Energy-Efficient Cluster-Based Wireless Sensor Networks Using Adaptive Modulation: Performance Analysis

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ABSTRACT Wireless Sensor Networks (WSNs) play a vital role in modern technology since they have recently emerged into enormous essential applications of the Internet of Things (IoT). However, WSNs encounter a shortage in the lifetime due to limitations in the power supply. Accordingly, many solutions are reported in literature to deal with energy saving problem in the WSNs. In this paper, a novel method is presented to minimize energy consumption using *adaptive modulation* that is jointly integrated with *clustering technique*. This method is considered as a promising solution for dense and sparse cluster-based WSNs to improve energy efficiency. In the suggested solution, the adaptive modulation is implemented in the communication link between cluster members (CMs) and cluster head (CH). Besides, distance-based adaptive modulation step function is proposed in which the optimum modulation order is selected to achieve the minimum energy consumption between CMs and CH. The proposed method is evaluated extensively in order to investigate the impact of adaptive modulation in cluster-based WSNs using M-ary Quadrature Amplitude Modulation (MQAM) system. The performance evaluation addresses both energy consumption and throughput by using two metrics: cluster density, and cluster size. Regarding simulation results, by varying cluster density and cluster size, the adaptive modulation shows significant saving in energy consumption where it constitutes a *lower bound* for energy consumption. Also, it shows a great impact on throughput where it constitutes an *upper bound* for the throughput. Moreover, the adaptive modulation shows a considerable leverage on energy saving for small number of clusters, conversely, the energy saving decreases as the number of clusters increase. Finally, it is concluded that these findings can provide a remarkable guidance for designing an energy efficient WSNs.

INDEX TERMS Wireless sensor networks (WSNs), cluster-based network, adaptive modulation, energy consumption, Internet of Things (IoT).

I. INTRODUCTION

Wireless sensor networks (WSNs) witness a great demand because they have recently integrated with the cutting-edge technologies. Besides, WSNs have also incorporated with the emerging applications of the Internet of Things (IoT) that has the capability to link different devices through the internet to exchange an enormous amount of information. However, WSNs encounter many challenges and limitations due to limited energy source where sensor node lifetime depends on battery lifetime [1], [2]. Therefore, the main objective is always to find an adequate solution to overcome these

challenges through minimizing the energy consumption and prolong the lifetime.

This paper proposes a solution that is embodied through a novel idea to mitigate the limitations of the WSNs. Mainly, this solution addresses the clustering approach and jointly combined with adaptive modulation technique. According to the sensor networks protocol stack [1], clustering is located in the *network layer*, while modulation is located in the *physical layer*.

Clustering is considered as one of the most promising solutions in which it guarantees an efficient exploitation for the limited availability of energy. Cluster-based WSNs decompose the network into non overlapping sub-networks called clusters. Each cluster consists of a set of sensor nodes called

cluster members (CM) in which they communicate with a special selected sensor node called cluster head (CH), where this is called intra-cluster communication. Further, the CH sends all aggregated data to the base station (BS) where this is called inter-cluster communication [3].

On the other hand, adaptive modulation technique plays an important role to achieve several objectives in terms of energy efficiency as well as spectral efficiency [4]–[6]. Unlike legacy systems, adaptive modulation is recently considered as one of the promising solution to provide an energy-efficient networks (e.g., 5G networks) [7], and also use the spectrum in an efficient manner to meet the demand of the high data rate since it becomes an essential requirements of the modern technology.

In this work, we consider adaptive modulation in cluster-based WSN since it has the capability to save more energy comparing with the traditional cluster-based WSN. In adaptive modulation the transmitter and receiver have the ability to adapt its modulation level according to the channel quality, where the feedback channel transmits information about the channel status which learned at the receiver so that the transmitter can adjust its modulation level based on it, the main idea of the adaptive feedback system is to minimize the probability of error, subject to power constraints on the transmitted signal [8].

The main purpose of this paper is to investigate the impact of the adaptive modulation technique in order to minimize the energy consumption of the cluster-based WSNs. Unlike most previous literature in which they focus on minimizing energy consumption in typical cluster-based WSNs, this work study the energy consumption in such networks by employing adaptive modulation, and how this technique could affect the energy efficiency (*energy consumption*) as well as the spectral efficiency (*throughput*).

The motivation of this study can be summarized as follows. Since the IoT is a network of interconnected sensor-based devices in which they are grouped into clusters, it requires minimum energy consumption to combat the energy limitations of the WSNs. Therefore, in such networks the main objective is to maintain the operational lifetime as well as provide reliable communication links. On the other side, this work motivates us to coming up with creative and novel ideas to improve the lifetime of the cluster-based WSNs where they are different from previous one.

The contributions of this paper can be summarized in the following points:

- An adaptive modulation technique has been integrated with cluster-based WSNs.
- An energy consumption model has been derived taking into account both signal and circuit energy.
- Distance-based adaptive modulation step function is proposed.
- Performance analysis has been carried out to evaluate the proposed work. The evaluation addresses both energy efficiency (energy consumption) as well as spectral

efficiency (throughput) in the cluster-based WSNs using two metrics: *cluster size* and *cluster density*.
- The *fairness* of the energy consumption for the clusters has been addresses.

The rest of the paper is organized as follows. In section II, some literature and related works are presented. In section III, an adaptive modulation technique is discussed. In section IV, models, derivations, and problem formulation are explained. In section V, performance evaluation of the proposed work is demonstrated and discussed. Finally, section VI concludes the paper.

II. LITERATURE REVIEW

In wireless sensor networks energy efficiency as well as network lifetime have become a critical design concerns. Therefore, a considerable amount of literature has been published to address this problem taking into account the design considerations related to different layers of the sensor networks protocol stack. Some of them have focused on the network layer and others have focused on the physical layer. This section presents the literature related to both area of research, but it places emphasis on physical layer.

In terms of clustering approach, there are several works have been carried out to develop and design a variety of clustering protocols for the WSNs. Such protocols usually take place in the network layer, where it is based on the network density for the deployed sensors in certain geographic region. Heinzelman *et al.* [9], [10] was the earlier work to develop a famous clustering protocol called LEACH (*Low-Energy Adaptive Clustering Hierarchy*), after that they updated it to another protocol called LEACH-C. Lindsey and Raghavendra [11] proposes PEGASIS (*Power-Efficient Gathering in Sensor Information Systems*). Younis and Fahmy [12] proposed another famous clustering protocol called HEED (*Hybrid Energy-Efficient Distributed clustering*). Moreover, Ding *et al.* [13] proposed a DWEHC (*Distributed Weight-Based Energy-Efficient Hierarchical Clustering*). Also, Buttyan and Schaffer [14] introduced another clustering protocol called PANEL (*position-based aggregator node election*). Farther, successive developments followed these works and some of them have been used and optimization technique [3] to minimize the energy consumption in the WSNs.

On the other hand, several research have been conducted to address the impact of adaptive modulation method in which it takes place in the physical layer. Besides, these literature presents significant results in terms of energy efficiency and spectral efficiency. In recent years, there has been an increase in the demand for this approach to provide energy-efficient systems with high data rate.

This section spot the light on some of these works. Thirunavukkarasu *et al.* [15] introduced an adaptive modulation for WSNs. The paper presents a systematic method of assigning the modulation technique by sensing the signal to noise ratio (*SNR*) and bit error rate (*BER*) instantaneously.

In order to implement the adaptive modulation, the authors used BPSK, QPSK, 16-QAM, and 64-QAM. The paper concludes that for lower *SNR* the lower order modulations are used such as BPSK, conversely, for higher *SNR* the higher order modulations are used such as 64-QAM.

Yang *et al.* [16] addressed the problem of the lower spectral efficiency in non-line-of-sight (NLOS) transmission of WSN. Therefore, they proposed a novel nondata-aided error vector magnitude based adaptive modulation (NDA-EVM-AM) to solve the problem.

Soltan *et al.* [17] showed how the physical layer can affect the energy consumption and the lifetime of the WSNs. They presented a location-aware modulation scheme. The work demonstrated that the proper selection of modulation scheme can balance the dissipated energy distribution among sensors within coverage area in WSNs.

Babber and Randhawa [18] enhanced the WSNs lifetime by considering modulation techniques as a one of the physical layer parameters. This work proposed uniform clustering with proper modulation techniques and evaluate it under varying channel conditions.

Okada and Itoh [19] developed a WSN system using 128-FSK where this system can prevent unwanted signals to be received from another system. Besides, The transmitted packets do not have a preamble and an error check code for low power wireless communication. Therefore, This system can reduce the power consumption.

Wang *et al.* [20] addressed the physical layer to study energy consumption of the cooperative MIMO WSNs under the MPSK modulation by using space time block coding. This work investigate the total energy consumption that includes circuit blocks energy, the transmission energy, and the extra cooperative MIMO energy consumption. Performance evaluation was performed for the total energy consumption for both short and long transmission distance as the constellation size increases. As a result, large amount of energy cost can be saved by utilizing cooperative MIMO especially at long transmission distance.

Moreover, Peng *et al.* [21] and Hojjati *et al.* [22] proposed a strategy to reduce the energy consumption in the WSN by jointly selecting sensor node with proper modulation constellation sized through cooperative spectrum sensing. Also, Peng and Youn [23] considered the optimization techniques to minimize the energy consumption and prolong the lifetime in multi-hop clustered WSNs. They utilized spatial modulation-based cooperative MIMO as the transmission scheme.

Anane *et al.* [24] investigated the best digital modulation scheme in the WSNS to reduce the total energy consumption. The authors presented an analytical study for modulation schemes including MQAM, MPSK, MFSK, and MSK and showed that MSK is a promising choice. Besides, Anane *et al.* [25] continue their work to investigate the best modulation scheme to minimize the total energy consumption considering both uncoded and coded modulation.

Correia and Carvalho [26] addressed enablers for the IoT by proposing passive WSNs based in 4-QAM backscatter modulation. This solution was combined with wireless power transfer (WPT) scheme in order to increase bit rate.

Further, the works presented by Costa and Ochiai [27], [28] and Abouei *et al.* [29] proposed an energy minimization scheme for the WSNs, considering both transmitted signal and circuit power consumption. They considered three modulation schemes: MQAM, MPSK, and MFSK, where an analytical comparison is presented for them. Their work have shown that the energy consumption for MQAM and MPSK are similar for all distances between any two sensors. Moreover, the work have shown that MFSK has poor performance in terms of energy consumption for shorter distances between sensor nodes because the circuit energy consumption is dominant, on the other side, it has good performance for longer distances because the signal energy consumption is dominant.

On the other side, Abouei *et al.* [29], [30] investigated green modulation schemes which is refer to energy-efficient modulation with a low-complexity implementation in the WSNs. A comparison study was performed for four modulations: MFSK, MQAM, OQPSK, and OOK (simplest form of ASK). The study showed that MFSK with small order is attractive in sparse WSNs and low data rates since it is energy-efficient scheme for different values of the path-loss exponent, while OOK is energy-efficient scheme in dense WSNs with small values of path-loss exponent. Also, MQAM is suitable modulation schemes for different distances among sensor nodes.

Shuguang *et al.* [31] have shown that MQAM is more energy-efficient than MFSK since in a practical WSNs it was shown that minimizing the total energy consumption highly depends on the channel bandwidth as well as transmission time duration.

Zhang *et al.* have presented several works [32]–[34] to demonstrate the important usage for employing adaptive modulation and coding in the state-of-the-art technology called Aeronautical Ad hoc Networking (AANET).

Also, a significant research were carried out by Migabo *et al.* [35], Mwakwata *et al.* [36], Yu *et al.* [37], and Lee and Lee [38] to introduce adaptive modulation as a solution for improving the spectral efficiency in Narrow band internet of things (NB-IoT).

Chehri and Mouftah [39] have employed adaptive modulation in the multi-hop WSNs. The found that total energy consumption through the rout from sensor node to the sink node was reduced significantly.

Moreover, Pramono *et al.* [40] addressed energy and spectral efficiency issues in WSNs. They studied the impact of a combination of power control and adaptive modulation in WSNs. They conclude that this approach has a significant impact to reduce power consumption, increase spectral efficiency, and extend the lifetime of the WSNs.

III. ADAPTIVE MODULATION

Adaptive modulation is a method in which a reliable, robust, and spectral efficient communication system can be achieved since the number of bits per symbol for the modulated signal is adapted depending on the channel conditions [5], [41]. Basically, adaptive modulation is built on the concept that is the data packet is transmitted at high data rate when the channel is good and also at lower data rate when the channel is poor. Consequently this technique can limit the number of dropped data packets [42], and also it ensures fairness among transmitters [43] since the transmission energy is varying because of different bit rate. As depicted in Fig. 1, the adaptive modulation depends on the channel estimation at the receiver side where it is fed back to the transmitter side in which the modulation scheme is adapted according the *channel state information* (*CSI*) [44].
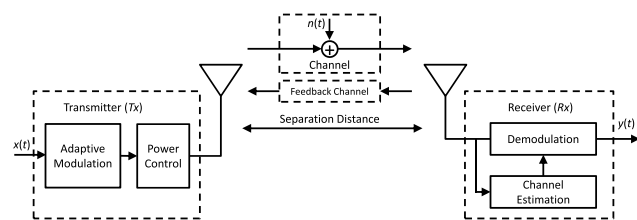

FIGURE 1. Adaptive modulation model in WSN [44].

Adaptive modulation method has several advantages on both energy efficiency and spectral efficiency due to adapting to the channel conditions. It reduces the transmit power, increases the throughput, and also reduces the probability of bit error. Besides, adapting to the channel conditions, enables the communication system to increase the data rates or reduce transmit power, as well as to reduce the data rate or increase transmit power [44], [45].

Recently, it has been revived the interest in adaptive modulation methods due to growing demand for spectral efficient communication systems. Further, the state-of-the-art communication systems are less constraining to the design considerations issues of the adaptive modulation methods [31], [44].

Adaptive techniques are used to satisfy Quality-of-Service requirements in end-to-end wireless applications. Therefore, in this work the *separation distance* between sensors in the WSN is considered as a metric to evaluate the quality of the link because of the power falloff with distance of signal propagation [46].

IV. MODELS AND PROBLEM FORMULATION

In this work, a cluster-based WSN is considered, in which a cluster member (*CM*) node transmits sensory data (*N-bit message*) to its cluster head (*CH*) node. The models and problem formulation is focused only on the transmission duration (active mode duration) of the sensors, in which the message is generated, modulated, and transmitted to the CH.

Besides, the candidate modulation scheme in this study is M-ary Quadrature Amplitude Modulation (MQAM).

In the following subsections, the paper will present the modeling, formulation, and derivation of the problem in details. Table. 1 lists the parameters and symbols used in this study.

TABLE 1. Models and problem formulation parameters.

Parameter	Description
E	The total energy consumption to transmit N-bit message.
E_c	Circuit energy consumption.
E_{tx}	Transmission signal energy.
P_c	Circuit power consumption.
P_{tx}	Transmission signal power.
T_t	Transmission duration (active mode duration).
P_{c_tx}	Circuit power consumption at the transmitter.
P_{c_rx}	Circuit power consumption at the receiver.
P_{DAC}	Digital-to-Analog Converter (DAC) power consumption.
P_{ADC}	Analog-to-Digital Converter (ADC) power consumption.
P_{Syn}	Frequency synthesizer power consumption.
P_{Mix}	Mixer power consumption.
P_{Filt_tx}	Active filter power consumption at the transmitter.
P_{Filt_rx}	Active filter power consumption at the receiver.
P_{Amp}	Power amplifier power consumption.
P_{IFA}	Intermediate Frequency Amplifier power consumption.
P_{LNA}	Low Noise Amplifier power consumption.
α	Power amplifier coefficient.
ξ	Peak to Average Ratio (PAR).
η	Drain efficiency of the RF power amplifier.
M	Constellation size or modulation index.
N	Message length in bits.
Ω	Rayleigh distribution parameter $\Omega = E[|h_i|^2]$.
N_0	Power spectral density.
P_s	Average Symbol Error Rate (SER).
G_d	Power gain factor at distance d meter.
G_1	Gain factor at d=1 m.
ℓ	Path-loss exponent.
d	Distance between transmitter and receiver.

A. CHANNEL MODEL

In a cluster-based WSN, the channel model between CM and CH is assumed to be *Rayleigh flat-fading* with pass-loss. This model has been adopted in many works as it is suitable for the structure of the WSN [20], [29], [39], [40]. The fading channel coefficient corresponding to the transmitted symbol i is h_i, where the amplitude $|h_i|$ is a random variable with a Rayleigh probability density function given by Eq. (1) [29]

$$f_{|h_i|}(r) = \frac{2r}{\Omega} e^{\frac{-r^2}{\Omega}} \qquad (1)$$

Rayleigh distribution is characterized by the single parameter $\Omega = E[|h_i|^2]$.

The power gain factor for the ℓth power path loss between the transmitter (*tx*) and receiver (*rx*) at distance d maters is given by Eq. (2) [31]

$$G_d \triangleq \frac{P_{tx}}{P_{tx}} = G_1 d^\ell M_l, \qquad (2)$$

where M_l is the link margin of the hardware process variations and background noise. G_1 is the gain factor at

$d = 1 \, m$ which is given by [29], [31]

$$G_1 = \frac{(4\pi)^2}{\mathcal{G}_{tx}\mathcal{G}_{rx}\lambda^2}, \tag{3}$$

where G_1 is defined by the antenna gains for the transmitter ($\mathcal{G}_{tx}$) and receiver ($\mathcal{G}_{rx}$), and also the wavelength λ.

When the transmitter transmits a symbol i with energy E_t, then the corresponding signal $x_i(t)$ will be added to noise signal $n_i(t)$ so that the received signal is given by Eq. (4) [29]

$$y_i(t) = \frac{h_i}{\sqrt{G_d}}x_i(t) + n_i(t) \tag{4}$$

In this work it is assumed that $n_i(t)$ is the additive white Gaussian noise (AWGN) having two-sided power spectral density $N_0/2$.

The corresponding signal to noise ratio *SNR* for the transmitted symbol i is

$$\gamma_i = \frac{|h_i|^2}{G_d}\frac{E_{tx}}{N_0} \tag{5}$$

Therefore, the average *SNR* is given by Eq. (6) [29]

$$\bar{\gamma} = \frac{E[|h_i|^2]}{G_d}\frac{E_{tx}}{N_0} \Rightarrow \bar{\gamma} = \frac{\Omega}{G_d}\frac{E_{tx}}{N_0} \tag{6}$$

B. ENERGY CONSUMPTION MODEL
1) M-ARY QUADRATURE AMPLITUDE MODULATION (MQAM)
MQAM is a modulation technique that is widely used in the modern telecommunication systems for data transmission. For QAM signal two quadrature carriers are combined and modulated $cos(2\pi f_c t)$ and $sin(2\pi f_c t)$, where f_c is the carrier frequency. Thus, the signal consists of two components *In-phase* ($I(t)$) and *Quadrature* ($Q(t)$) where this characteristic can increase the immunity to the noise as well as reduce the errors [47]. The QAM waveform can be expressed as [48]

$$s_i(t) = \underbrace{A_{Ii}g(t)cos(2\pi f_c t)}_{I(t)} - \underbrace{A_{Qi}g(t)sin(2\pi f_c t)}_{Q(t)}, \tag{7}$$

where $i = 0, 1, \ldots, M - 1$, also A_{Ii} and A_{Qi} are the information signal amplitudes of the orthogonal carriers and $g(t)$ is signal pulse. From Eq.(7) it is noticed that the QAM signal waveforms may be viewed as combined amplitude and phase modulation [48].

In particular, with MQAM modulation each symbol i is transmitted over the channel as one of $M = 2^b$ possible constellation points as depicted in Fig.2, where b ($b = \log_2 M$) is the information bits that can be mapped into one complex symbol [44]. Further, the bit error rate (*BER*) performance of MQAM over AWGN is explained in Fig.3.

2) ENERGY CONSUMPTION MODEL FOR MQAM SYSTEM
The energy consumption model for the MQAM system which is proposed in this study follows similar derivation approach as in [29]–[31], and [39]. The model takes into account the energy consumption for both transmit signal (RF signal) (E_t)
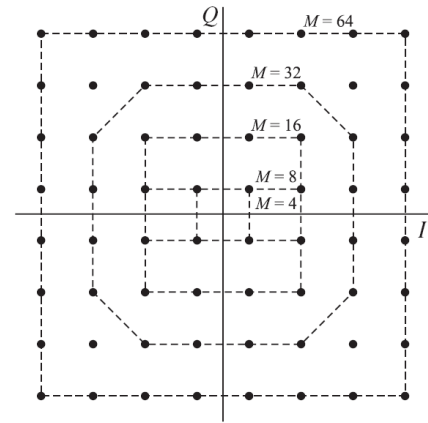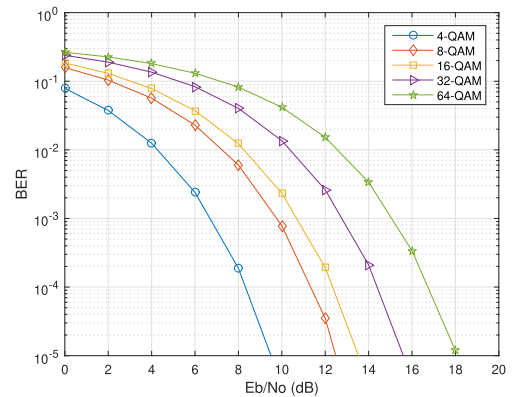

FIGURE 2. QAM constellation [48].

FIGURE 3. BER performance for MQAM modulation over AWGN.

and circuit (E_c). Therefore the energy (E) consumed by the sensor node to transmit *N-bit* message during active period of time will basically given by

$$E = E_t + E_c \tag{8}$$

The RF transmit energy consumption is

$$E_t = P_t \times T_t \tag{9}$$

T_t can be calculated as follows. If T_s is the symbol duration, then the channel bandwidth, which is assumed to be fixed, of the QAM signal is [30]

$$B = \frac{1}{2T_s} \tag{10}$$

During active mode, the transmission duration to transmit *N-bit* message is

$$T_t = \frac{N}{b}T_s \Rightarrow T_t = \frac{N}{2B\log_2 M} \tag{11}$$

On the other hand, E_t is calculated at predefined symbol error rate *SER* P_s which is in the case of MQAM it is upper bounded by [29], [30]

$$P_s \le \frac{4(M - 1)}{3\bar{\gamma} + 2(M - 1)}\left(1 - \frac{1}{\sqrt{M}}\right) \tag{12}$$

since $\bar{\gamma} = \frac{\Omega}{G_d} \frac{E_t}{N_0}$, then Eq.(12) becomes

$$P_s \leq \frac{4(M-1)}{3\left(\frac{\Omega E_t}{G_d N_0}\right) + 2(M-1)}\left(1 - \frac{1}{\sqrt{M}}\right) \quad (13)$$

By solving Eq.(13) for E_t we got

$$E_t \leq \frac{2(M-1)}{3}\left[\frac{2}{P_s}\left(1 - \frac{1}{\sqrt{M}}\right) - 1\right]\frac{G_d N_0}{\Omega} \quad (14)$$

But E_t in Eq.(14) is calculated for symbol duration time T_s, therefore, E_t for the transmission duration T_t is

$$E_t = \frac{2(M-1)}{3}\left[\frac{2}{P_s}\left(1 - \frac{1}{\sqrt{M}}\right) - 1\right]\frac{G_d N_0 N}{\Omega \log_2 M} \quad (15)$$

On the other side, the energy consumption for the circuit is given by

$$E_c = P_c \times T_t \quad (16)$$

By substitute the value of T_t we got

$$E_c = \frac{P_c N}{2B \log_2 M} \quad (17)$$

The power consumption by the circuit (P_c) is given by

$$P_c = P_{c\_tx} + P_{c\_rx}, \quad (18)$$

where P_{ct} is the power consumption by the transmitter, and P_{cr} is the power consumption by the receiver. Both of them can be calculated as follows [29], [31]

$$P_{c\_tx} = P_{DAC} + P_{Syn} + P_{Mix} + P_{Filt\_tx} + P_{Amp} \quad (19)$$
$$P_{c\_rx} = P_{ADC} + P_{Syn} + P_{Mix} + P_{Filt\_rx} + P_{IFA} + P_{LNA} \quad (20)$$

In MQAM systems, the power consumption for the amplifier (P_{Amp}) is given by [29], [31]

$$P_{Amp} = \alpha \times P_t, \quad (21)$$

where P_t is the RF transmit power consumption, and α is the power amplifier coefficient. The calculations of α is given by $\alpha = \frac{\xi}{\eta} - 1$, where ξ is the Peak to Average Ratio (*PAR*) and it depends on the modulation scheme as well as modulation index (M), which is given by $\xi = 3\frac{\sqrt{M}-1}{\sqrt{M}+1}$, and η is the drain efficiency of the RF power amplifier [31]. It is assumed that $\eta = 0.35$ for the MQAM.

Therefore, by substituting Eq.(15) and Eq.(17) into Eq. (8), the total energy consumption by the sensor node becomes

$$E = (1+\alpha)\frac{2(M-1)}{3}\left[\frac{2}{P_s}\left(1 - \frac{1}{\sqrt{M}}\right) - 1\right]\frac{G_d N_0 N}{\Omega \log_2 M}$$
$$+ \frac{N(P_c - P_{Amp})}{2B \log_2 M} \quad (22)$$

C. NETWORK MODEL

WSN is modeled as a connected directed graph for set of n sensor nodes $S = \{s_1, s_2, s_3, \ldots, s_n\}$ communicate with a single base station (*BS*). The cluster-based WSN has more than one BS called *Cluster Heads* (*CH*). In addition, the cluster-based WSN is decomposed into set of m clusters $C = \{c_1, c_2, c_3, \ldots, c_m\}$. Each cluster consists of k *Cluster Members* (*CMs*) which can communicate with a predetermined cluster head. In this work, a *grid-clustering* is proposed and the CH is placed in the center of each cluster (*grid cell*) where it is assumed to act as a beacon node without limitations of energy (Fig. 4). In particular, the proposed grid-based clustering approach in this work ensures that CMs are evenly distributed within each cluster and also the burden is balanced. As a result, the computational complexity can be reduced when the data load for CMs becomes larger. Besides, the time complexity for the grid-based clustering technique is linear (i.e., $O(n)$) since it generates a single hop clusters [13].
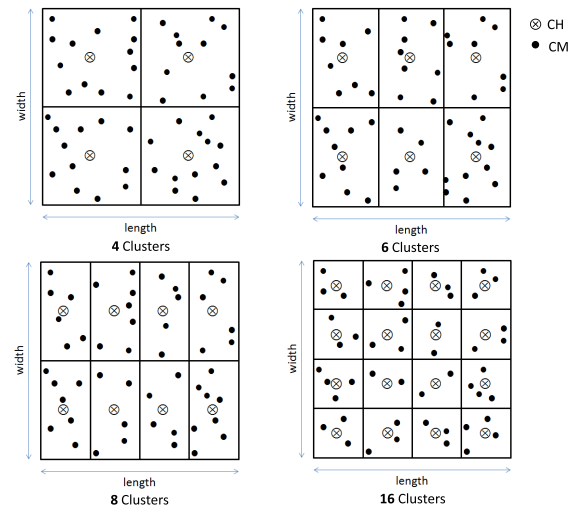

FIGURE 4. Grid-based clustering for WSN showing the distribution of sensor nodes (CMs) in grid cells, and the CH is located in the center.

The intra-communication within single cluster is performed through sending sensed data from CMs to CH, and then the CH aggregate the received data and sends it to the main base station. In this work, it is assumed that the channel model between the sensor node and BS is *Rayleigh flat fading* with path-loss, and perfect channel estimation is also assumed.

In order to implement adaptive communication links within single cluster, a *feedback channel* between CMs and CH is employed. Adaptive modulation is affected by the quality of the link (*channel conditions*) between CMs (sensor nodes) and CH (designated sink node) [40]. The high-quality link is corresponded to the high value of the received *SNR*. In contrast, the low-quality link is corresponded to the low value of the received *SNR*. Therefore, the CMs should adapt the transmit power in order to maintain higher efficiency for both spectral and energy. However, the distances between CMs and CH will affect the transmit power as well as the

modulation order because longer distances have higher signal attenuation than shorter one. Consequently, the CMs with longer distances from CH will have lower modulation order and also the CMs with shorter distances from CH will have higher modulation order and this will save more energy and increase the throughput. In this context, the CH is responsible to estimate the received *SNR*, select an appropriate modulation order in which it is corresponded to an adequate transmission rate, and then feed this information back to the CMs.

In other words, the CH (*receiver*) can estimate the CSI and send the required information back to the CM (*transmitter*). The feedback channel can express the response from CH that gives the CM an idea of how the data is being received and whether it needs to be modified. Therefore, the modulation order is adapted by the CM according to the CSI to achieve reliable intra-communication within single cluster. Adjusting M-ary order is necessary for implementing adaptive modulation. In case of MQAM (as it is the candidate modulation scheme for this work) at certain bandwidth (B), *increasing M* results in *decreasing* in the transmission duration (active mode duration) (T_t) of the sensor node. Besides, *decreasing T_t* results in *decreasing* the symbol duration (T_s). Finally, when T_s *decrease* the data rate (R) will *increase*.

This work proposes a novel model called *distance-based adaptive modulation* depicted in Fig. 5. Basically, the model is a step function describing the relation between the modulation order (M) and the distance between cluster member and cluster head. This function determines an optimized value of modulation order, which is the optimal choice for the cluster member, subject to certain distance value (*threshold*), where the cluster member will have minimum energy consumption during the communication with the cluster head. The function has been derived according to the study performed in [29].
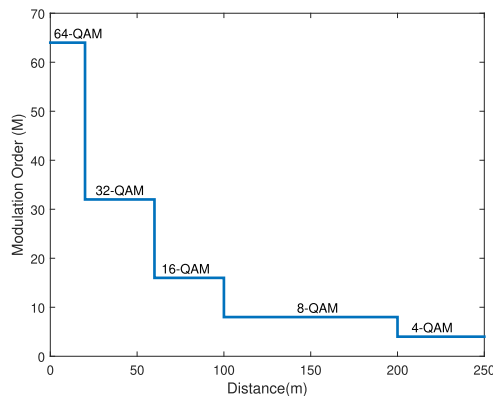

FIGURE 5. Distance-based adaptive modulation step function.

V. PERFORMANCE EVALUATION

This section demonstrates performance evaluation for the proposed approach where simulations have conducted and analyzed extensively. The evaluations have considered two metrics: cluster density, and cluster size (number of sensor nodes). This work refers to the density D as the number of sensor nodes N per unit area A, ($D = \frac{N}{A}$). Also, it refers to the throughput as the percentage or rate of successful packets or messages in which it is received from the clusters of the WSN. In this context, the setup of the area is controlled by the density as well as the number of the sensors.

Moreover, this study has adopted MQAM modulation scheme to carry out the performance analysis, in which it is handled in the 2.4 GHz ISM unlicensed band that is employed in the IEEE 802.15.4 standard. Table 2 lists the simulation parameters.

TABLE 2. Simulation parameters.

Parameter	Value
P_s	10^{-4}
N	1024 bit
f_c	2.4 GHz
B	10 KHz
N_0	-180 dBm/Hz
G_1	30 dB
M_l	40 dB
ℓ	3.5
η	0.35
Ω	1
P_{sy}	10 mW
P_{Filt}	2.5 mW
P_{Filr}	2.5 mW
P_{Mix}	7 mW
P_{LNA}	9 mW
P_{IFA}	3 mW
P_{DAC}	7 mW
P_{ADC}	7 mW

In cluster-based WSN, the intra-communication within single cluster occurs as follows. During the transmission duration (active mode duration) (T_t), each cluster member senses data, then the data is digitized by an *ADC* and *N-bit* message is generated. Then, the *N-bit* message is modulated using a designated modulation scheme and the cluster member transmits this signal to the cluster head. The proposed cluster-based WSN of N sensor nodes decomposes into certain number of clusters increased gradually started from four clusters, six clusters, eight clusters, and finally sixteen clusters. Each cluster consists of certain cluster members in which they are deployed randomly and communicate with their corresponding cluster head. The intra-communication among cluster members and cluster head takes into account the distance between them in order to select the suitable modulation order adaptively.

In this research, the performance analysis for the cluster-based WSN which employing adaptive modulation considers five main aspects, as it will be shown in the next sections: (1) cluster density, (2) cluster size, (3) number of clusters, (4) distribution of energy consumption and fairness, and (5) efficiency of adaptive modulation. Moreover, the WSN under consideration is employing different modulation orders of MQAM in which they are investigated separately.

A. THE IMPACT OF CLUSTER DENSITY

This section addresses the impact of cluster density in terms of energy consumption and throughput for the WSN (Fig. 6 and Fig. 7). The assumption here is that WSN of 1000 sensor nodes decomposed into four grid-based clusters. That means the cluster size is fixed. Besides, the WSN density is gradually increased from sparse ($D = \frac{1}{1000}$) to dense ($D = \frac{1}{100}$).
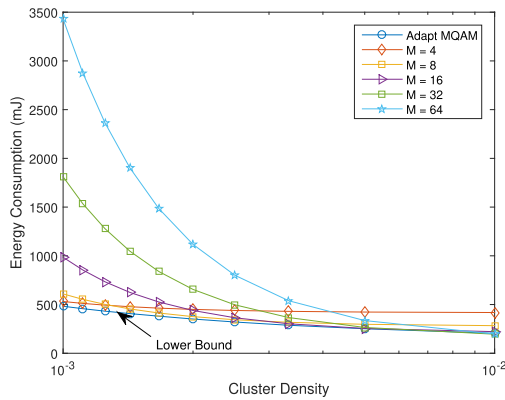

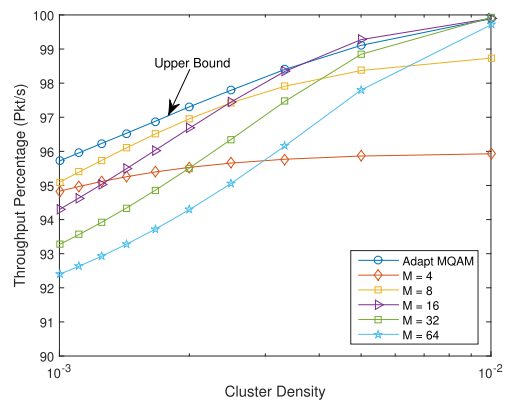**FIGURE 6.** The impact of cluster density on energy consumption.

FIGURE 7. The impact of cluster density on throughput.

Regarding WSN energy consumption, Fig. 6 presents comparison between cluster density and energy consumption. Generally, it can be noticed that as the cluster density increases the total energy consumption decreases. Besides, for low density the smaller modulation orders (i.e., M = 4, and M = 8) have less energy consumption comparing to other ones with significant variations. In contrast, for high density the larger modulation orders (i.e., M = 32, and M = 64) have less energy consumption comparing to other ones with insignificant variations. On the other side, it is noticed that in case of adaptive modulation, the energy consumption is always less than other modulation orders regardless of the cluster density. In this sense, it can be concluded that the adaptive modulation constitutes *lower bound* for the energy consumption. Therefore, it has a significant energy saving comparing with the fixed modulation.

Furthermore, the WSN throughput is depicted in Fig. 7, where it presents comparison between cluster density and throughput. In particular, it is shown that as the cluster density increases the throughput also increases. It is also noticed that for low density the smaller modulation orders (i.e., M = 4, and M = 8) have higher throughput comparing to other ones with significant variations. As opposed, for high density the larger modulation orders (i.e., M = 32, and M = 64) have higher throughput comparing to other ones with insignificant variations. Moreover, it is noticed that in case of adaptive modulation, the throughput is always higher than other modulation orders regardless of the cluster density. In this sense, it can be concluded that the adaptive modulation constitutes *upper bound* for the throughput. Therefore, it has a significant throughput gain comparing with the fixed modulation.

Thereby, these two findings (i.e., Fig. 6 and Fig. 7) can be explained as follows. *In the case of low density (sparse WSN), the distances among sensor nodes are long which makes small modulation order best selection and consequently high throughput can be achieved. In the case of high density (dense WSN), the distances among sensor nodes become short which makes high modulation order best selection and consequently a higher throughput can be achieved.*

B. THE IMPACT OF CLUSTER SIZE

In this section, same methodology for analysis has followed as describes in previous section. The section addresses the impact of cluster size (number of nodes) in terms of energy consumption and throughput for the WSN (Fig. 8 and Fig. 9). In this case, the assumption is that WSN of varying number of sensor nodes decomposed into four grid-based clusters. The number of nodes is gradually increased from small ($N = 100$) to large ($N = 1000$). Besides, the WSN density is fixed and it is assumed to have value of $D = \frac{1}{800}$.

Regarding WSN energy consummation, Fig. 8 presents comparison between number of nodes and energy consumption. Generally, it can be noticed that as the number of nodes increases the total energy consumption is also increases. Besides, for small number of nodes the larger modulation orders (i.e., M = 32, and M = 64) have less energy consumption comparing to other ones with insignificant variations. In contrast, for large number of nodes the small modulation orders (i.e., M = 4, and M = 8) have less energy consumption comparing to other ones with significant variations. On the other side, it is noticed that in case of adaptive modulation, the energy consumption is always less than other modulation orders regardless of the number of nodes. In this sense, it can be concluded that the adaptive modulation constitutes *lower bound* for the energy consumption (*similar result for the density metric*). Therefore, it has a significant energy saving comparing with the fixed modulation.

Furthermore, the WSN throughput is depicted in Fig. 9, where it presents comparison between number of nodes and throughput. In particular, it is shown that as then number of nodes increases the throughput also increases. It is also noticed that for small number of nodes the larger modulation
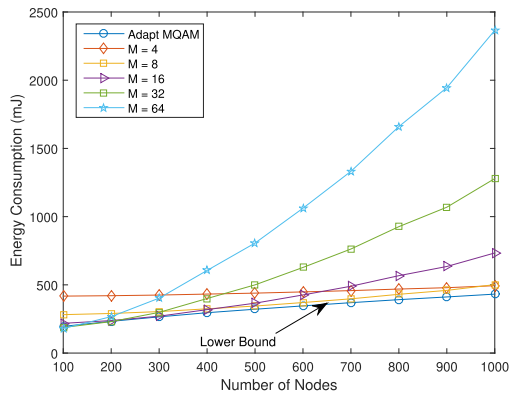
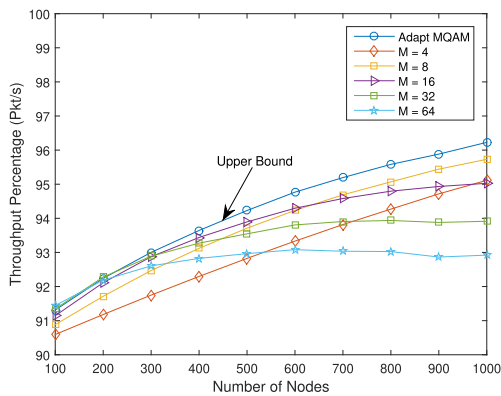**FIGURE 8.** The impact of number of nodes on energy consumption.

FIGURE 9. The impact of number of nodes on throughput.

FIGURE 10. Comparison of energy consumption for different number of clusters subject to diffident cluster densities.

FIGURE 11. Comparison of energy consumption for different number of clusters subject to diffident number of nodes.

orders (i.e., M = 32, and M = 64) have higher throughput comparing to other ones with insignificant variations. As opposed, for large number of nodes the small modulation orders (i.e., M = 4, and M = 8) approximately have higher throughput comparing to other ones with insignificant variations. Moreover, it is noticed that in case of adaptive modulation, the throughput is always higher than other modulation orders regardless of the number of nodes. In this sense, it can be concluded that the adaptive modulation constitutes *upper bound* for the throughput. Therefore, it has a significant throughput gain comparing with the fixed modulation.

Thereby, also these two findings (i.e., Fig. 8 and Fig. 9) can be explained as follows. *In the case of small number of nodes, the distances among sensor nodes are short which makes large modulation order best selection and consequently high throughput can be achieved. In the case of large number of nodes, the distances among sensor nodes become long which makes small modulation order best selection and consequently a high throughput can be achieved.*

C. THE IMPACT OF NUMBER OF CLUSTERS
This section presents detailed analysis for the adaptive modulation technique that is implemented in this study. Besides,
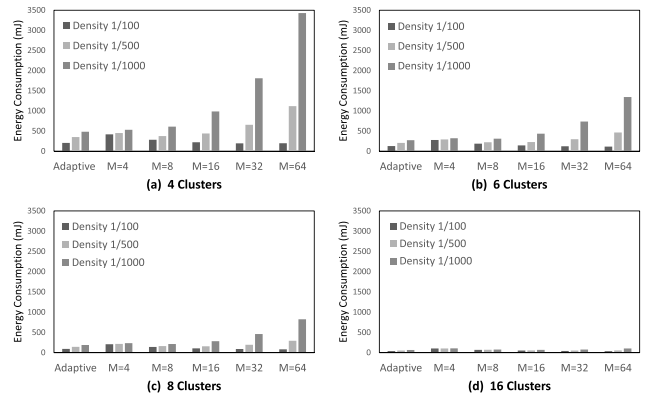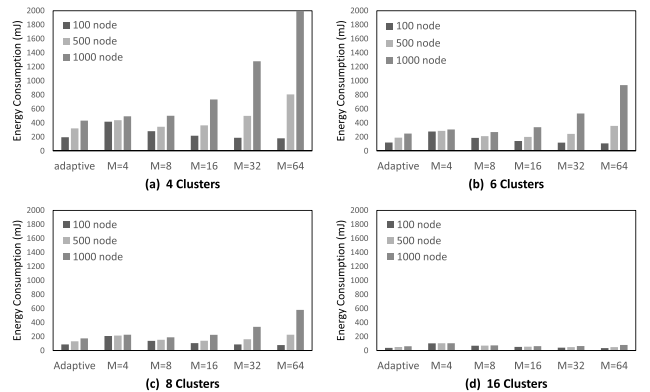
the energy consumption is investigated taking into account the variations of the number of clusters subject to certain constrains: cluster density and cluster size. To handle this issue, the WSN is clustered gradually into 4 clusters, 6 clusters, 8 clusters, and 16 clusters. Then, each case is investigated separately and compared with the others.

In order to study the relation between the energy consumption and number of clusters, two cases are considered: (1) varying cluster density, and (2) varying cluster size.

In case of varying cluster density, which is depicted in Fig. 10, three scenarios of cluster density are investigated: low density ($D = \frac{1}{1000}$), medium density ($D = \frac{1}{500}$), and high density ($D = \frac{1}{100}$). In this case the number of nodes is fixed at ($N = 1000$).

On the other side, for the case of varying cluster size, which is depicted in Fig. 11, three scenarios of cluster size are investigated: small cluster size ($N = 100$), medium cluster size ($N = 500$), and large cluster size ($N = 1000$). In this case the cluster density is fixed at ($D = \frac{1}{800}$).

Both figures (Fig. 10 and Fig. 11) show similar results, where the energy consumption decreases as the number of clusters increase. For small number of clusters (i.e., 4 clusters) the adaptive modulation outperforms other modulation
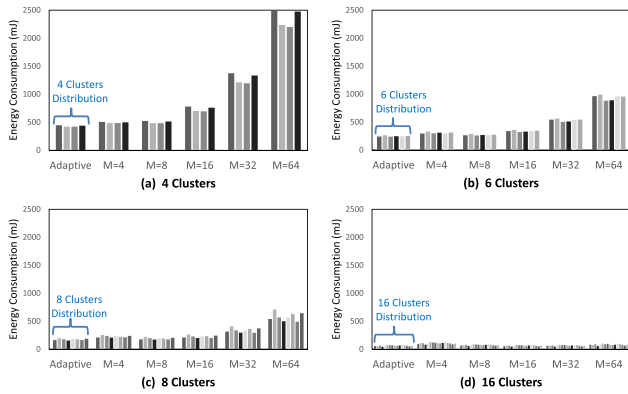
FIGURE 12. The distribution of energy consumption for different number of clusters.

FIGURE 13. The impact of the cluster density on the energy efficiency of the adaptive modulation.

orders. On other hand, as long as the number of clusters increases (i.e., 16 clusters) the performance of the adaptive modulation converge from other modulation orders. The reason for that is because the distances between cluster members and cluster head becomes shorter as the number of clusters increases.

On the other hand, in this context we can point out that the diversity of the number of clusters subject to variations in cluster density and cluster size will lead to differences in computational complexity. Specifically, the computational complexity for the grid-based clustering is linearly proportional to the two metrics: cluster density and cluster size.

D. THE DISTRIBUTION OF ENERGY CONSUMPTION AMONG CLUSTERS

One more important factor which is investigated in this section is the energy consumption distribution and the fairness among clusters. In this investigation it is assumed that number of nodes is $N = 1000$ and network density is $D = \frac{1}{800}$.

It can be noticed from Fig. 12 that the adaptive modulation maintains the fairness of energy consumption among clusters regardless of the number of clusters. The reason for this property is that the adaptive modulation has uniformly (evenly) distributed of energy consumption among clusters. On the other hand, some modulation orders cannot provide this fairness among clusters for small number of cluster. However, as the number of clusters increases the distribution of energy consumption converges from the fairness.

E. THE EFFICIENCY OF CLUSTER-BASED ADAPTIVE MODULATION

Since the adaptive modulation plays an important role in energy saving, as it has been seen in previous sections of this research, it is necessary to study the efficiency of the proposed work and discover its limitations.

Regarding the cluster density metric, Fig. 13 shows significant saving in energy consumption for small number of clusters (i.e., about 60% in the case of 4 clusters), but this
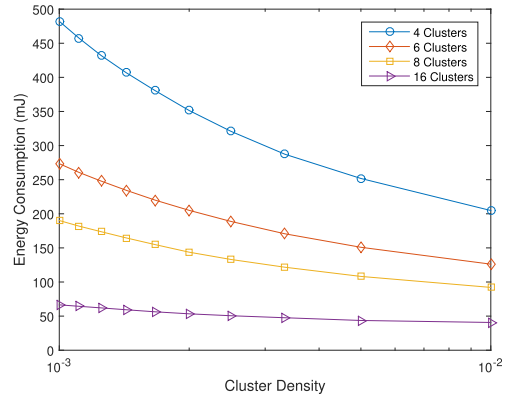
saving becomes insignificant by increasing the number of clusters (i.e., about 25% in the case of 16 clusters). However, as the number of clusters increases, the energy consumption decreases. Further, it can be noticed that in the case of sparse WSNs the differences in the energy consumption is large and these differences decrease as the density increases. Therefore, it is expected that as long as the density increases these differences will be very small and converge to certain value in which the cluster-based adaptive modulation becomes impractical to be employed for such cases.

On the other side, regarding the cluster size metric, Fig. 14 shows significant saving in energy consumption for small number of clusters (i.e., about 55% in the case of 4 clusters), but this saving becomes insignificant by increasing the number of clusters (i.e., about 20% in the case of 16 clusters). Moreover, it can be noticed that in the case of small number of sensor nodes the differences in the energy consumption is small and these differences increase as the number of sensor nodes increases. Therefore, it can be concluded that the cluster-based adaptive modulation is more practical to be employed for larger cluster size than smaller one.
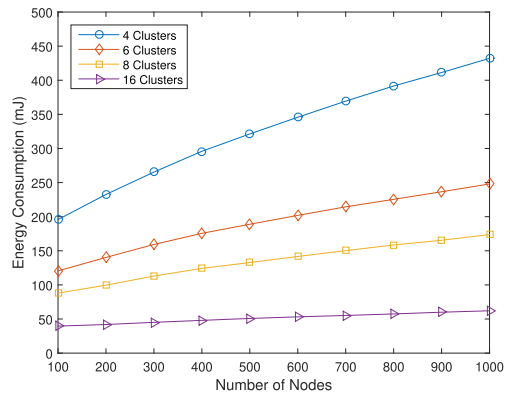

FIGURE 14. The impact of the number of node on the energy efficiency of the adaptive modulation.

The measures for the both metrics provide a remarkable feature about the efficiency and the limitations of the adaptive

modulation technique. The adaptive modulation shows higher efficiency for small number of clusters and this efficiency decreases as the number of clusters increases. The reason for the reduction in efficiency is that as long as the number of clusters increases the distances among sensors become smaller. Therefore, the efficiency of the adaptive modulation will be smaller since the higher modulation order will be suitable choice for short distances between cluster members and cluster head.

VI. CONCLUSION

In this work we shed the light literally on the impact of the adaptive modulation on the cluster-based WSN. Distance-based adaptive modulation step function was proposed to select an optimum modulation order that can achieve the minimum energy consumption between CMs and CH. Performance evaluation for the adaptive modulation technique was performed and analyzed extensively. The simulation results demonstrated that an adaptive modulation constitutes a *lower bound* for the energy consumption by varying cluster density and cluster size. Also, the adaptive modulation demonstrated a great impact on throughput where it constitutes an *upper bound* for the throughput by varying cluster density and cluster size. In addition, the adaptive modulation presented a great efficiency in energy saving for small number of clusters, however, this efficiency has limitations since it decreases as the number of clusters increases. The bottom line is that these findings provide a great guidance for designing and deploying an energy efficient cluster-based WSNs.

In future work, our plan is to study the adaptive modulation in random cluster-based WSNs. Also, we look forward to demonstrate a comparison study between grid-based clustering design and random-based clustering design. This may provide us with other new findings regarding the impact of the adaptive modulation on the cluster-based WSN.

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