARAMETERS

f_c = 2.5 GHz	η = 0.35
G_tG_r = 5 dBi	N_0 = -171 dBm/Hz
B = 10 KHz	k = 2 for local com.
P_b = 10^{-3}	k = 3 for long haul com.
N_f = 10 dB	p = 0
M_l = 40 dB	Pmix = 30.3 mW
E_{ch} = 28 μJ/bit/signals	Psyn = 50.0 mW
L_{ch} = 8	P_{LNA} = 20 mW
L_c = 8	E_{da} = 5 nJ/bit/signals
P_{fil_t} = 2.5 mW	P_{fil_r} = 2.5 mW

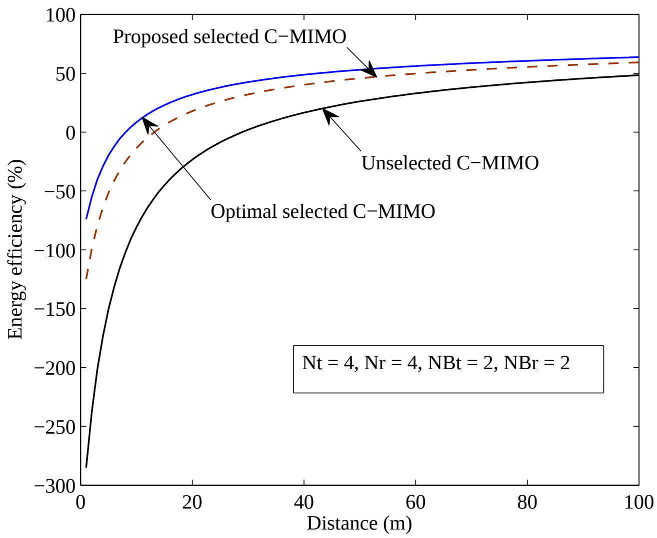

Fig. 4. Energy efficiency over distance for cluster to cluster transmission

I have evaluated and simulated energy efficiency and is calculated using the following formula

$$\text{Energy efficiency} = \frac{E_{SISO} - E_{CO}}{E_{SISO}} \tag{38}$$

Energy efficiency is the key term to evaluate the energy efficient performance. For simulation we consider all the sensors in a cluster are transmitting the same data size L_i = 10 kb. Cluster size with N_t = 4 and N_r = 4 are chosen for the data transfer. In our simulation, we have taken the unselected approach as a special case of selected approach where all the sensors in a cluster are selected for transmission. While choosing all the sensors from a cluster we consider not including the extra overhead taken by the selective approach. We evaluated the energy efficiency to compare the energy efficient performance. Fig. 4 shows the energy efficiency comparison. It shows that the proposed selective approach is more energy efficient than the existing unselected approach [2]. This is because the unselected approach is using all the available sensors to transmit the data without considering their parameter conditions and therefore remains inefficient. In this figure, our selected approach is also compared with the optimal selection. Our selection function is not the optimal one but is close to optimal especially in the smaller cluster to cluster distances. In smaller distances, local communication plays a key role in total energy consumption. As d_m is one of the parameters in the proposed selection function, it helps to reduce total energy consumption at smaller longhaul distances.

VI. Conclusion

An energy efficient selective cooperative technique for the cluster based wireless sensor networks have been proposed. The selection of nodes in the transmitting end is based on a selection function which is a combination of channel condition, residual energy, inter sensor distance in a cluster and geographical location whereas the selection in receiving side is performed on the basis of channel condition. A probabilistic model has been developed using the proposed selection function. A mathematical model has been developed for energy consumption using cooperative scheme and has been simulated. The simulation results show that the selected cooperative MIMO structure outperforms the unselected MIMO. Our model can be considered as a special case of multi hop wireless sensor structure where the cluster to cluster communication is only considered. So, our proposal can well be extended to the multi hop wireless sensor network considering both the cluster to cluster and cluster to DGN transmission.

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