Improving Energy Efficiency in a Wireless Sensor Network by Combining Cooperative MIMO with Data Aggregation

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Abstract

In wireless sensor networks where nodes are powered by batteries, it is critical to prolong the network lifetime by minimizing the energy consumption of each node. In this paper, the cooperative multi-input–multi-output (MIMO) and data aggregation techniques are jointly adopted to reduce the energy consumption per bit in wireless sensor networks by reducing the amount of data for transmission and better using network resources through cooperative communication. For this purpose, we derive a new energy model that considers the correlation between data generated by nodes and the distance between them for a cluster-based sensor network employing the combined techniques. Using this model, the effect of the cluster size on the average energy consumption per node can be analyzed. It is shown that the energy efficiency of the network can be enhanced significantly in cooperative MIMO systems with data aggregation, compared to either cooperative MIMO systems without data aggregation or data aggregation systems without cooperative MIMO, if sensor nodes are properly clusterized. Both centralized and distributed data aggregation schemes for the cooperating nodes to exchange and compress their data are also proposed and appraised, which lead to diverse impacts of data correlation on the energy performance of the integrated cooperative MIMO and data aggregation systems.

Index Terms: Cooperative MIMO, data aggregation, energy efficiency, wireless sensor networks.

I. INTRODUCTION

The wireless sensor networks (WSNs) have received significant attention from researchers as they find applications spanning over vast and varied areas such as habitat monitoring, object tracking, military systems, industrial and home automation [1]. Sensor nodes are typically powered by batteries with a limited lifetime and, in most cases, the batteries cannot be recharged. The energy problem in wireless sensor networks remains as one of the major barriers preventing the complete exploitation of this technology.

To save energy in WSNs, many techniques and protocols have been investigated using different approaches, such as reducing transmit power or condensing data for transmission or the combination of the two. By creating diversity using the multi-input–multi-output (MIMO) technique in a wireless network, less transmit power is required than that in a single-input–single-output (SISO) system under the same bit-error-rate and throughput performance requirements [2]. However, due to size, cost, or hardware limitations, a wireless sensor node is unable to support multiple antennas on its small operation platform. Under this circumstance, the cooperative MIMO technique that exploits distributed single antennas on a group of neighboring nodes is proposed in WSNs to improve energy efficiency via transmit power reduction [3][4][5]. In [3] sensor nodes within a cluster participate in cooperation in order to reduce energy consumption in so called long-haul transmission between clusters. It is shown that over certain distance ranges the total energy consumption can be reduced by joint information transmission and reception in cooperative MIMO systems, in comparison with non-cooperative or SISO systems. The superiority of cooperative MIMO over SISO in energy efficiency can also be achieved even when the effect of extra training overhead required in MIMO systems and different channel propagation conditions are taken into account [4]. The overall energy consumption of the model proposed in [3] can be further reduced by properly balancing the power allocation between intra-cluster (local) and inter-cluster (long-haul) transmissions [5].

The energy consumed in long-haul transmission can also be saved by applying the data aggregation technique to reduce the amount of data in transmission. In many applications of wireless sensor networks such as environment monitoring, the sensing data from neighboring nodes may be spatially correlated. Data aggregation has been naturally considered as an essential tool to integrate such data to reduce redundancy and minimize the number of transmissions, resulting in lowered energy consumption [6]. In general, some studies that combine data aggregation with other techniques for saving energy in WSNs, such as with cluster-based routing [7], channel assignment [8] and power scheduling [9] protocols, have been reported.

Recently, an approach that combines cooperative MIMO and data aggregation is presented [10] based on the model given in [3]. It examines the effect of the distance of long-haul transmission on the energy efficiency of the network and has demonstrated that the total energy consumption can be further reduced by jointly considering both cooperative MIMO and data aggregation. However, most results of this work are based on a cluster of no more than two sensor nodes, thus it is difficult to properly gauge the impact of data aggregation within the cluster and to discriminate between different aggregation schemes. Furthermore, when the size of a WSN in terms of the number of sensor nodes is given and the long-haul transmission distance is fixed (which is normally the case once a sensor network is deployed), it is always desirable to find a way to maximize the energy efficiency by choosing appropriate cluster sizes. Therefore, the scheme presented in [10] is limited in carrying out such an investigation.

In fact, correlation between the data collected by sensor nodes is related to the distance between these nodes. Consequently, the cluster size chosen for a network can affect both the amount of data that can be compressed and the energy consumption of cooperative communication within the cluster. This observation leads naturally to the consideration in this paper to optimize the cluster size, which can effectively deal with the energy efficiency problems in combining data aggregation with cooperative communication. This is also the major difference between our work and what is presented in [10] where only a data compression ratio between two nodes is assumed without considering the effect of the distance distribution of sensor nodes on data correlation.

In this paper, we propose a framework for improving energy efficiency in WSNs, in which both cooperative MIMO and data aggregation techniques are jointly investigated and the average energy consumption per node required to send a given number of bits is minimized through the optimization of the cluster size. Fig. 1 illustrates an overview of this framework, where local communication required by both cooperative MIMO and data aggregation takes place within each of the clusters indicated and long-haul communication for cooperative MIMO occurs between one cluster and the access point (AP) in the air. During local communication, the data aggregation method is used to exploit the information generated through data exchanges among the nodes (this process is originally designed for the purpose of cooperative MIMO), in order to reduce the redundancy of the data. The data aggregation method adds no extra energy consumption to the local communication process and, instead, can reduce the amount of data or save energy consumption for long-haul communication. Overall, this combined approach, namely cooperative MIMO systems with data aggregation (CMIMO-A), can save energy consumption mainly for long-haul communication in two ways: by reducing transmit power through employing cooperative MIMO and by condensing data through data aggregation. For data aggregation, two different schemes, namely, centralized and distributed, are introduced and their performance in terms of energy efficiency versus the degree of spatial correlation in data is also examined.

The remainder of this paper is organized as follows. In Section II, the energy consumption model for cooperative MIMO systems with data aggregation is proposed and both centralized and distributed data aggregation schemes are presented. In Section III, the average energy consumption per node is minimized and the optimal cluster size is obtained through numerical methods. The energy efficiency performance of both data aggregation schemes is evaluated. Finally, the paper is concluded in Section IV.

II. ENERGY MODEL

In this section we present an energy model for cooperative MIMO systems with data aggregation. As explained previously, the model is built upon a cluster-based sensor network, which is distinct from those used in [3] and [10].

Referring to Fig. 1, the sensor nodes are uniformly distributed in the region with nodal density ρ and subjected to strict energy constraints. The nodes are self-organized into clusters and cooperate on data transmission to the AP. We assume that each cluster consists of n sensor nodes (i.e. the cluster size is n), and that the amount of data sensed by each node is L bits within a defined period of time. Since the nodes in the same cluster are closely spaced, the data sensed by them are correlated. Through the aggregation process data are compressed as a result of exploiting their correlation properties and consequently much less data needs to be transmitted from the cluster to the remote AP. We assume that each node in the wireless sensor network is equipped with a single antenna due to the limited physical size. The individual nodes with a single antenna in the same cluster transmit information cooperatively to the AP. For simplicity, we assume that the AP is also equipped with a single antenna. The nodes in a cluster and the AP form a cooperative multi-input–single-output (MISO) system. As MISO is a variation of MIMO, we choose to use the term MIMO or cooperative MIMO thereafter in the paper to describe this scenario and this does not affect the conclusion we draw with regard to the performance comparison with the SISO system.

The communication based on cooperative MIMO with data aggregation can be divided into two steps: local communication and long-haul communication. During local communication, sensor nodes in the same cluster exchange their data with each other or via a central node for the preparation of cooperative transmission in the next step and, at the same time, data are compressed during the exchange procedure using appropriate aggregation schemes, and then distributed to individual nodes. During long-haul communication, individual nodes transmit the compressed data concurrently over the wireless channel to the AP using a space-time block coding scheme.

A square-law path loss with additive white Gauss noise (AWGN) is assumed for local communication, while for long-haul communication, a Rayleigh-fading channel with square law path loss is assumed. We adopt orthogonal space time block coding (STBC) in long-haul cooperative communication and the channel is assumed constant during the transmission of each orthogonal STBC codeword. The channel gain of the Rayleigh-fading channel between a transmitting node and a receiving node is a scalar. Therefore, the fading factors of the cooperative MIMO channel can be represented as a scalar matrix. In other words, the signal is attenuated further on top of the square-law path loss by a scalar fading matrix **H**, in which each entry is a zero-mean circulant symmetric complex Gaussian (ZMCSCG) random variable with unit variance [2].

The total energy consumption for transmitting L bits from each of the n nodes in a cluster to the AP, E_{tot}, can be divided into two components: the energy consumption of local communication for data exchange and compression, E_{intra}, and the energy consumption of long-haul communication for cooperatively transmitting the compressed data by the nodes in a cluster to the AP, E_{lh}, which is given by

$$E_{\text{tot}} = E_{\text{intra}} + E_{\text{lh}} \tag{1}$$

A. Energy consumption of local communication E_{intra}

We propose two data aggregation schemes in a CMIMO-A system that provide different ways for nodes to exchange and compress their data and result in different forms of energy consumption in local communication. One is the centralized data aggregation scheme (CAS), in which a central node of a cluster collects data sensed by all the nodes in the cluster, integrates and compresses the data, and then distributes the compressed data back to the nodes. The other is the distributed data aggregation scheme (DAS), in which each node exchanges its data with all other nodes in a cluster and then compresses the data separately. The energy consumption for local communication, E_{intra}, depends on the aggregation scheme used.

1) Centralized data aggregation scheme

The centralized data aggregation scheme works in three phases as follows:

Gathering phase: The nodes in a cluster use different time slots to transmit their raw sensing data to a central node with a data rate R_{intra}. The central node can be any node in the cluster but normally the node located at the center of the cluster is chosen for this role.

Compressing phase: As the data sensed by different sensor nodes within a cluster are correlated due to the relatively small spatial arrangement, some redundancy can be taken off from them through compression at the central node alongside the process of data integration in this phase. The degree of correlation in the data from different nodes is a function of the distance between them, thus the size of the cluster has an impact on the compression efficiency of the cluster.

Broadcasting phase: The central node broadcasts the compressed and integrated data to the nodes within the same cluster at the same data rate as used in the gathering phase. All the nodes in the cluster receive the data simultaneously.

The energy consumption of the CAS in a cluster is the sum of the energy consumed in the three phases, which is given by

$$E_{\text{intra}} = E_{\text{ga}}^{\text{CAS}} + E_{\text{comp}}^{\text{CAS}} + E_{\text{bro}}^{\text{CAS}} \tag{2}$$

where $E_{\text{ga}}^{\text{CAS}}$, $E_{\text{comp}}^{\text{CAS}}$ and $E_{\text{bro}}^{\text{CAS}}$ are the energy consumptions of the gathering, compressing and broadcasting phase in the CAS, respectively.

To maintain the efficiency of the model, baseband signal processing overheads and corresponding energy consumptions from coding and digital modulation are omitted here. The energy dissipated in the gathering phase can be divided into two main components: the energy consumption of the power amplifier and the energy consumption of all other circuit blocks, i.e.

$$E_{\text{ga}}^{\text{CAS}} = (n-1) P_{\text{SISO}}^{d} \frac{L}{R_{\text{intra}}} + (n-1)(P_T + P_R) \frac{L}{R_{\text{intra}}} \tag{3}$$

where P_{SISO}^{d} denotes the power consumption of the power amplifier at the transmitter side, P_T and P_R are the power consumptions of circuit blocks at the transmitter side and the receiver side, respectively. The transmission data rate is given by $R_{\text{intra}} = b \cdot B$ with b the constellation size (bits per symbol) and B the modulation bandwidth.

The power consumption of the power amplifier, P_{SISO}^{d}, can be calculated based on the link budget relationship [11], [12]. Specifically, when the channel experiences only a square-law path loss, we have

$$P_{\text{SISO}}^{d} = (1+\alpha)E_{\text{intra}}^{b} R_{\text{intra}} \frac{(4\pi)^2 d^2}{G_t G_r \lambda^2} M_l N_f \qquad (4)$$

Here $\alpha = (\xi/\eta) - 1$ with ξ the peak to average ratio (PAR) and η the drain efficiency of the RF power amplifier. The energy per bit required for a given BER requirement is represented by E_{intra}^{b}. For simplicity, we approximate all the clusters with a circular area of the same size and the radius of the circular area is used as the transmission distance, denoted by *d*, for all the nodes in a cluster to exchange their data through a central node. Also in (4), 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 additive background noise or interference, N_f is the receiver noise level defined as $N_f = N_r / N_0$ with N_r the power spectral density (PSD) of the total effective noise at the receiver input and N_0 the single-sided thermal noise PSD at the room temperature.

The PAR ξ depends on the modulation scheme used and the associated constellation size b. Multi-quadrature amplitude modulation (MQAM) is used for local communication, thus we have [13]

$$\xi = 3\left[\frac{2^{\frac{b}{2}} - 1}{2^{\frac{b}{2}} + 1}\right] \qquad (5)$$

In order to obtain P_{SISO}^{d}, the power consumption of the power amplifier, the energy per bit E_{intra}^{b} required for a given BER, $\varepsilon_{\text{intra}}^{b}$, needs to be determined. The average BER of a SISO with MQAM when $b = 2$ is given by [11]

$$\varepsilon_{\text{intra}}^{b} \approx Q\left(\sqrt{2\gamma_{\text{intra}}}\right) \tag{6}$$

where $Q(x)$ is the Q-function, defined as $Q(x) = \left(1/\sqrt{2\pi}\right)\int_{x}^{\infty} e^{-t^2/2} dt$, and γ_{intra} denotes the instantaneous received SNR, which can be written as

$$\gamma_{\text{intra}} = \frac{E_{\text{intra}}^{b}}{N_0} \tag{7}$$

We can substitute (7) into (6), and then invert the formula to obtain the required E_{intra}^{b} for the given $\varepsilon_{\text{intra}}^{b}$.

The energy dissipated in compressing phase is given by

$$E_{\text{comp}}^{\text{CAS}} = nLE_{\text{comp}} \tag{8}$$

where E_{comp} denotes the energy cost per bit for data compression.

The energy dissipated in broadcasting phase is also contributed by the power amplifier and other circuitry, which is given by

$$E_{\text{bro}}^{\text{CAS}} = P_{\text{SISO}}^{d} \frac{I_n}{R_{\text{intra}}} + \left(q(n)P_T + (n-1)P_R\right)\frac{I_n}{R_{\text{intra}}} \tag{9}$$

For (9) to be valid when n is any positive integer, a binary function $q(n)$ is defined as:

$$q(n) = \begin{cases} 0 & n = 1 \\ 1 & n \geq 2 \end{cases}$$

I_n is the total amount of data after data compression in a cluster with n nodes and the general expression of I_n is application-dependent. To calculate I_n, an empirical data-set pertaining to rainfall [14] is adopted in this paper. The total amount of compressed data generated by a set of n nodes after lossless compression can be calculated approximately by an iterative formula as follows:

$$I_i = I_{i-1} + \left[1 - \frac{1}{\left(d_i/c + 1\right)}\right]L, \quad i = 2, 3, \cdots, n \tag{10}$$

where c is a constant and represents the degree of spatial correlation in the data and d_i is the minimum distance between the new source node (the *i*-th node) and the existing set of nodes. An example of how to determine this distance is illustrated in Fig. 2.

The initial set of nodes consists of only one source node, thus we have $I_1 = L$. At each iteration, the new source node makes a certain amount of contribution to the total compressed data, which is equal to $\left[1-1/\left(d_i/c+1\right)\right]L$. To determine d_i, $i = 2, 3, \cdots, n$, we adopt the results from Monte Carlo simulations by averaging the values of distances calculated from 20,000 randomly generated network topologies. Fig. 3 shows the first nine minimum distance d_i ($i = 2, 3, \cdots, 10$) between the new source node and the existing set of nodes versus the number of the nodes, *i*, with nodal density $\rho = 10^{-6}/\mathrm{m}^2$. We see from this figure that when the number of nodes involved increases from 2 to 10, the distance increases from 736m to 877m. Furthermore, we can conclude based on (10) that the amount of compressed data contributed by the new source node, $\Delta I_i = I_i - I_{i-1}$, increases as the total number of the nodes involved increases.

Combining (2), (3), (8) and (9), the energy consumption during local communication under the centralized data aggregation scheme can be expressed as

$$\begin{aligned} E_{\text{intra}} = &\frac{1}{R_{\text{intra}}}\left\{\left[(n-1)L + I_n\right]P_{\text{SISO}}^d + \left[(n-1)L + q\left(n\right)I_n\right]P_T + \left[(n-1)(L+I_n)\right]P_R\right\} \\ &+ nLE_{\text{comp}} \end{aligned} \tag{11}$$

2) Distributed data aggregation scheme

The distributed data aggregation scheme works in two phases as follows:

<u>*Gathering phase*</u>*:* Each node in a cluster uses different time slots to broadcast its data to other nodes within the same cluster, so that each node in the cluster will have a copy of data sensed by all the nodes in the cluster. For simplicity the diameter of the approximating circular area of the clusters is used as the transmission distance in this

phase.

Compressing phase: Each node integrates and compresses the data gathered from the first phase separately, and thereafter the data are ready for long haul communication.

The energy consumption of the DAS in a cluster is the sum of the energy consumed in two phases, which is given by

$$E_{\text{intra}} = E_{\text{ga}}^{\text{DAS}} + E_{\text{comp}}^{\text{DAS}} \tag{12}$$

where $E_{\text{ga}}^{\text{DAS}}$ and $E_{\text{comp}}^{\text{DAS}}$ are the energy consumptions in the gathering and compressing phases, respectively, which are given by

$$E_{\text{ga}}^{\text{DAS}} = nP_{\text{SISO}}^{d} \frac{L}{R_{\text{intra}}} + n\left(q(n)P_T + (n-1)P_R\right)\frac{L}{R_{\text{intra}}} \tag{13}$$

and

$$E_{\text{comp}}^{\text{DAS}} = n^2 L E_{\text{comp}} \tag{14}$$

B. Energy consumption of long-haul communication E_{lh}

During the long-haul communication, the sensor nodes in a cluster encode the compressed data with the orthogonal STBC scheme and transmit them to the AP cooperatively. The energy consumption during long-haul communication, E_{lh}, is given by

$$E_{\text{lh}} = P_{\text{MIMO}}^{D} \frac{I_n}{R_{\text{lh}}} + \left(nP_T + P_R\right)\frac{I_n}{R_{\text{lh}}} \tag{15}$$

where P_{MIMO}^{D} is the power consumption of the power amplifiers on the transmitting side and R_{lh} denotes the transmission bit rate defined as $R_{\text{lh}} = R_S bB$, with R_S the spatial rate of the encoding scheme. Here $R_S = 1/2$ as we use an orthogonal space-time block code with the code rate of $1/2$.

In our scenario the AP flies over the sensor field to collect data. The AP retrieves the data of a cluster when it is right above the cluster. Since the long-haul distance between the AP and the cluster is usually much larger than the maximum separation of the clusters, we assume that this distance, denoted as *D*, is the same for all transmitting sensor nodes. When the channel experiences only a square-law path loss the power consumption of the power amplifiers in one cluster, P_{MIMO}^{D}, is given by [11], [12]

$$P_{\text{MIMO}}^{D} = (1+\alpha)\bar{E}_{\text{lh}}^{b} R_{\text{lh}} \frac{(4\pi)^2 D^2}{G_t G_r \lambda^2} M_l N_f \tag{16}$$

where $\bar{E}_{\text{lh}}^{b}$ is the average energy per bit required for a given BER requirement. The average BER, $\bar{\varepsilon}_{\text{lh}}^{b}$, of a MIMO with MQAM when $b=2$ is given by [11]

$$\begin{aligned} \bar{\varepsilon}_{\text{lh}}^{b} &= \mu_{\mathbf{h}}[Q(\sqrt{2\gamma_{\text{lh}}})] \\ &= \int_0^{\infty} Q(\sqrt{2\gamma_{\text{lh}}}) f(\gamma_{\text{lh}}) d\gamma_{\text{lh}} \end{aligned} \tag{17}$$

where $\mu_{\mathbf{h}}(x)$ denotes the expectation of *x* with channel vector **h**, and γ_{lh} is the instantaneous received SNR for the cooperative MIMO system [2], which is given by

$$\gamma_{\text{lh}} = \frac{\bar{E}_{\text{lh}}^{b}}{nN_0} \|\mathbf{h}\|_F^2 \tag{18}$$

For *n* cooperative nodes communicating to the AP, the channel vector is $\mathbf{h} = [h_1, h_2, \cdots, h_n]$. Each channel gain h_i is independent and identically distributed with a Rayleigh fading, and $\|\mathbf{h}\|_F^2$ is subject to a central chi-square distribution with $2n$ degrees of freedom. During the long-haul communication, the same bit is transmitted by all *n* sensors at staggered times according to the OSTBC (orthogonal space-time block code) mapping.

According to the Chernoff bound [15] (in the high SNR regime), we can derive the upper bound for the required energy per bit as

$$\bar{E}_{\text{lh}}^{b} \le \frac{nN_0}{\left(\bar{\varepsilon}_{\text{lh}}^{b}\right)^{1/n}} \tag{19}$$

By taking the equality in (19) and substituting it into (16), we can calculate the power consumption of the power amplifiers in one cluster, P_{MIMO}^{D}.

With E_{intra} for local communication and E_{lh} for long-haul communication, the total energy consumption for nodes in a cluster to transmit their sensed data to the AP, E_{tot}, can then be obtained accordingly. The average energy consumption per node will be used as an indicator to evaluate the energy efficiency of cooperative MIMO systems with data aggregation, which is expressed as

$$E_{\text{node}}^{\text{CMIMO-A}} = \frac{E_{\text{tot}}}{n} \tag{20}$$

For the centralized data aggregation scheme, $E_{\text{node}}^{\text{CMIMO-A}}$ can be worked out by combining (1), (11), (15) and (20) as

$$\begin{aligned} E_{\text{node}}^{\text{CMIMO-A}} = & \frac{1}{nR_{\text{intra}}}\left\{\left[(n-1)L + I_n\right]P_{\text{SISO}}^{d} + \left[(n-1)L + q(n)I_n\right]P_T + \left[(n-1)(L+I_n)\right]P_R\right\} \\ & + LE_{\text{comp}} + \frac{I_n}{nR_{\text{lh}}}\left[P_{\text{MIMO}}^{D} + (nP_T + P_R)\right] \end{aligned} \tag{21}$$

III. EVALUATION OF ENERGY-EFFICIENT CMIMO-A SYSTEMS

In this section, we first compare the performance in terms of energy efficiency of CMIMO-A systems with cooperative MIMO systems without data aggregation (CMIMO), data aggregation systems without cooperative MIMO (DATAG), and SISO systems. For this purpose, we take CAS as a special case in carrying out the comparisons based on the energy model built in the last section.

The local communication in a CMIMO system operates in the same way as in the CMIMO-A system except without the process of data aggregation. Due to this difference, CMIMO will transmit more data than CMIMO-A during long-haul communication. The average energy consumption per node of CMIMO can be derived using the approach described in Section II as

$$E_{\text{node}}^{\text{CMIMO}} = \frac{L}{nR_{\text{intra}}}\left[(2n-1)P_{\text{SISO}}^{d} + q\left(n\right)(2n-1)P_T + (n^2-1)P_R\right] + \frac{L}{R_{\text{lh}}}\left[P_{\text{MIMO}}^{D} + (nP_T + P_R)\right] + LE_{\text{comp}} \tag{22}$$

In the DATAG system, the central node collects and compresses the data sensed by nodes in the cluster, and then transmits the compressed data to the AP. The average energy consumption per node of DATAG can be derived as

$$E_{\text{node}}^{\text{DATAG}} = \frac{L}{nR_{\text{intra}}}(n-1)\left(P_{\text{SISO}}^{d} + P_T + P_R\right) + LE_{\text{comp}} + \frac{I_n}{nR_{\text{lh}}}\left[P_{\text{SISO}}^{D} + P_T + P_R\right] \tag{23}$$

where P_{SISO}^{D} is power consumption of the power amplifier during data transmission from the cluster to the AP, which is the same as P_{SISO}^{d} expressed by (4) except replacing *d* with *D*. Both energy models given in (22) and (23) are derived for the cluster-based WSN in the scenario illustrated in Fig. 1, which was not the case investigated in either [3] or [10].

In the SISO system, each node transmits their own sensing data to the AP directly without data exchanges with other nodes. The average energy consumption per node of SISO can be derived as

$$E_{\text{node}}^{\text{SISO}} = P_{\text{SISO}}^{D}\frac{L}{R_{\text{intra}}} + \left(P_T + P_R\right)\frac{L}{R_{\text{intra}}} + LE_{\text{comp}} \tag{24}$$

which is similar to that given in [3] but has included the energy consumed by data compression.

There are some assumptions made in simulations for CMIMO-A, CMIMO, DATAG and SISO systems. We suppose that the WSN concerned can be clusterized using a certain algorithm among many that are available. The energy consumption on signalling such as for clusterization and channel distribution for transmission within the cluster is neglected. We also assume that the AP’s movement is predefined to collect data from the WSN. Sensor nodes can communicate with the AP only when it moves right above the cluster they are located in. Energy consumed on hand-shaking for this communication is also neglected. The time synchronization among the nodes is assumed and, like in [3], related energy consumption is not counted. Finally, the baseband signal processing overhead and corresponding energy consumption on coding and modulation are omitted as well. As the above assumptions apply to all the systems, the conclusions drawn based on the results through comparisons among the different systems will not be affected.

The energy consumption related results presented in this section are based on the four analytical models derived in (21) ~ (24). When demonstrating the effect of one parameter on another such as the cluster size versus energy consumption, other system and environment settings will be specified and fixed, such as operating frequency, antenna gains, bandwidth, and power and energy consumption of certain device and circuit. The parameter settings we adopt, in line with other research work, are summarized in Table I.

Fig. 4 shows the average energy dissipated per node as a function of the number of nodes in one cluster, or the cluster size, for CMIMO-A, CMIMO, DATAG and SISO systems, respectively. Clearly from this figure, CMIMO-A outperforms all other systems in energy efficiency in most cases. At the same time, as we can see, choosing a proper cluster size is essential for making the combination of cooperative MIMO and data aggregation beneficial in terms of achieving higher energy efficiency. If no clusterization ($n=1$) is applied, there will be no difference in energy efficiency for all the four systems. If the cluster size is too large, CMIMO-A and CMIMO could be less energy-efficient than DATAG and SISO. This feature has not been investigated in previous work.

Note that the optimal cluster size corresponding to the minimum average energy consumption per node for CMIMO-A or CMIMO relates to the settings of a number of parameters in (21) or (22). In Fig. 4, for the settings given in Table I, CMIMO-A achieves the minimum energy consumption at the cluster size of 4, 50% less than CMIMO, 93% than DATAG, and 97% than SISO.

To better understand the performance difference between CMIMO-A and CMIMO, we demonstrate the two components of the energy consumption (for local communication and long-haul communication, respectively) for these two systems in Fig. 5. As we can observe, CMIMO-A consumes less energy than CMIMO in both local and long-haul communication processes for all cluster sizes. This is because in the broadcasting phase of local communication the central node in CMIMO-A transmits compressed data back to other sensor nodes, while in CMIMO uncompressed data are transmitted in the same phase. The reduction in the data volume per node after this phase, due to data aggregation adopted in CMIMO-A systems, increases with the cluster size. Consequently, fewer data need to be transmitted in CMIMO-A than CMIMO during long-haul communication.

In order to examine how spatial correlation affects energy saving in the CMIMO-A system, we define the saving gain as a ratio of the reduction in energy consumption per node between CMIMO and CMIMO-A versus the energy consumption per node of CMIMO, i.e.,

$$\psi_{\text{energy}} = \frac{E_{\text{node}}^{\text{CMIMO}} - E_{\text{node}}^{\text{CMIMO-A}}}{(1+\theta)\, E_{\text{node}}^{\text{CMIMO}}}, \quad \theta \geq 0 \tag{25}$$

The impact of overhead energy consumption due to signaling, baseband processing etc. on the energy saving gain has been considered in this definition and $\theta E_{\text{node}}^{\text{CMIMO}}$ denotes the overhead energy consumption.

Fig. 6 shows the energy saving gain of a CMIMO-A system for θ = 0, 0.5 and 1, respectively. It can be seen from Fig. 6 that the saving gain decreases with the increase in the average distance because spatial correlation in the data produced by sensor nodes will decrease for the increased average distance. When any two neighboring nodes in a sensor network are close enough, nearly all the nodes in the network will duplicate data and the energy consumed by the CMIMO-A system is fractional compared to that of the CMIMO system. It can also be seen that the saving gain decreases with the increase of overhead energy consumption. In Fig. 6, the degree of spatial correlation is set to be $c = 500$.

We now look at the optimization problem for the energy model developed, which can be expressed as

$$\begin{aligned} &\min_n E_{\text{node}}^{\text{CMIMO-A}} \\ &\text{Subject to: } n \text{ is integer} \\ &\qquad\qquad\quad\; n \geq 1 \end{aligned} \tag{26}$$

The energy consumption per node in CMIMO-A systems with CAS, $E_{\text{node}}^{\text{CMIMO-A}}$, is a function of the cluster size *n*, defined in (21) and demonstrated in Fig. 4. To minimize $E_{\text{node}}^{\text{CMIMO-A}}$, our goal is to find the optimal cluster size $n*$. A straightforward optimization process is conducted by allowing the cluster size *n* to vary and fixing other parameters given in Table 1 while computing (21). As (21) contains an iterative function of *n*, I_n, the optimal value of *n* for achieving the minimum $E_{\text{node}}^{\text{CMIMO-A}}$ cannot be obtained through a simple derivative process. However, we can show that (21) is an integer concave function [16]. Firstly, it is easy to show that when $n = 1$ the gradient of $E_{\text{node}}^{\text{CMIMO-A}}$ is $\nabla E(n = 1) < 0$. We then show that $\nabla E(n \to \infty) > 0$ by the following proposition.

Proposition 1: The gradients of the energy consumption function given in (21) are more than zero when the cluster size *n* increases towards positive infinity.

The proof of Proposition 1 is provided in Appendix A.

For examining the impact from other factors on the optimization result, we also alter the values of one other parameter each time to show how the optimal cluster size $n*$ correlates with other parameters. Fig. 7 shows the relationship between the optimal cluster size $n*$ and the distance from the cluster to the AP, D. As we can see, for example, when the distance increases from 5000m to 15000m the optimal cluster size increases linearly from 3 to 5, whilst between 15000m and 20000m there is no change in the optimal cluster size.

The effect from the nodal density ρ on the optimal cluster size is plotted in Fig. 8. The effect results are mixed over different ranges of the density values. For example, when the density is one node per 10 km^2 ($\rho = 10^{-7}$ /m^2) the optimal cluster size $n*= 2$ nodes, while when the density is increased to one node per 1 km^2 ($\rho = 10^{-6}$ /m^2) $n*= 4$ nodes.

We then examine the effect of the degree of spatial correlation c on the optimal cluster size. In this case, we demonstrate the results for the two different data aggregation schemes, CAS and DAS. It can be seen from Fig. 9 that the degree of spatial correlation has little impact on the value of the optimal cluster size, showing that nearly the same value of $n*$ (4 in this case) is obtained for all the schemes. However, the degree of spatial correlation does affect the energy consumption per node, $E_{\text{node}}^{\text{CMIMO-A}}$, for different data aggregation schemes. We can observe that when $c = 200$ DAS is better than CAS in terms of energy efficiency, while when $c = 5000$ CAS outperforms DAS for the same account.

To further demonstrate the difference in energy efficiency performance between CAS and DAS, we plot their minimized $E_{\text{node}}^{\text{CMIMO-A}}$ against a wide range of the values of c in Fig. 10. Clearly, there exists a threshold of the degree of spatial correlation ($c = 1740$ in this case), above which CAS outperforms DAS in terms of energy efficiency, and vice versa. The energy consumptions of the two data aggregation schemes are the same for long-haul communication but different for local communication. During local communication, the average transmission distance used in DAS is longer than that in CAS, hence DAS consumes more energy in the gathering phase than CAS; but, unlike CAS, it has no broadcasting phase. When c is low, not much redundancy can be taken off from the original data through data compression and consequently a similar amount of data transmitted in the gathering phase will need to be transmitted in the broadcasting phase of CAS as well. Therefore, in this case, more energy will be consumed overall in CAS than DAS. When c is high, however, much less data are transmitted in the broadcasting phase of CAS due to larger data reduction through compression. As a result, CAS becomes more energy efficient than DAS in this scenario.

IV CONCLUSION

In this paper, an energy saving strategy that exploits the combination of cooperative MIMO and data aggregation techniques in cluster-based wireless sensor networks has been investigated. Compared to traditional SISO systems and MIMO systems without data aggregation, the proposed strategy has demonstrated its performance superiority in terms of energy efficiency for different cluster sizes. Two data aggregation schemes, centralized and distributed, are introduced in CMIMO-A systems and their energy performances with the effect of the degree of spatial correlation are examined. The optimal cluster size that minimizes the average energy consumption per node is also obtained based on the energy model we have derived. It is shown that the optimal value achieved is independent of the degree of spatial correlation and the data aggregation scheme used. However, as demonstrated by our results, the optimal cluster size is affected by the long-haul transmission distance and the nodal density of the network. It is also observed that to ensure the cooperative MIMO and combined cooperative MIMO with data aggregation schemes to be more energy-efficient than other schemes, the sensor nodes should be properly clustered and the cluster size cannot be too big. Otherwise, no benefit could be achieved or even more energy could be consumed as a result.

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Figures:

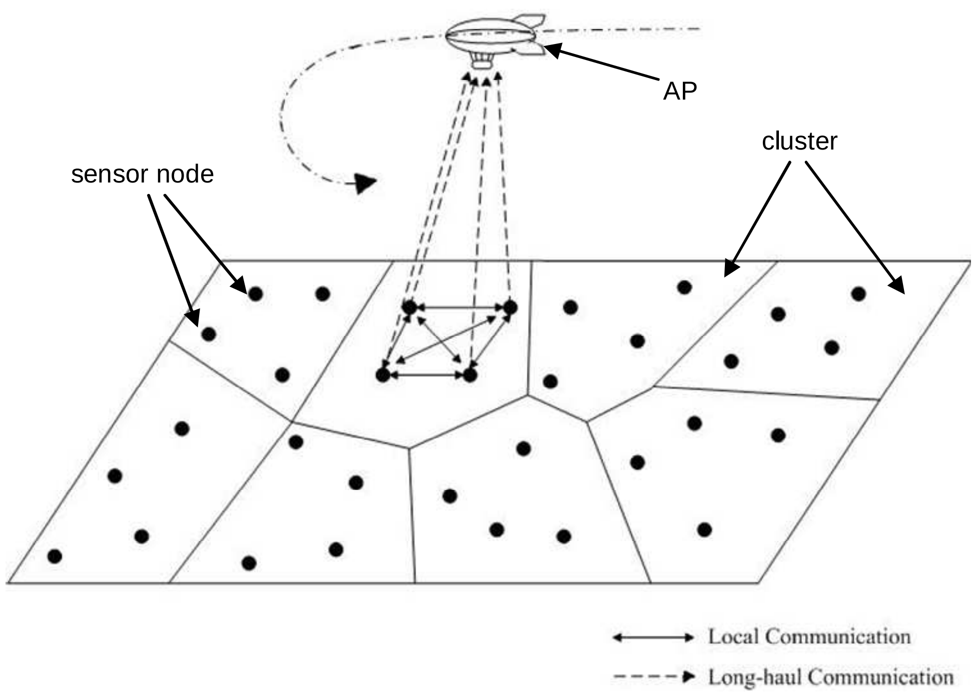

Fig. 1. Overview of cooperative MIMO systems with data aggregation.

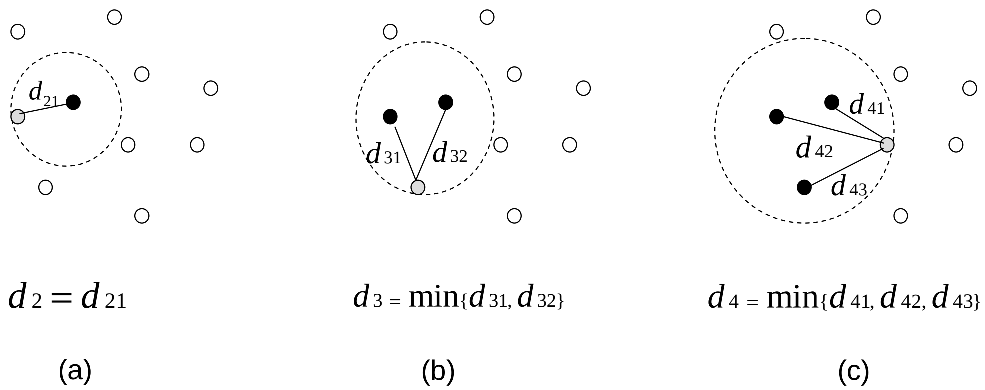

Fig. 2. An example of the minimum distance between the new source node and the existing set of nodes.

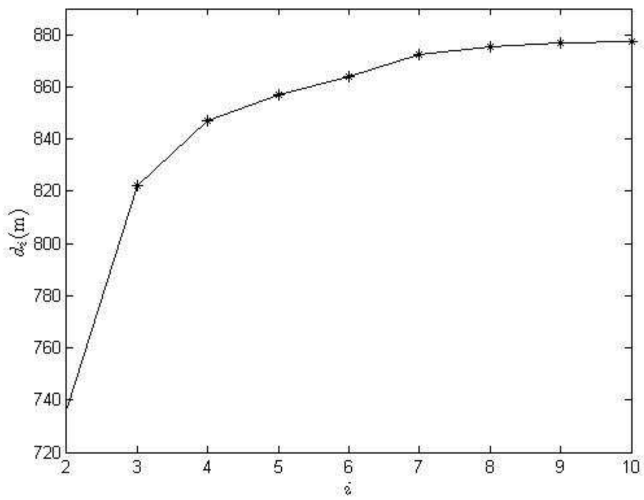

Fig. 3. The minimum distance d_i versus the number of nodes involved *i*.

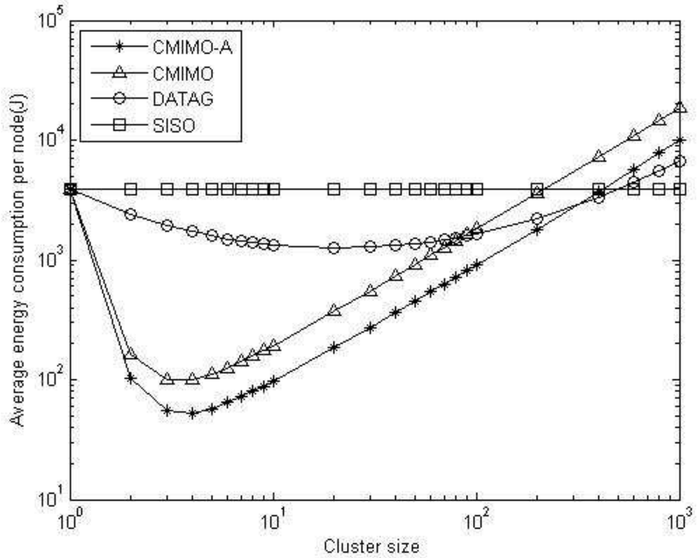

Fig. 4. Average energy consumption per node against cluster size for CMIMO-A, CMIMO, DATAG and SISO.

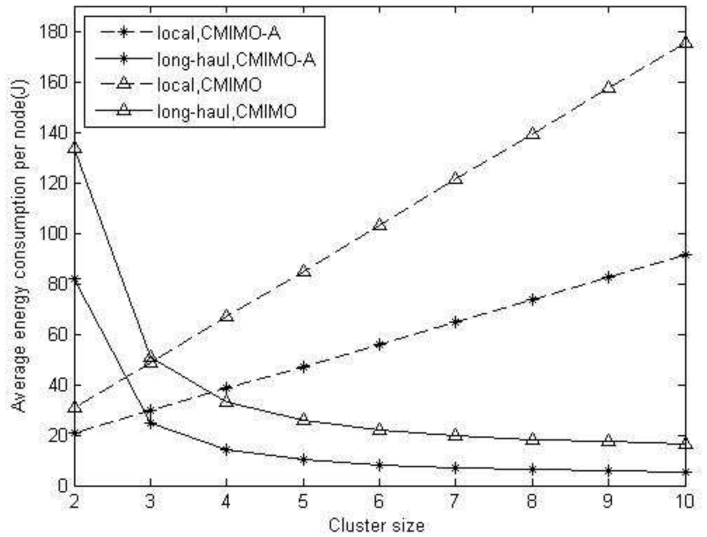

Fig. 5. The energy consumption comparison between CMIMO-A and CMIMO for both local communication and long haul communication.

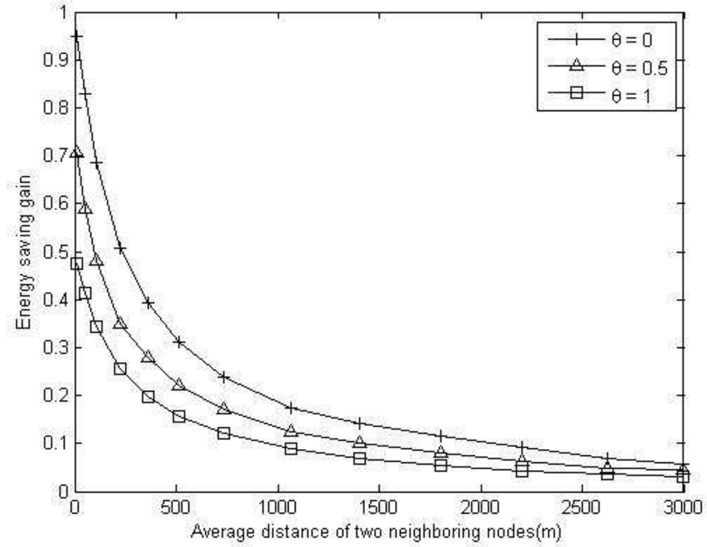

Fig. 6. Energy saving gain of CMIMO-A compared with CMIMO versus average distance of two neighboring nodes when $\theta = 0$, 0.5 and 1.

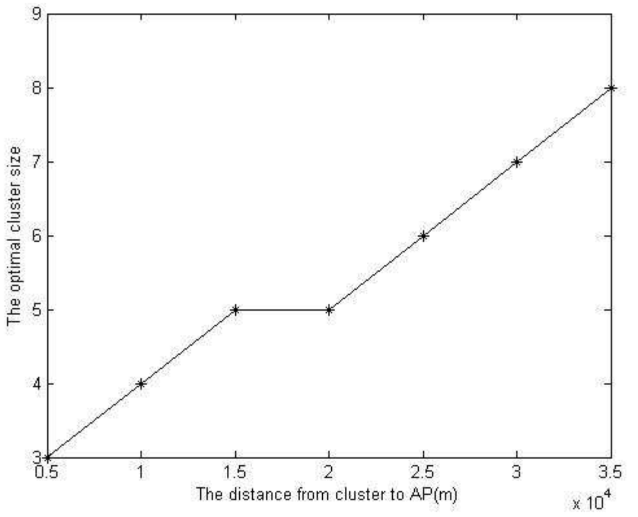

Fig. 7. The optimal cluster size versus the distance from sensor nodes to the AP.

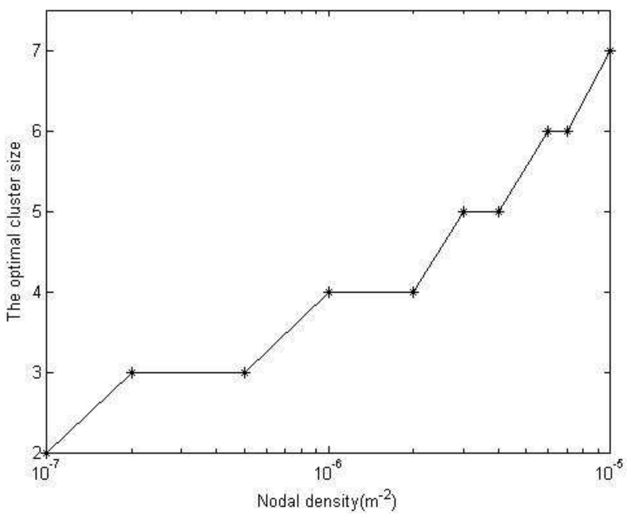

Fig. 8. The optimal cluster size versus nodal density.

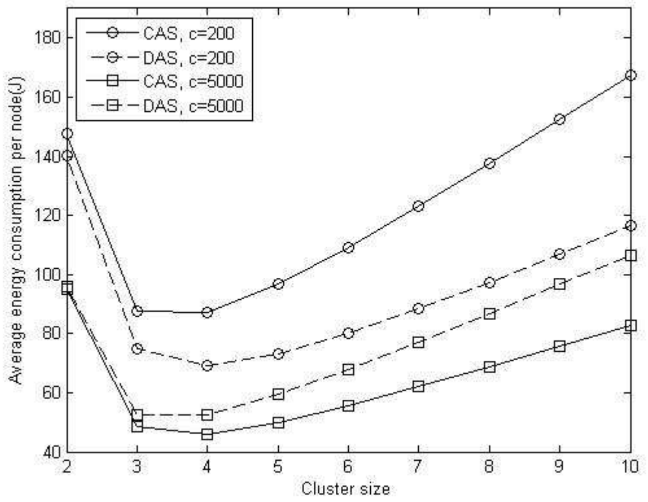

Fig. 9. Average energy consumption per node over cluster size for CMIMO-A when $c = 200$ and 5000, CAS versus DAS.

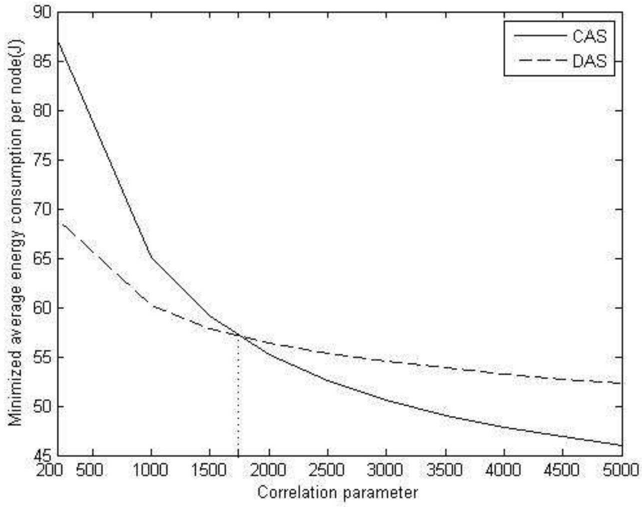

Fig. 10. Minimized average energy consumption per node versus the degree of spatial correlation for CAS and DAS of CMIMO-A systems.

Tables:

Table I System parameters

$P_T = 150mW$	$P_R = 100mW$
$\eta = 0.35$	$B = 10KHz$
$G_t G_r = 5dBi$	$M_l = 40dB$
$N_f = 10dB$	$N_0 = -171\text{dBm/Hz}$
$\lambda = 0.12\text{m}$	$E_{\text{comp}} = 5\text{nJ/bit/signal}$
$\varepsilon_{\text{intra}}^b = \bar{\varepsilon}_{\text{lh}}^b = 10^{-4}$	$L = 2000\text{bits}$
$D = 10000\text{m}$	$b = 2$
$\rho = 10^{-6}/\text{m}^2$	$c = 2500$

Appendix A:

Proof of Proposition 1: To prove this proposition, i.e. $\nabla E(n \to \infty) > 0$, is equivalent to showing that:

$$\lim_{m\to\infty} E_{\text{node}}^{\text{CMIMO-A}} \big|_{n=m+1} - E_{\text{node}}^{\text{CMIMO-A}} \big|_{n=m} > 0 .$$

We split (21) into a number of components in order to examine their trends when $n \to \infty$.

$$E_{\text{node}}^{\text{CMIMO-A}} = \frac{(n-1)LP_{\text{SISO}}^d}{nR_{\text{intra}}} + \frac{I_n P_{\text{SISO}}^d}{nR_{\text{intra}}} + \frac{(n-1)L\left(P_T + P_R\right)}{nR_{\text{intra}}} + \frac{q(n)I_n P_T}{nR_{\text{intra}}} + \frac{I_n P_R}{nR_{\text{lh}}} + \frac{(n-1)I_n P_R}{nR_{\text{intra}}} + \frac{I_n P_{\text{MIMO}}^D}{nR_{\text{lh}}} + \frac{I_n P_T}{R_{\text{lh}}} + LE_{\text{comp}} \quad \text{(A1)}$$

Let

$$E_1 = \frac{(n-1)LP_{\text{SISO}}^d}{nR_{\text{intra}}} \quad \text{(A2)}$$

$$E_2 = \frac{I_n P_{\text{SISO}}^d}{nR_{\text{intra}}} \tag{A3}$$

$$E_3 = \frac{(n-1)L\left(P_T + P_R\right)}{nR_{\text{intra}}} \tag{A4}$$

$$E_4 = \frac{q(n) I_n P_T}{nR_{\text{intra}}} + \frac{I_n P_R}{nR_{\text{lh}}} \tag{A5}$$

$$E_5 = \frac{(n-1) I_n P_R}{nR_{\text{intra}}} \tag{A6}$$

$$E_6 = \frac{I_n P_{\text{MIMO}}^D}{nR_{\text{lh}}} \tag{A7}$$

$$E_7 = \frac{I_n P_T}{R_{\text{lh}}} \tag{A8}$$

$$E_8 = LE_{\text{comp}} \tag{A9}$$

We then show that $\lim_{m\to\infty} E_i \big|_{n=m+1} - E_i \big|_{n=m} \geq 0, i = 1, 2, \ldots, 8$.

1. E_1

$$E_1 \big|_{n=m+1} - E_1 \big|_{n=m} = \frac{L}{R_{\text{intra}}} \left(\frac{m^2 P_{\text{SISO}}^d \big|_{n=m+1} - \left(m^2 - 1\right) P_{\text{SISO}}^d \big|_{n=m}}{m\left(m+1\right)} \right) \tag{A10}$$

From (4), we have

$$P_{\text{SISO}}^d = \beta n \tag{A11}$$

where β represents all the variables in (4) that are relative to *n*, i.e.

$$\beta = (1+\alpha)E_{\text{intra}}^{b} R_{\text{intra}} \frac{(4\pi)^2}{G_t G_r \lambda^2 \rho\pi} M_l N_f \tag{A12}$$

Thus

$$E_1\big|_{n=m+1} - E_1\big|_{n=m} = \frac{L\beta}{R_{\text{intra}}} > 0 \tag{A13}$$

2. E_2

$$E_2\big|_{n=m+1} - E_2\big|_{n=m} = \frac{\beta}{R_{\text{intra}}}\left(I_{m+1} - I_m\right) > 0 \tag{A14}$$

3. E_3

$$E_3\big|_{n=m+1} - E_3\big|_{n=m} = \frac{L\left(P_T + P_R\right)}{R_{\text{intra}}}\left(\frac{1}{m\left(m+1\right)}\right) > 0 \tag{A15}$$

4. E_4

$$E_4\big|_{n=m+1} - E_4\big|_{n=m} = \left(\frac{q(n)P_T}{R_{\text{intra}}} + \frac{P_R}{R_{\text{lh}}}\right)\left(\frac{I_{m+1} - I_m}{m+1} - \frac{I_m}{m\left(m+1\right)}\right) \tag{A16}$$

From (10), we have

$$I_{m+1} - I_m = \left[1 - \frac{1}{\left(d_{m+1}/c + 1\right)}\right] L \tag{A17}$$

When $m \to \infty$, $d_m \to const$ (constant). Therefore,

$$\lim_{m\to\infty} I_{m+1} - I_m = const \tag{A18}$$

$$\lim_{m\to\infty} \frac{I_{m+1} - I_m}{m+1} = 0 \tag{A19}$$

$$\lim_{m\to\infty} \frac{I_m}{m} = const \tag{A20}$$

According to (A16), (A19) and (A20), we have

$$\lim_{m\to\infty} E_4\big|_{n=m+1} - E_4\big|_{n=m} = 0.$$

5. E_5

$$E_5\big|_{n=m+1} - E_5\big|_{n=m} = \frac{P_R}{R_{\text{intra}}}\left(\frac{m\left(I_{m+1} - I_m\right)}{m+1} + \frac{I_m}{m\left(m+1\right)}\right) \tag{A21}$$

According to (A18)，(A20) and (A21), we have

$$\lim_{m\to\infty} E_5\big|_{n=m+1} - E_5\big|_{n=m} = const > 0\,.$$

6. E_6

$$E_6\big|_{n=m+1} - E_6\big|_{n=m} = \frac{1}{R_{\text{lh}}}\left(\frac{I_{m+1}P_{\text{MIMO}}^{D}\big|_{n=m+1}}{m+1} - \frac{I_m P_{\text{MIMO}}^{D}\big|_{n=m}}{m}\right) \tag{A22}$$

From (16) and (19), we have

$$P_{\text{MIMO}}^{D} = \beta' \frac{n}{\left(\bar{\varepsilon}_{\text{lh}}^{b}\right)^{1/n}} \tag{A23}$$

Again, β' is not relative to n, i.e.

$$\beta' = (1+\alpha)R_{\text{lh}} \frac{N_0(4\pi)^2 D^2}{G_t G_r \lambda^2} M_l N_f \tag{A24}$$

According to (A22), (A23) and (A24), we have

$$\lim_{m\to\infty} E_6\big|_{n=m+1} - E_6\big|_{n=m} = const > 0\,.$$

7. E_7

$$\lim_{m\to\infty} E_7\big|_{n=m+1} - E_7\big|_{n=m} = \lim_{m\to\infty} \frac{P_T}{R_{\text{lh}}}\left(I_{m+1} - I_m\right) = const > 0 \tag{A25}$$

8. E_8 is a constant, hence $E_8\big|_{n=m+1} - E_8\big|_{n=m} = 0$.

Based on the above results, we conclude that $\lim_{m\to\infty} E_{\text{node}}^{\text{CMIMO-A}}\big|_{n=m+1} - E_{\text{node}}^{\text{CMIMO-A}}\big|_{n=m} > 0$.