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Optimal Clustering in Underwater Wireless Sensor Networks: Acoustic, EM and FSO Communication Compliant Technique

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ABSTRACT With a wide scope for exploration and research, underwater wireless sensor network (UWSN) is a fast growing research area in current scenario. UWSNs need energy efficient designing approach, because underwater sensor nodes are battery driven. Also the deployed batteries cannot be easily recharged by non-conventional energy resources, like solar energies. Clustering is an effective technique to design an energy efficient UWSNs. Due to the sparse deployment of nodes and dynamic nature of the channel, the clustering characteristics of UWSNs are different from those of terrestrial wireless sensor networks. In this paper, we focused on optimal clustering for UWSNs which are compliant with any one of the acoustic, free space optical (FSO) and electromagnetic (EM) wave-based communication techniques. Besides, we proposed an energy dissipation model of sensor node for FSO and EM wave-based communication and compared with the contemporary energy dissipation model for acoustic-based communication. In particular, the suitability of the above three techniques for underwater communication is investigated and their performance is compared on the basis of energy consumption and optimal clustering.

INDEX TERMS Acoustic wave, optical wave, electromagnetic wave, Gaussian distribution, clustering, cluster size optimization, energy efficiency and underwater wireless sensor networks (UWSNs).

LIST OF ACRONYMS

BS	Base Station
CH	Cluster Head
DAR	Data Aggregation Ratio
DBS	Distance Based Segmentation
EM	Electro Magnetic
FSO	Free Space Optical
GPS	Global Positioning System
LEACH	Low-Energy Adaptive Clustering Hierarchy
MI	Magnetic Induction
MP	Multi Path
PDF	Probability Density Function
RSS	Received Signal Strength
TDMA	Time-Division Multiple Access
TR	Two Ray
TWSNs	Terrestrial Wireless Sensor Networks
UW-ASN	Underwater Wireless Acoustic Sensor Networks
UW-EMSN	Underwater Wireless Electro Magnetic Sensor Networks
UW-FSOSN	Underwater Wireless Free Space Optical Sensor Networks
UWSNs	Underwater Wireless Sensor Networks

I. INTRODUCTION

Underwater wireless sensor networks (UWSNs) are envisioned to enable applications for a wide variety of purposes such as tsunami warnings, offshore exploration, tactical surveillance, monitoring of oil and gas spills, assisted navigation, pollution monitoring, and for many commercial purposes. To make those applications viable, there is a need to enable communications among underwater devices. The major challenges associated with underwater applications are as follows: (i) A high propagation delay which is about five orders of magnitude higher than that in the terrestrial environment. (ii) The channel is dynamic in nature, especially because of multi-path fading problem. (iii) Owing to dynamic channel characteristics, high bit error rates and temporary losses of connectivity can be

TABLE 1. Comparison of communication techniques in underwater scenario.

Characteristics	Acoustic wave	EM wave	FSO wave
Propagation speed	Very less	High	Very high
Network coverage	Very long range	Short range	Very short range
Line of sight (LOS)	Not required	Not required	Required
Impact of environment (temperature change, ambient noise, turbidity)	High	Minimum	High
Impact of marine life	Affected	Not affected	Not affected
Data rates	Very low	High	Very high
Power loss	$> 0.1\ dB/m/Hz$	$28\ dB/km/100MHz$	$Turbidity$
Bandwidth	KHz	MHz	$10 - 150\ MHz$
Antenna size	$0.1\ m$	$0.5\ m$	$0.1\ m$
Range	Km	$10\ m$	$10 - 100\ m$

experienced. (iv) Battery power is limited and usually it is non-rechargeable, solar energy also cannot be exploited. (v) Underwater sensors are prone to failure because of pollution and corrosion [1], [2]. An underwater acoustic, free space optical and EM sensor networks (UW-ASN, UW-FSOSN, UW-EMSN) can be conceived of as an adhoc network consisting of sensor nodes connected by an acoustic, optical and EM medium to perform distributed sensing tasks. Owing to the saline nature of the water medium, the high frequency EM waves are affected by severe attenuation. So, these high frequency waves are not suitable for underwater environments. On the other hand, low-frequency waves ranging from 30–300 Hz can propagate over long spaces in such a dynamically changing environment. However, for transmission of such low frequency signals, a large sized antenna with high transmission ability is needed, which is impractical. In contrast, although optical waves do not suffer from the problem of attenuation, they need a high precision pointing beams which generally are affected by scattering. On the other hand, for underwater medium; acoustic waves are less lossy and support long range signal transmission. Thus, acoustic signals are majorly employed in underwater communication. However, underwater acoustic waves are also limited by multipath and fading losses, Doppler effects, high propagation delay, and low available bandwidth [3], [4]. The Table 1 lists the advantages and disadvantages of all communication techniques in an underwater environment.

It is well known that low energy adaptive clustering hierarchy (LEACH) is a terrestrial clustering protocol. In this protocol, in order to evenly distribute energy load, all the nodes are given the role of being a cluster head (CH). The CH is chosen based on random probabilities, variation of node residual energies with time. Let us consider using LEACH protocol in a big network. In the course of transmitting data to the BS, sometimes a farthest node becomes a CH. Then that CH has to drain a lot of energy because of large distance to BS. Owing to this, the lifetime of nodes significantly decreases. Therefore LEACH is not suitable for large scale networks and is limited to small scale networks [5]–[7]. From the above mentioned literature, it can be understood that clustering can be possible in small scale networks. By using clustering in small scale networks, energy can be further conserved. Especially, clustering becomes useful in energy hungry underwater wireless sensor networks.

In our work, we have used distance based segmentation (DBS) clustering protocol which is a variant of LEACH protocol. we assumed the availability of underwater EM as well as FSO nodes in simulation. These nodes have small transmission range. So, even for a small area, we require to deploy many sensor nodes. So, it gives rise to a small-scale dense network. In a dense network, clustering topology is the best way to optimize the energy consumption. Thus, in order to achieve energy efficiency, it is necessary to apply clustering technique in underwater scenarios even with EM and FSO communication based sensor nodes.

In order to deal with the limited supply of energy, the technique of clustering is generally incorporated. The fundamental concept of clustering is to partition the sensing area into many small segments which are mostly non-overlapping in nature. In every cluster, there is one cluster head (CH) and many cluster members (non-CHs) [8]. The CH fuses the received information bits into a single lump of data and transfers it to base station (BS). By means of clustering, the transmission distance can be minimized by the communication of short distant CHs, and the energy dissipation is minimized by removal of redundant transmissions. To enhance the performance of clustering scheme, a proper topology of intra and inter-cluster communication needs to be chosen either as single-hop or multi-hop. This choice depends not merely on the cluster size, but also on the distance between CH and BS. In addition to that, in UWSNs, the overall energy performance is affected also by the optimal number of clusters.

In this paper, we assumed a random Gaussian distribution for deployment of nodes; due to following reasons: It is the most common distribution used for system modelling in networking. Any analytical model developed for uniform and random distribution can be applied to Gaussian distribution under some special constraints [9]. Especially in underwater applications, where sensor nodes easily move out of desired sensing areas due to tide, wind, human and animal intervention.

A. MOTIVATION

To improve the network longevity, a weighted probability based energy efficient heterogeneous clustering scheme is introduced by Kumar *et al.* [10]. Herein, by taking advantage of node heterogeneity, achieves a higher network lifetime which outperforms LEACH protocol. However, the effect of more than two levels of hierarchy needs to be evaluated. An energy effective cluster head selection algorithm based on particle swarm optimization was introduced by Rao et al. [11], which considers BS distance, in-cluster distance and residual energy of nodes for finding the energy efficiency of algorithm. This technique performs better than the existing ones, especially in terms of number of packets received by the BS. The robustness of the algorithm, however needs to be verified with the heterogeneous nature of nodes.

Addressing the energy limitations in the underwater environment Tran and Oh [12], proposed a new clustering scheme for UWSNs based on data aggregation with a similarity function that can be used to reduce data redundancy. This outperforms the protocols without data aggregation. A distributed clustering scheme was proposed by Domingo and Prior [13] which especially suits long-term non-time critical marine monitoring applications. This protocol shows a consistent packet delivery ratio and throughput. However, it can be further improved by incorporating the formation of adaptive clusters by understanding the interrelation between energy consumption and overhead cost.

Förster et al. [14] through an experimental analysis quantified the optimal cluster size and showed how an optimal cluster should look like. But, this algorithm needs to focus on optimizing and evenly distributing the overhead among all the nodes. Zhang et al. [15] proposed an energy efficient algorithm which has energy-harvesting (EH) nodes, which simply take part in relaying the data from CH to the BS. With this new architecture, the overall network lifetime is prolonged. It is shown that the optimal number of clusters are not affected by the presence of these EH nodes. Ahmed et al. [16] introduced a Markov Chain model-based optimal cluster heads (MOCHs) selection for WSNs, by which the uneven energy distribution is mitigated by a control mechanism wherein, the BS controls the number of CHs while the CHs control the cluster members. This protocol tackles the problem of backward transmission and provides stable clustering. This protocol can further be improved by incorporating energy harvesting schemes. Amini et al. [17] provided a mathematical framework to determine the optimal cluster size considering EM wave and applied it to a generalized LEACH protocol. In [18], Kumar et al. by considering a Gaussian node distribution in a square sensing field with the BS at the centre of sensing field, developed a closed form expression of optimal number of clusters for TWSNs. Kumar et al. [19] incorporated a Tunable elfes sensing model and studied its impact on network coverage and provided an expression for optimal number of clusters for the same. All of the above optimal clustering models are developed for terrestrial WSNs with EM wave as the means of communication. Goyal et al. [20] introduced an intra and inter cluster communication technique, which is a fuzzy based cluster head and cluster size selection technique. Also, it uses different means for intra and inter cluster communication. This technique is a generic method of finding optimal clusters and it is more energy efficient even in a densely deployed network. Choi and Lee [21] proposed an energy model to find the energy dissipated in a probabilistic cluster-head selection method. Using this model, the optimal number of cluster is determined. The energy analysis is done with an assumption that the sensing field is in disc shape, however, the model needs to be further improved for a realistic sensing field as well.

Zhang et al. [22] developed a parallel processing underwater clustering technique which optimises the number of clusters by using particle swarm optimization. By considering residual energy, cluster head load and cluster range, this algorithm reasonably balances the load and enhances network longevity with less complexity. Zhao and Liang [23] for the first time proposed an energy model of acoustic wave propagation for UWSNs. Further, authers found the minimum required cluster size by considering the BS to be at the centre of sensing field. De Souza et al [24] studies the effect of joint optimization of the number of hops, re-transmissions, code rate and signal to noise ratio. It provides a limit for an optimum number of multi-hops and re-transmissions.

In our work, in contrast to the above literature, we considered the acoustic, EM and FSO based underwater communication techniques. Also, we proposed an energy dissipation model for sensor node based on EM and FSO wave communication in underwater scenario. Besides, we placed the BS at the three different positions viz., at the center of sensing field, at the corner of sensing field and at the lateral midpoint of sensing field. Also for these positions, we analytically calculated the closed form expression for optimal number of clusters for all the above three underwater communication techniques.

B. CONTRIBUTIONS

The main contributions of our work are enumerated herein.

- Development of the energy dissipation model of sensor node for EM and optical wave communication in underwater environment.
- Derivation of analytical expressions of optimal number of clusters for UW-EMSN, UW-FSOSN and UW-ASN.
- Development of Gaussian distributed UWSNs in which the BS follows a classical sensing model along with consideration of boundary effects.
- Comparison of the UW-EMSN, UW-FSOSN and UW-ASN based on the optimal number of clusters and energy consumption for different positions of BS (center, corner and lateral midpoint of the square sensing field).

The following sections of this paper are organized as follows: In Section II, network model is described along with an informative background. Section III presents the proposed method along with an energy consumption model of sensor nodes. It also explains the analytical model of optimized cluster size for Gaussian distributed UWSNs. Section IV covers the results and analysis. Finally, Section V concludes the paper along with future scope.

II. PRELIMINARIES AND DEFINITION

In UWSNs, sensor nodes are grouped into non overlapping subset called cluster in order to attain perfect data aggregation and high scalability [12]. In clustering process, CHs are selected on the basis of these parameters: residual energy, heterogeneity, dynamics of node deployment etc. Fig. 1 shows the detection of submarine by using clustering in UWSNs. In this figure, many acoustic sensor nodes are distributed over underwater seabed which detect the movement of underwater submarine. These nodes communicate with their CHs through acoustic signals. Further, CHs send all the received signals to the BS. Finally, the BS sends the signal to man-controlled computer via satellite communication. In the place of acoustic signals, FSO and EM signals also can be used. But these communication techniques have their own pros and cons in underwater medium.

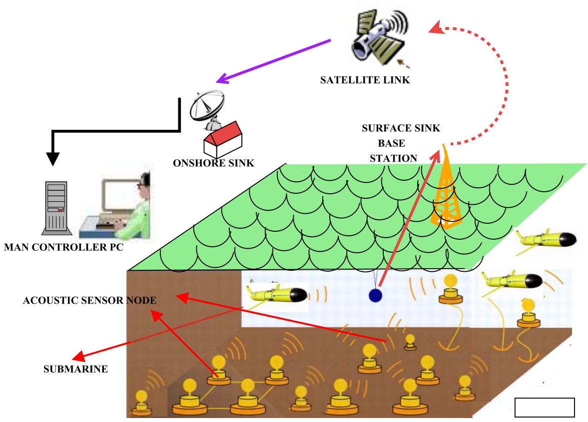

FIGURE 1. Underwater wireless sensor network.

The following assumptions are made in this work:

1) All sensor nodes are considered as stationary and identical after deployment. Each node is assigned a unique ID.
2) The nodes have the power control ability and all are time synchronized.
3) Nodes are always in active state.
4) Nodes do not have global positioning system (GPS) and therefore, they are not location-aware. On the basis of received signal strength (RSS) from the BS, they can approximate their distance from the BS.

A. DATA AGGREGATION

In clustering, the CHs are liable for aggregating data signals of their non-CHs and produce a complete single signal.

B. SENSING COVERAGE

Sensing coverage is defined as the ratio of the actual network coverage area to the desired area of coverage and it lies between 0 and 1. The sensing coverage depends on the density of the deployed sensor nodes. For a densely deployed sensor network the sensing coverage will be 100% for some initial time and based on the number of alive nodes its value eventually changes [25].

C. OPTIMAL CLUSTERING

Optimal clustering plays a key role in achieving energy efficiency of a sensor network. Having a more number of clusters while keeping equal processing load on each CH, will increase the overall communication overhead. As a result, the overall energy consumption gets increased. In contrast, if the number of cluster is less, then it will result in a large size of each cluster. In a large sized cluster, the farther nodes need more energy to transmit data to its respective CH. Therefore, cluster size cannot be too big or too small, an optimal cluster size needs to be chosen. Eventually, there will be an optimal number of clusters. Forming optimal number of clusters improves network lifetime, energy efficiency, and scalability.

D. DECENTRALIZED CLUSTER-BASED ALGORITHM

In Distance based segmentation (DBS) clustering, the nodes self-organize themselves into a number of clusters in a decentralized way. DBS protocol provides a parallel version of LEACH algorithm to eliminate the energy imbalance that LEACH usually incurs. DBS modifies the cluster selection policies by giving more consideration to sensing coverage and the distance between the node and the BS.

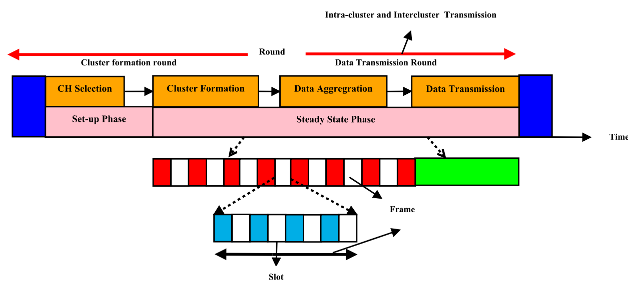

FIGURE 2. Timing diagram of a single round of clustering technique.

Decentralized cluster-based protocols split the network schedule into multiple rounds of fixed duration. As shown in Fig. 2, each round comprises a set-up phase, and a steady-state phase which has a number of time frames. During set-up phase, some sensor nodes elect themselves as cluster heads by using a distributed algorithm performed in each node. Later, the selected nodes state their election as cluster head to the other remaining nodes in the network. Then, the rest of the nodes organize themselves into local clusters by electing the most suitable CH (normally the closest CH). In the steady-state phase, within each frame, a non-CH node sends the sensed data to its CH (using TDMA), and in turn CH transfers the data to the BS.

In DBS protocol [26], the central idea is that, the nodes that are closer to the BS become a CH more often than the nodes which are farther to the BS. This is to avoid the occurrence of great difference between the energy levels of a near node and a far node. This technique enhances the energy efficiency of system as well as the network sensing coverage. To this end, in DBS, the total sensing area is divided into a finite number of identical segments. It can be easily understood that in each round of DBS, the cluster count is same as that in LEACH, and the CH probabilities of nodes are distributed as $(p \pm \delta p, p \pm 2\delta p \dots)$ equal to that for LEACH. The optimal percentage of cluster head nodes (p) is equal to the ratio of the optimal number of clusters (K_{opt}) to the total number of sensor nodes in the network (N), i.e., $p = K_{opt}/N$. If δp is set to, then DBS becomes LEACH protocol, and therefore DBS can be considered as a special case of LEACH.

E. DEPLOYMENT OF NODES

In Gaussian distribution, the probability density function (PDF) for a sensor node residing at the point (x, y) with respect to deployment point (x_0, y_0) is given as follws [27]

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\frac{(x-a)^2}{2\sigma_x^2}} e^{\frac{(y-a)^2}{2\sigma_y^2}} \tag{1}$$

where σ_x and σ_y are the standard deviations of x and y co-ordinate. For one dimensional Gaussian distribution, the PDF can be defined as follows:

$$f(y) = \frac{1}{\sqrt{2\pi}\sigma_y} e^{\frac{(y-a)^2}{2\sigma_y^2}} \tag{2}$$

where a is the mean distance and σ_y represents standard deviation.

From the literature, we can infer that the existing underwater communication is viable with acoustic communication technology. The range of an acoustic modem is up to 10 Km. Due to this large communication range the under acoustic nodes are generally sparsely dispersed inside water. This kind of node deployment is used in applications like habitat monitoring, pollution monitoring etc, which are non data-critical applications (data loss is acceptable to certain extent). But in data-critical, coverage critical defense applications like tactical surveillance, intruder detection, a slightest data loss also may not be accepted. In such cases, a dense deployment of nodes is required [28]–[31]. So, in UWSNs also, both sparse and dense node deployments are possible.

F. ACOUSTIC ENERGY DISSIPATION MODEL

Generation of acoustic wave takes place when compression and dilations have passed from one point to the other point by the propagation of mechanical perturbation. It is the elastic property of the propagation medium. Jurdak *et al.* [32] proposed the acoustic wave propagation model on the basis of data and formulae available in [23], [33]

$$SL = TL + 85 \tag{3}$$

where TL is the transmission loss and SL is the source level. All the parameters present in the equation (3) are in $dB\ re\ \mu Pa$, and value of $1\mu Pa$ is equal to $0.67 \times 10^{-22} Watts/cm^2$. Transmission loss depends on the shape of the signal. For cylindrical spread signals its value is equal to

$$TL = 10\log d + \alpha d \times 10^{-3} \tag{4}$$

where α is the medium absorption coefficient which depends on the frequency, d is the distance between transmitter and receiver in meters. For a temperature range from 4^0C to 20^0C, the measured value of medium absorption in shallow seawater is given by [32], [34]

$$\bar{\alpha} = \begin{cases} 0.0601 \times f^{.8552} & \text{for } 1 \le f \le 6 \\ 9.7888 \times f^{1.7885} \times 10^{-3} & \text{for } 7 \le f \le 20 \\ 0.3026 \times f - 3.7933 & \text{for } 21 \le f \le 35 \\ 0.504 \times f - 11.2 & \text{for } 36 \le f \le 50 \end{cases} \tag{5}$$

The required threshold value of α, indicated by $\bar{\alpha}$, must be larger than $\bar{\alpha}$ for getting better reception quality. But $\bar{\alpha}$ is a monotonically decreasing function of frequency f. We considered $\bar{\alpha}$ as $\alpha(f)$ in the rest of this paper for the sake of easiness. The essential transmitter power P_t to obtain intensity I_t at a distance of 1 m is given as,

$$P_t = 2\pi \times 1m \times H \times I_t \tag{6}$$

where I_t is defined in term of SL by

$$I_t = 10^{\frac{SL}{10}} \times 0.67 \times 10^{-18} \tag{7}$$

Finally, P_t will be represented by the equation. (6)

$$P_t = ZHde^{a(f)d} \tag{8}$$

where $Z \cong 2\pi(0.67)10^{-9.5}$, $a(f) \cong 0.001\alpha(f)ln10$, H is the water depth in meters.

To transmit l bits over distance d, the dissipated transmission energy can be expressed as

$$E_{TX}(l,d) = lE^T_{elect} + lT_bZHd_{toCH}e^{a(f)d_{toCH}}. \tag{9}$$

and the receiver radio energy consumption can be expressed as

$$E_{RX}(l,d) = lE^R_{elect} \tag{10}$$

where, E^T_{elect} and E^R_{elec} is the energy consumed by the transmitter and receiver electronics to process the l bit data and T_b is the bit duration in second.

III. PROPOSED WORK

In this section, we propose the energy dissipation model of sensor node which uses EM and FSO communication in underwater medium. Moreover, we have also derived analytical expression to find the optimal number of clusters in EM, FSO and acoustic wave based UWSNs. Finally, the proposed concept has been validated for Gaussian distributed UWSNs, where BS is positioned at different locations in the sensing field.

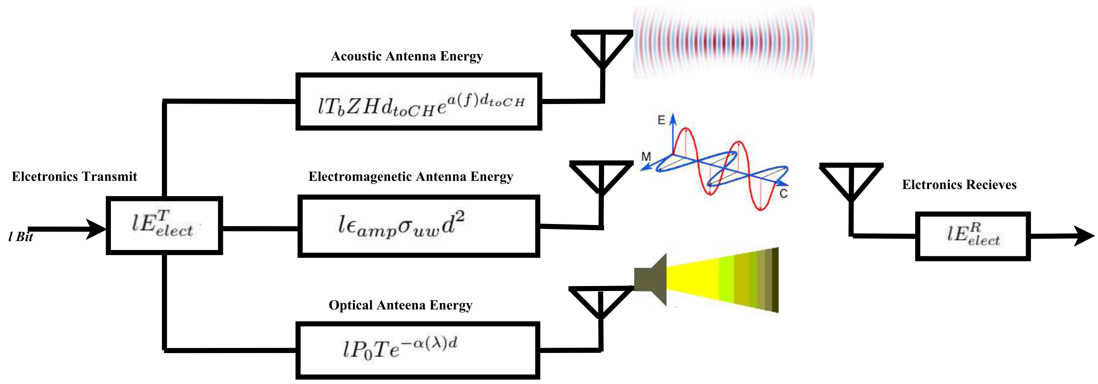

FIGURE 3. Energy dissipation model of sensor node based on acoustic, FSO and EM wave.

A. DEVELOPMENT OF ENERGY DISSIPATION MODEL OF SENSOR NODES

In this subsection, considering FSO and EM wave based communication we derived an expression for energy dissipation of sensor node. Fig. 3 shows the integrated energy dissipation model of a sensor node based on acoustic, FSO and EM wave communication.

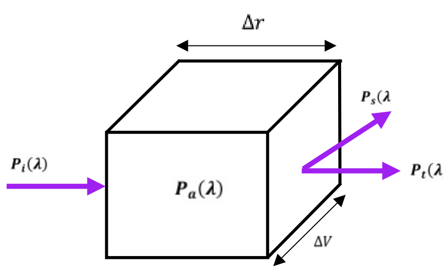

FIGURE 4. Geometry of optical property [37].

1) OPTICAL WAVE COMMUNICATION

Underwater free space optics is an appropriate alternative for underwater wireless communication technology, especially for coastal, shallow and fresh water environments where, some of the problems related with acoustic communication can be overcome [35], [36]. Two main factors that result in loss of optical power in underwater medium are absorption and scattering coefficient. For simple understanding of absorption and scattering coefficient, a geometrical model of elemental volume of water ΔV with thickness Δr is shown in Fig. 4. When a light beam of incident power (P_i) having a wavelength λ is sent in water, a small fraction of the incident light is absorbed by the water which is expressed as (P_a) and other fraction is scattered denoted by (P_s). The remaining light power P_t is passed through the water unaffected. So on the basis of the concept of energy conservation it can be stated as [37]

$$P_i(\lambda) = P_a(\lambda) + P_s(\lambda) + P_t(\lambda) \tag{11}$$

The absorbance (A) can be defined as the ratio of absorbed power to the incident power, scatterance (B) is the ratio of scattered power to the absorbed power [37].

$$A(\lambda) = \frac{P_a(\lambda)}{P_i(\lambda)}, \quad B(\lambda) = \frac{P_s(\lambda)}{P_i(\lambda)} \tag{12}$$

The absorption and scattering coefficients are obtained by taking thickness (Δr) infinitesimally small [37]

$$a(\lambda) = \lim_{\Delta r \to 0} \frac{A(\lambda)}{\Delta r} = \frac{dA(\lambda)}{dr} \tag{13}$$

$$b(\lambda) = \lim_{\Delta r \to 0} \frac{B(\lambda)}{\Delta r} = \frac{dB(\lambda)}{dr} \tag{14}$$

So, the overall attenuation in underwater can be expressed as a linear combination of absorption and scattering coefficients, which is given by beam attenuation coefficient α [37]

$$\alpha(\lambda) = a(\lambda) + b(\lambda) \tag{15}$$

where a is related with the absorption of water and b models the scattering which depends both on the wavelength of light and turbidity. Table 2 illustrates the attenuation coefficients for four types of water: pure sea water, clean ocean water, coastal ocean water, and turbid harbor water at 520 nm wavelength. The optical propagation loss factor, $L_{LF}(\lambda, d)$ can be given as [37]

$$L_{LF}(\lambda, d) = e^{-\alpha(\lambda)d} \tag{16}$$

where $\alpha(\lambda)$ is attenuation coefficient in (m^{-1}), λ is the operating wavelength in nanometer (nm) and d is the distance between transmitter and receiver in meters. On the basis of attenuation coefficient, Beer-Lambert law introduces the simplest and most widely used scenario to describe the light attenuation effects in underwater environment [38]. The transmitted optical power loss in underwater can be expressed as an exponentially decaying function of path length d as [37]

$$P_T = P_0e^{-\alpha(\lambda)d} \tag{17}$$

where P_0 is the power of the optical source in milliwatt (mW), P_T is the transmitted power.

So, to transmit l bits of data over a distance d, the transmitted energy consumption can be expressed as

$$E_{TX}(l, d) = lE^T_{elect} + lP_0Te^{-\alpha(\lambda)d} \tag{18}$$

TABLE 2. Attenuation coefficient of different water conditions [39].

Water type	Attenuation coefficient (m^{-1})
Pure sea water	0.043
Clean ocean	0.141
Coastal ocean	0.398
Turbid harbor	2.190

and the receiver energy consumption can be expressed as

$$E_{RX}(l,d) = lE^{R}_{elect} \tag{19}$$

where, E^{T}_{elect} and E^{R}_{elec} is the energy consumed by the transmitter and receiver electronics to process the l bit data, T is transmission time and P_0 is the power of the optical source in milliwatt (mW).

2) EM WAVE COMMUNICATION

EM waves can propagate in air at a propagation speed of 3×10^8 m/s, but in other media, the speed of the wave slightly decreases according to the characteristics of propagation medium [40]. Generally, EM waves are being used in air. But, in order to develop a realistic energy dissipation model for EM wave in the underwater environment, the underwater behaviour of EM wave must be discussed. The foremost property is conductivity. With an increase of conductivity of the medium, the transmitted signal experiences more attenuation [41]. The secondary properties are permeability and permittivity. Permeability is the capacity of the medium to store magnetic energy. Since water is nonmagnetic, the permeability of the water is same as that of free space, $\mu_{seawater} = \mu_{freespace}$. The relative permittivity is also called as the dielectric constant of the medium and it describes the capability of a medium to transmit an electric signal. The underwater propagation experiences ohmic losses due to relatively high conductivity of seawater. Channel model formulation for underwater is done by expressing the conductivity in terms of frequency dependent propagation constant. The complex-valued propagation constant k is given by [41]

$$k = \beta - j\alpha = \sqrt{\mu\varepsilon(1 - j\frac{\sigma}{\omega\varepsilon})} \tag{20}$$

where, ε is the permittivity, μ is the permeability, and $\omega = 2\pi f$ is the angular frequency, σ is the conductivity of propagation medium, β is the attenuation coefficient and α is the phase constant. The characteristic impedance η of the medium is defined as

$$\eta = \sqrt{\frac{\mu}{\varepsilon}(1 - j\frac{\sigma}{\omega\varepsilon})^{-1}} \tag{21}$$

where $\sigma \geq 2\pi f\varepsilon$ and $\alpha = \beta \simeq \sqrt{\pi f\mu\sigma}$. Finally wavelength can be defined as

$$\lambda = \frac{2\pi}{\beta} \tag{22}$$

putting the value of β in equation (22), the approximate value of λ is

$$\lambda \approx \sqrt{\frac{4\pi}{f\mu\sigma}} \tag{23}$$

since $\mu = \mu_0 = 4\pi \times 10^{-7} H/M$

$$\lambda \approx \sqrt{\frac{10}{f_{MHz}\sigma}} \tag{24}$$

where f_{MHz} is the frequency in MHz and the path loss equation for EM wave is $(\frac{4\pi d}{\lambda})^2$. By putting the value of λ in this, it shows that the path loss depends on both transmission distance as well as conductivity ($\sigma = \sigma_{uw}$) of the medium. The variation in the values of conductivity for different underwater media is shown in Table 4. The energy dissipation model for underwater EM wave communication depends on both distance and conductivity. To transmit l bits over distance d, the transmitted energy consumption can be expressed as

$$E_{TX}(l,d) = lE^{T}_{elect} + l\epsilon_{amp}\sigma_{uw}d^2 \tag{25}$$

and the receiver energy dissipation can be expressed as

$$E_{RX}(l,d) = lE^{R}_{elect} \tag{26}$$

where, σ_{uw} is the conductivity of underwater medium, E^{T}_{elect} and E^{R}_{elec} is the energy consumed by the transmitter and receiver electronics to process the l bit data. In underwater environment, the amount of energy dissipated in transmitting and receiving the signal by acoustic, FSO and EM wave is summarized in Table 3.

B. ANALYTICAL EXPRESSION FOR OPTIMAL NUMBER OF CLUSTERS OF ACOUSTIC, EM AND OPTICAL WAVE COMMUNICATION

To enhance the network lifetime total energy expenditure should be minimized and therefore, total energy consumption during a round (E_{round}) shown in Fig. 2. In this subsection, an analytical expression for optimal number of clusters is derived with consideration of acoustic, EM and optical communication in UWSNs. In this paper, we assume $M\times M$ a square sensing field with N number of sensor nodes. K denotes the number of clusters in the sensing field. If we assume same size and shape of clusters, then $\frac{N}{K}$ number of average nodes will be there in a particular cluster.

1) EXPRESSION FOR OPTIMAL NUMBER OF CLUSTERS USING ACOUSTIC WAVE

The energy dissipated in non-CH members during a single round is given as

$$E_{NonCH} = lE^{T}_{elect} + lT_bZHd_{toCH}e^{a(f)d_{toCH}} \tag{27}$$

where l is the number of bits transmitted from transmitter to receiver and d_{toCH} is the distance between non-CHs to its CH. In case of acoustic signal up to a 15 KHz frequency, we can

TABLE 3. Transmitter and receiver dissipation energy for acoustic, EM and optical wave.

Communication technique in underwater	Energy dissipation model	
Acoustics	Transmitter Energy (T_X)	$lE^T_{elect} + lT_bZHd_{toCH}e^{a(f)d_{toCH}}$.
	Receiver Energy (R_X)	lE^R_{elect}
Optical	Transmitter Energy (T_X)	$lE^T_{elect} + lP_0Te^{-\alpha(\lambda)d}$.
	Receiver Energy (R_X)	lE^R_{elect}
EM wave	Transmitter Energy (T_X)	$lE^T_{elect} + l\epsilon_{amp}\sigma_{uw}d^2$
	Receiver Energy (R_X)	lE^R_{elect}

approximate the exponential term present in the equation (27) up to two terms. Now the Equation becomes

$$\begin{aligned} &= lE^T_{elect} + lT_bZHd_{toCH}(1 + a(f)d_{toCH}) \\ &= lE^T_{elect} + lT_bZHE[d_{toCH}] + a(f)lT_bZHE[d^2_{toCH}] \end{aligned} \tag{28}$$

For the given area of $M \times M$ and total number of cluster K, the mean square distances from a non-CH to its CH; for $K = 1$ and $K > 1$ are $\frac{M^2}{12}$ and $\frac{M^2}{6K}$ respectively. By putting this value, Equation (28) is modified as follows

$$= lE^T_{elect} + lT_bZH(\frac{M^2}{12}) + a(f)lT_bZH(\frac{M^2}{6K}) \tag{29}$$

Energy dissipated by the CHs during the single round is as given below (we assume that in each round there is one frame)

$$E_{CH} = (\frac{N}{K} - 1)lE^R_{elect} + lE^T_{elect} + lT_bZH(d_{toBS} + a(f)d^2_{toBS}) \tag{30}$$

Hence, the total energy dissipated in the entire cluster during a single round will be equal to the sum of energies consumed by CH and non-CH.

$$E_{Cluster} = E_{CH} + (\frac{N}{K} - 1)E_{NonCH} \tag{31}$$

So E_{round} can be expressed as follows:

$$\begin{aligned} E_{round} &= KE_{Cluster} \\ &= NlE^R_{elect} - KlE^R_{elect} + KlE^T_{elect} + KlT_bZH(d_{toBS} \\ &\quad + a(f)d^2_{toBS}) + NlT_bZH(\frac{M^2}{12}) + Na(f)lT_bZH(\frac{M^2}{6K}) \\ &\quad + NlE^T_{elect} - KlE^T_{elect} - KlT_bZH(\frac{M^2}{12}) \\ &\quad - a(f)lT_bZH(\frac{M^2}{6}) \end{aligned} \tag{32}$$

Taking the first and second partial derivative of E_{round} with respect to K will provide the maximum or minimum value of K,

$$\begin{aligned} \frac{\partial E_{round}}{\partial K} &= -lE^R_{elect} + lT_bZH(d_{toBS} + a(f)d^2_{toBS}) \\ &\quad - Na(f)lT_bZH(\frac{M^2}{6K^2}) - lT_bZH(\frac{M^2}{12}) \end{aligned}$$

For maxima or minima of the function E_{round}

$$\frac{\partial^2 E_{round}}{\partial K^2} = 2Na(f)lT_bZH(\frac{M^2}{6K^3}) \tag{33}$$

Since the second partial derivative of E_{round}, is positive so it will be minimum. By equating $\frac{\partial E_{round}}{\partial K}$ to zero, we get the optimal number of clusters $(K_{opt})_{Acoustic}$ for acoustic communication

$$(K_{opt})_{Acoustic} = \sqrt{(\frac{(\frac{N}{6})a(f)T_bZHM^2}{T_bZH(d_{toBS} + a(f)d^2_{toBS}) - \frac{M^2}{12}T_bZH - E^R_{elect}})} \tag{34}$$

2) EXPRESSION FOR OPTIMAL NUMBER OF CLUSTERS USING OPTICAL WAVE

Energy dissipation model of sensor node using an optical communication can be expressed as

$$\begin{aligned} E_{TX}(l, d) &= lE^T_{elect} + E_{TX-OPT}(l, d) \\ E_{TX}(l, d) &= lE^T_{elect} + lP_0Te^{-\alpha(\lambda)d} \end{aligned} \tag{35}$$

where l is the number of bits that are transmitted from transmitter to receiver, P_0 is the optical power, T is transmission time, α (λ) is attenuation coefficient and d_{toCH} is the distance between non-CHs to CHs. In case of optical signal up to a 532 nm wavelength we can approximate the exponential term present in the Equation (35) up to two terms. So energy dissipated in non-CHs during a single round is given by

$$\begin{aligned} E_{NonCH} &= lE^T_{elect} + lP_0T(1 - \alpha(\lambda)d_{toCH} + \frac{\alpha^2(\lambda)d^2_{toCH}}{2}) \\ &= lE^T_{elect} + lP_0T - lP_0T\alpha(\lambda)E[d_{toCH}] \\ &\quad + lP_0T\frac{\alpha^2(\lambda)E[d^2_{toCH}]}{2} \end{aligned} \tag{36}$$

For the given area of $M \times M$ and total number of cluster K, the mean square distances from a non-CH to its CH; for $K = 1$ and $K > 1$ are $\frac{M^2}{12}$ and $\frac{M^2}{6K}$ respectively. By putting this value, Equation (36) is modified as follows

$$= lE^T_{elect} + lP_0T - lP_0T\alpha(\lambda)\frac{M^2}{12} + lP_0T\alpha^2(\lambda)\frac{M^2}{12K} \tag{37}$$

Energy dissipated by the CHs during the single round is (we assume that in each round there is one frame):

$$\begin{aligned} E_{CH} &= (\frac{N}{K} - 1)lE^R_{elect} + lE^T_{elect} + lP_0T(1 - \alpha(\lambda)d_{toBS} \\ &\quad + \frac{\alpha^2(\lambda)d^2_{toBS}}{2}) \end{aligned} \tag{38}$$

Hence, the total energy dissipated in the entire cluster during a single round will be equal to the sum of energies consumed by CHs and non-CHs.

$$E_{Cluster} = E_{CH} + (\frac{N}{K} - 1)E_{NonCH} \tag{39}$$

So E_{round} can be expressed as follows:

$$E_{round} = KE_{Cluster} \tag{40}$$

$$\begin{aligned} E_{round} &= NlE^R_{elect} - KlE^R_{elect} + KlE^T_{elect} - KlP_0T\alpha(\lambda)d_{toBS} \\ &\quad + KlP_0T\frac{\alpha^2(\lambda)d^2_{toBS}}{2} + NlE^T_{elect} + NlP_0T \\ &\quad - NlP_0T\alpha(\lambda)\frac{M^2}{12} + NlP_0T\alpha^2(\lambda)\frac{M^2}{12K} \\ &\quad - KlE^T_{elect} + KlP_0T\alpha(\lambda)\frac{M^2}{12} \end{aligned} \tag{41}$$

First and second partial derivative of E_{round} with respect to K will provide the maximum or minimum value of K. Since $\frac{\partial^2 E_{round}}{\partial K} > 0$ so it will be minimum and minimum value is obtained by putting $\frac{\partial E_{round}}{\partial K} = 0$

$$\begin{aligned} 0 &= -lP_0T\alpha(\lambda)d_{toBS} + lP_0T\frac{\alpha^2(\lambda)d^2_{toBS}}{2} - lP_0TN\alpha^2(\lambda) \\ &\quad \times \frac{M^2}{12K^2} + lP_0T\alpha(\lambda)\frac{M^2}{12} - lE^R_{elect} \end{aligned}$$

Finally we get the optimal number of clusters $(K_{opt})_{FSO}$ for optical wave

$$(K_{opt})_{FSO} = \sqrt{\frac{NP_0T\alpha^2(\lambda)\frac{M^2}{12}}{P_0T\alpha(\lambda)(-d_{toBS} + \frac{\alpha(\lambda)d^2_{toBS}}{2}) - E^R_{elect} + P_0T\alpha(\lambda)\frac{M^2}{12}}} \tag{42}$$

3) EXPRESSION FOR OPTIMAL CLUSTERS USING EM WAVE

Energy dissipation model of sensor node using EM wave communication can be expressed as

$$\begin{aligned} E_{TX}(l,d) &= lE^T_{elect} + E_{TX-EM}(l,d) \\ E_{TX}(l,d) &= lE^T_{elect} + l\epsilon_{amp}\sigma_{uw}d^2 \end{aligned}$$

where l is the number of bits that are transmitted from transmitter to receiver, ϵ_{amp} is the amplifier energy, σ_{uw} is the conductivity of water.

The energy dissipated in non-CHs during a single round.

$$E_{NonCH} = lE^T_{elect} + l\epsilon_{fs}\sigma_{uw}d^2_{toCH}$$

Where d_{toCH} is the distance between non-CHs to CHs.

$$E_{NonCH} = lE^T_{elect} + l\epsilon_{fs}\sigma_{uw}E[d^2_{toCH}] \tag{43}$$

For the given area of $M \times M$ and total number of cluster K, the mean square distances from a non-CH to its CH; for $K = 1$ and $K > 1$ are $\frac{M^2}{12}$ and $\frac{M^2}{6K}$ respectively. By putting this value, equation (43) is modified as follows

$$E_{NonCH} = lE^T_{elect} + l\epsilon_{fs}\sigma_{uw}\frac{M^2}{6K} \tag{44}$$

Energy dissipated by the CH during the single round is (we assume that in each round there is one frame):

$$E_{CH} = (\frac{N}{K} - 1)lE^R_{elect} + lE^T_{elect} + l\epsilon_{amp}\sigma_{uw}d^2_{toBS} \tag{45}$$

Hence, the total energy dissipated in the entire cluster during a single round will be equal to the sum of energies consumed by CHs and non-CHs.

$$E_{Cluster} = E_{CH} + (\frac{N}{K} - 1)E_{NonCH} \tag{46}$$

So E_{round} can be expressed as follows:

$$\begin{aligned} E_{round} &= KE_{Cluster} \\ E_{round} &= NlE^R_{elect} - KlE^R_{elect} + Kl\epsilon_{amp}\sigma_{uw}(d^2_{toBS}) \\ &\quad + NlE^T_{elect} - l\epsilon_{fs}\sigma_{uw}\frac{M^2}{6} + Nl\epsilon_{fs}\sigma_{uw}\frac{M^2}{6K} \end{aligned} \tag{47}$$

First and second partial derivative of E_{round} with respect to K will provide the maximum or minimum value of K. Since $\frac{\partial^2 E_{round}}{\partial K} > 0$ so it will be minimum and minimum value is obtained by putting $\frac{\partial E_{round}}{\partial K} = 0$

$$0 = -lE^R_{elect} + l\epsilon_{amp}\sigma_{uw}(d^2_{toBS}) - Nl\epsilon_{fs}\sigma_{uw}\frac{M^2}{6K^2}$$

Finally we get the optimal number of clusters $(K_{opt})_{EM}$ for EM wave

$$(K_{opt})_{EM} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(d^2_{toBS}) - E^R_{elect}}} \tag{48}$$

TABLE 4. Water conductivity.

Water	Conductivity values
Fresh water	$0 \leq \sigma < 1$
River water	$1 \leq \sigma < 2$
Sea water	$2 \leq \sigma$

TABLE 5. Parameter used in paper and its definition.

Parameter	Definition
Sensing field	Square shaped
Base station location	Center, corner and lateral midpoint
N	Number of nodes
$a(f)$	Absorption coefficent
l	Number of bit
T_b	Bit duration
Z	Constant
H	Depth
M	Length
E^T_{elec}	Transmission energy
E^R_{elec}	Energy dissipation in electrical circuit
P_0	Optical power
$\alpha(\lambda)$	Attenuation coefficient
ε_{amp}	Energy dissipation in amplifier circuit
σ_{uw}	Conductivity of water

C. ANALYTICAL MODEL FOR GAUSSIAN DISTRIBUTED UWSNs

In this model, we consider the sensing field as of square-shaped (side length = M). Due to central and axial symmetry, square shaped sensing fields are of special interest in most of the research projects [17], [42]. Therefore, squared shapes are assumed for the sensing field to evaluate the optimal cluster size. In our model, we have varying locations of BS. We put the BS at the center, at a corner, and at the lateral mid point of

TABLE 6. Closed-form expressions for the optimal number of clusters for acoustic, EM and FSO communication based UWSNs.

Radio model	Location of BS	Optimal number of clusters
Acoustic wave	Center	$(K_{opt})_{Acoustic} = \sqrt{(\frac{(\frac{N}{6})a(f)T_bZHM^2}{T_bZH(0.0196M + a(f)0.2040M^2) - \frac{M^2}{12}T_bZH - E^R_{elect}})}$
Acoustic wave	Corner	$(K_{opt})_{Acoustic} = \sqrt{(\frac{(\frac{N}{6})a(f)T_bZHM^2}{T_bZH(2.297M + a(f)1.287M^2) - \frac{M^2}{12}T_bZH - E^R_{elect}})}$
Acoustic wave	Lateral midpoint	$(K_{opt})_{Acoustic} = \sqrt{(\frac{(\frac{N}{6})a(f)T_bZHM^2}{T_bZH(.7422M + a(f).8048M^2) - \frac{M^2}{12}T_bZH - E^R_{elect}})}$
FSO wave	Center	$(K_{opt})_{FSO} = \sqrt{\frac{P_0TN\alpha(\lambda)^2(\frac{M^2}{12})}{P_0T\alpha(\lambda)(-0.0196M+\frac{\alpha(\lambda)(0.2040M^2}{2})+P_0T\alpha(\lambda)(\frac{M^2}{12})-E^R_{elect}}}$
FSO wave	Corner	$(K_{opt})_{FSO} = \sqrt{\frac{P_0TN\alpha(\lambda)^2(\frac{M^2}{12})}{P_0T\alpha(\lambda)(-2.297M+\frac{\alpha(\lambda)(1.287M^2}{2})+P_0T\alpha(\lambda)(\frac{M^2}{12})-E^R_{elect}}}$
FSO wave	Lateral midpoint	$(K_{opt})_{FSO} = \sqrt{\frac{lP_0TN\alpha(\lambda)^2(\frac{M^2}{12})}{P_0T\alpha(\lambda)(-.7422M+\frac{\alpha(\lambda)(.8048M^2}{2})+P_0T\alpha(\lambda)(\frac{M^2}{12})-E^R_{elect}}}$
EM wave	Center	$(K_{opt})_{EM} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(0.2040M^2) - E^R_{elect}}}$
EM wave	Corner	$(K_{opt})_{EM} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(1.287M^2) - E^R_{elect}}}$
EM wave	Lateral midpoint	$(K_{opt})_{EM} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(.8048M^2) - E^R_{elect}}}$
EM wave (two ray)	Center	$(K_{opt})_{EM(two-ray)} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(.0970M^4) - E^R_{elect}}}$
EM wave (two ray)	Corner	$(K_{opt})_{EM(two-ray)} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(1.845M^4) - E^R_{elect}}}$
EM wave (two ray)	Lateral midpoint	$(K_{opt})_{EM(two-ray)} = \sqrt{\frac{N\epsilon_{fs}\sigma_{uw}\frac{M^2}{6}}{\epsilon_{amp}\sigma_{uw}(.7453M^4) - E^R_{elect}}}$

the sensing field which is shown in Fig. 6. In case when the BS is located at the center, the probability p that the distance between a randomly chosen point and the BS is less than y should be obtained [43]–[45]. The minimum and maximum value of angle γ are 0 and $\frac{\pi}{4}$ radian respectively, where

$$\gamma = \arctan \frac{\sqrt{y^2 - \frac{M^2}{4}}}{\frac{M}{2}} \tag{49}$$

The PDF can be expressed as:

$$f(y) = \begin{cases} \frac{\sqrt{2\pi}y}{M^2\sigma_y} e^{\frac{(y-a)^2}{2\sigma_y^2}} & \text{for } 0 \leq y \leq \frac{M}{2} \\ \frac{1}{\sqrt{2\pi\sigma_y}}(\frac{2\pi y}{M^2} - \frac{8y\gamma}{M^2})e^{\frac{(y-a)^2}{2\sigma_y^2}} & \text{for } \frac{M}{2} \leq y \leq \frac{M}{\sqrt{2}} \end{cases} \tag{50}$$

For simplicity takes $\sigma_y = \sigma$.

1) WHEN BS IS AT THE CENTER OF THE SENSING FIELD

a: CALCULATION OF EXPECTED VALUE OF d_{toBS}

Let the dimensions of the sensing field are $M \times M$ and assume that the BS is located at the center of the sensing field. Nodes in the sensing field follow the Gaussian distribution that can be shown in Fig. 5. To evaluate the expected distance from the center to the overall area of the sensing field, we integrate $yf(y)$ in the interval of $[0, \frac{M}{\sqrt{2}}]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

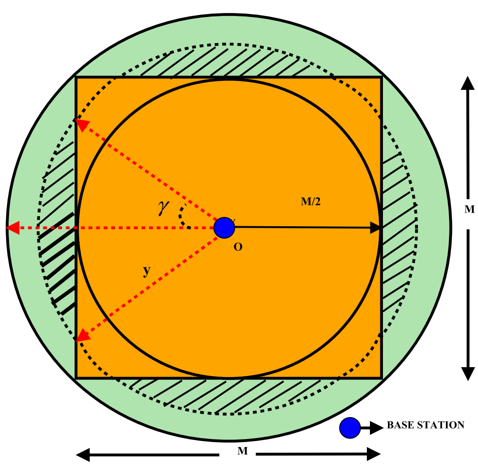

FIGURE 5. Square-shaped sensing field with BS at the center ($y > M/2$).

TABLE 7. Average value of d_{toBS}, d^2_{toBS}, d^4_{toBS} when BS at center, corner and lateral mid point of sensing field.

Average value of d_{toBS}, d^2_{toBS}, d^4_{toBS} (BS at the Center)												
	$E[d_{toBS}]$				$E[d^2_{toBS}]$				$E[d^4_{toBS}]$			
σ/a	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$
$0.10M$	$0.0125M$	$0.0196M$	$0.0049M$	0.0008M	$0.0991M^2$	$0.2040M^2$	$0.0101M^2$	$0.0081M^2$	$0.0133M^4$	$0.0695M^4$	$0.0154M^4$	$0.0136M^4$
$0.20M$	$0.0111M$	$0.0131M$	$0.0073M$	$0.0018M$	$0.1053M^2$	$0.1036M^2$	$0.0283M^2$	$0.0015M^2$	$0.0204M^4$	$0.0346M^4$	$0.0206M^4$	$0.0483M^4$
$0.30M$	$0.0088M$	$0.0095M$	$0.0070M$	$0.0034M$	$0.0913M^2$	$0.0695M^2$	$0.0307M^2$	$0.0068M^2$	$0.0208M^4$	$0.0227M^4$	$0.0171M^4$	$0.0842M^4$
$0.40M$	$0.0071M$	$0.0074M$	$0.0061M$	$0.0040M$	$0.0762M^2$	$0.0553M^2$	$0.0297M^2$	$0.0110M^2$	$0.0199M^4$	$0.0183M^4$	$0.0144M^4$	$0.0922M^4$
$0.50M$	$0.0059M$	$0.0060M$	$0.0053M$	$0.0040M$	$0.0618M^2$	$0.0465M^2$	$0.0283M^2$	$0.0136M^2$	$0.0182M^4$	$0.0162M^4$	$0.0129M^4$	$0.0924M^4$
$0.60M$	$0.0050M$	$0.0051M$	$0.0046M$	$0.0038M$	$0.0497M^2$	$0.0393M^2$	$0.0265M^2$	$0.0150M^2$	$0.0164M^4$	$0.0146M^4$	$0.0120M^4$	$0.0915M^4$
$0.70M$	$0.0043M$	$0.0044M$	$0.0041M$	$0.0035M$	$0.0402M^2$	$0.0332M^2$	$0.0242M^2$	$0.0154M^2$	$0.0147M^4$	$0.0133M^4$	$0.0113M^4$	$0.0900M^4$
$0.80M$	$0.0038M$	$0.0038M$	$0.0036M$	$0.0032M$	$0.0329M^2$	$0.0281M^2$	$0.0217M^2$	$0.0151M^2$	$0.0132M^4$	$0.0121M^4$	$0.0106M^4$	$0.0877M^4$
$0.90M$	$0.0034M$	$0.0034M$	$0.0033M$	$0.0030M$	$0.0272M^2$	$0.0239M^2$	$0.0193M^2$	$0.0143M^2$	$0.0119M^4$	$0.0111M^4$	$0.0991M^4$	$0.0846M^4$
Average value of d_{toBS}, d^2_{toBS}, d^4_{toBS} (BS at the Corner)												
	$E[d_{toBS}]$				$E[d^2_{toBS}]$				$E[d^4_{toBS}]$			
σ/a	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$
$0.10M$	$0.6227M$	$0.9686M$	$1.5460M$	$2.2970M$	$0.0998M^2$	$0.3400M^2$	$0.7399M^2$	$1.2500M^2$	$0.01358M^4$	$0.1288M^4$	$0.5766M^4$	$1.6260M^4$
$0.20M$	$0.6319M$	$1.0420M$	$1.5520M$	$1.8210M$	$0.1539M^2$	$0.3965M^2$	$0.7472M^2$	$0.9700M^2$	$0.0433M^4$	$0.2127M^4$	$0.6585M^4$	$1.1130M^4$
$0.30M$	$0.6844M$	$1.0610M$	$1.3850M$	$1.4460M$	$0.2234M^2$	$0.4370M^2$	$0.6594M^2$	$0.7462M^2$	$0.1034M^4$	$0.2938M^4$	$0.5831M^4$	$0.7572M^4$
$0.40M$	$0.7187M$	$0.9963M$	$1.1850M$	$1.1930M$	$0.2719M^2$	$0.4280M^2$	$0.5579M^2$	$0.5975M^2$	$0.1589M^4$	$0.3113M^4$	$0.4758M^4$	$0.5536M^4$
$0.50M$	$0.7107M$	$0.9014M$	$1.0150M$	$1.0110M$	$0.2889M^2$	$0.3959M^2$	$0.4741M^2$	$0.4949M^2$	$0.1866M^4$	$0.2936M^4$	$0.3888M^4$	$0.4290M^4$
$0.60M$	$0.6769M$	$0.8076M$	$0.8800M$	$0.8742M$	$0.2858M^2$	$0.3592M^2$	$0.4088M^2$	$0.4209M^2$	$0.1928M^4$	$0.2659M^4$	$0.3240M^4$	$0.3471M^4$
$0.70M$	$0.6332M$	$0.7247M$	$0.7729M$	$0.7676M$	$0.2734M^2$	$0.3248M^2$	$0.3578M^2$	$0.3655M^2$	$0.1877M^4$	$0.2382M^4$	$0.2756M^4$	$0.2900M^4$
$0.80M$	$0.5880M$	$0.6538M$	$0.6873M$	$0.6830M$	$0.2576M^2$	$0.2945M^2$	$0.3174M^2$	$0.3226M^2$	$0.1778M^4$	$0.2135M^4$	$0.2387M^4$	$0.2483M^4$
$0.90M$	$0.5452M$	$0.5937M$	$0.6178M$	$0.6144M$	$0.2411M^2$	$0.2683M^2$	$0.2849M^2$	$0.2885M^2$	$0.1664M^4$	$0.1923M^4$	$0.2100M^4$	$0.2166M^4$
Average value of d_{toBS}, d^2_{toBS}, d^4_{toBS} (BS at the Lateral midpoint)												
	$E[d_{toBS}]$				$E[d^2_{toBS}]$				$E[d^4_{toBS}]$			
σ/a	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$	$0.20M$	$0.40M$	$0.60M$	$0.80M$
$0.10M$	$0.6325M$	$0.7527M$	$0.1679M$	$0.1509M$	$0.1490M^2$	$0.1899M^2$	$0.3899M^2$	$0.7245M^2$	$0.0274M^4$	$0.0432M^4$	$0.1672M^4$	$0.5590M^4$
$0.20M$	$0.6188M$	$0.5503M$	$0.2804M$	$0.0657M$	$0.1872M^2$	$0.2462M^2$	$0.4216M^2$	$0.5953M^2$	$0.0526M^4$	$0.0920M^4$	$0.2314M^4$	$0.4484M^4$
$0.30M$	$0.5619M$	$0.4646M$	$0.2985M$	$0.1381M$	$0.1872M^2$	$0.2996M^2$	$0.4108M^2$	$0.4937M^2$	$0.0902M^4$	$0.1484M^4$	$0.2501M^4$	$0.3534M^4$
$0.40M$	$0.5030M$	$0.4196M$	$0.3003M$	$0.1798M$	$0.2690M^2$	$0.3232M^2$	$0.3882M^2$	$0.4317M^2$	$0.1250M^4$	$0.1779M^4$	$0.2423M^4$	$0.2949M^4$
$0.50M$	$0.4470M$	$0.3849M$	$0.2968M$	$0.2033M$	$0.2901M^2$	$0.3289M^2$	$0.3680M^2$	$0.3931M^2$	$0.1460M^4$	$0.1868M^4$	$0.2274M^4$	$0.2569M^4$
$0.60M$	$0.3977M$	$0.3529M$	$0.2879M$	$0.2153M$	$0.2999M^2$	$0.3272M^2$	$0.3520M^2$	$0.3675M^2$	$0.1557M^4$	$0.1858M^4$	$0.2127M^4$	$0.2302M^4$
$0.70M$	$0.3557M$	$0.3233M$	$0.2751M$	$0.2188M$	$0.3035M^2$	$0.3228M^2$	$0.3393M^2$	$0.3495M^2$	$0.1585M^4$	$0.1807M^4$	$0.1990M^4$	$0.2103M^4$
$0.80M$	$0.3204M$	$0.2966M$	$0.2604M$	$0.2167M$	$0.3038M^2$	$0.3178M^2$	$0.3293M^2$	$0.3363M^2$	$0.1575M^4$	$0.1741M^4$	$0.1871M^4$	$0.1947M^4$
$0.90M$	$0.2907M$	$0.2729M$	$0.2453M$	$0.2111M$	$0.3025M^2$	$0.3129M^2$	$0.3211M^2$	$0.3262M^2$	$0.1547M^4$	$0.1673M^4$	$0.1768M^4$	$0.1822M^4$

b: CALCULATION OF EXPECTED VALUE OF d^2_{toBS}

To evaluate the expected distance from the center to the overall area of the sensing field, we integrate $d^2_{toBS} = x^2 + y^2$ to PDF $f(y)$ in the interval of $[-\frac{M}{2}, \frac{M}{2}]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

c: CALCULATION OF EXPECTED VALUE OF d^4_{toBS}

To evaluate the expected distance from the center to the overall area of the sensing field, we integrate $d^4_{toBS} = (x^2 + y^2)^4$ to PDF $f(y)$ in the interval of $[-\frac{M}{2}, \frac{M}{2}]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

2) WHEN BS IS AT THE CORNER OF THE SENSING FIELD

a: CALCULATION OF EXPECTED VALUE OF d_{toBS}

Let the dimensions of the sensing field are $M \times M$ and assume that the BS is located at the corner of the sensing field. Nodes in the sensing field follow the Gaussian distribution. To evaluate the expected distance from the corner to the overall area of the sensing field, we integrate $yf(y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

b: CALCULATION OF EXPECTED VALUE OF d^2_{toBS}

To evaluate the expected distance from the corner of the sensing field to the overall area of the sensing field, we integrate $(x^2 + y^2)f\ (y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

c: CALCULATION OF EXPECTED VALUE OF d^4_{toBS}

To evaluate the expected distance from the corner of the sensing field to the overall area of the sensing field, we integrate $(x^2 + y^2)^2 f\ (y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

TABLE 8. Simulations parameters [17], [37], [46].

Parameter	Definition
Sensing field	Square shaped
BS location	Center, corner and lateral midpoint of sensing field of sensing field
N	$50-300$
f	$20\ KHz$
$a(f)$	0.0062
l	$500\ Byte$
H	$100\ m$
M	$50\times50\ m^2$, $100\times100\ m^2$, $150\times150\ m^2$, $200\times200\ m^2$, $500\times500\ m^2$
E^T_{elec}	$50\ nJ/bit$
E^R_{elec}	$50\ nJ/bit$
P_0	$10\ mw$
$\alpha(\lambda)$	0.043
ε_{fs}	$100\ pJ/bit/\ m^2$
σ_{uw}	2

3) WHEN BS IS AT THE LATERAL MIDPOINT (MIDPOINT OF ANY OF THE SIDES OF A SQUARE) OF THE SENSING FIELD

a: CALCULATION OF EXPECTED VALUE OF d_{toBS}

Let the dimensions of the sensing field are $M \times M$ and assume that the BS is located at the lateral midpoint of the sensing field. Nodes in the sensing field follow the Gaussian distribution. To evaluate the expected distance from the lateral midpoint of the square to the overall area of the sensing field, we integrate $(M\sqrt{y^2 + M^2} + y^2 \arcsin(\frac{M}{y}))f(y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

b: CALCULATION OF EXPECTED VALUE OF d^2_{toBS}

To evaluate the expected distance from the lateral midpoint of the square to the overall area of the sensing field, we integrate $((x-\frac{M}{2})^2+y^2)f(y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

c: CALCULATION OF EXPECTED VALUE OF d^4_{toBS}

To evaluate the expected distance from the lateral midpoint of the square to the overall area of the sensing field, we integrate $((x-\frac{M}{2})^2+y^2)^2 f(y)$ in the interval of $[0, M]$. The values for all combinations of standard deviation of Gaussian distribution σ and mean distance a are shown in Table 7.

IV. RESULTS AND ANALYSIS

We derived a closed form mathematical expression to find the optimal number of clusters in acoustic, EM wave, FSO communication based underwater sensor networks. In this section, the performance of optimal clustering in all these sensor networks is analyzed. The optimal number of clusters depends on the factors like dimensions of sensing field M, number of sensor nodes (N), distance between the node and BS (d_{toBS}), and energy consumption of the receiver circuitry (E^R_{elect}). For simulation, we considered a square shaped sensing field, in which BS is located at three different positions. The simulation is performed using MATLAB. All the simulation parameters and their values are listed in Tables 5 and 8 respectively.

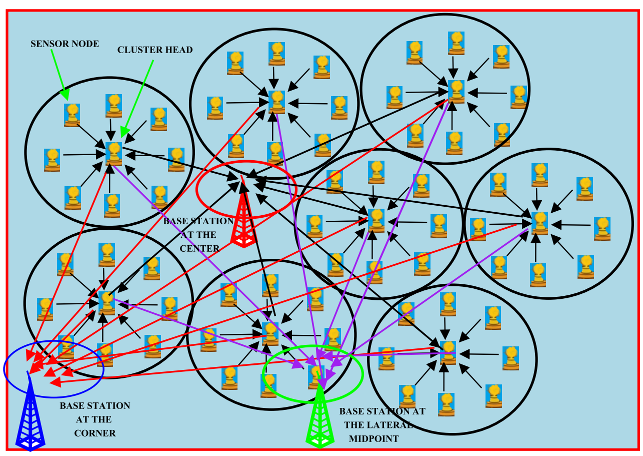

FIGURE 6. Clustering when BS is at the center, corner and lateral midpoint of the sensing field.

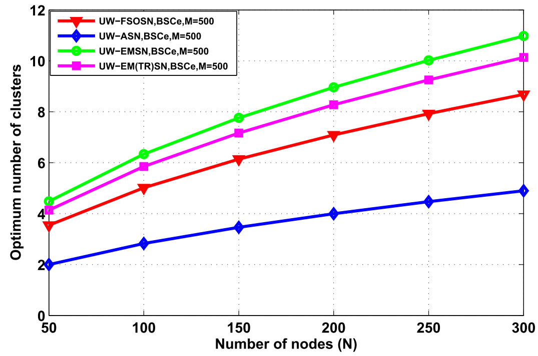

FIGURE 7. Optimal number of cluster versus node density for acoustic, FSO and EM wave based UWSNs when BS is at the center.

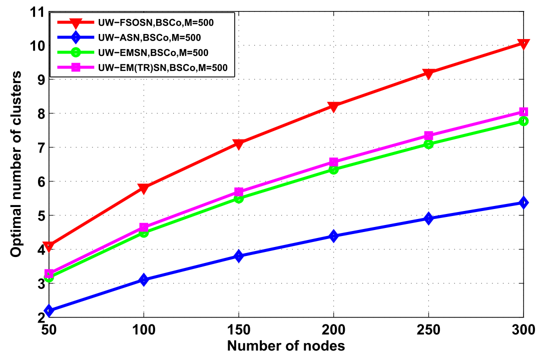

FIGURE 8. Optimal number of cluster versus node density for acoustic, FSO and EM wave based UWSNs when BS is at the corner.

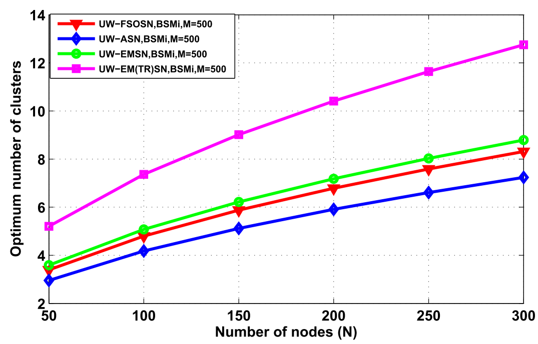

FIGURE 9. Optimal number of cluster versus node density for acoustic, FSO and EM wave based UWSN when BS is at the lateral midpoint of the sensing field.

From Table 6, it can be seen that the optimal number of clusters is independent of the transmitter electronics energy consumption. The size of the optimal cluster is expressed as $(\frac{N}{K})$. By considering the symmetry condition, the expected value of distance between the nodes and the BS such as d_{toBS}, d^2_{toBS} and d^4_{toBS} is calculated. Considering the suitable expected value, and by putting it in derived K_{opt} equation, we get the optimal number of clusters. Thus, we obtained the energy-efficient cluster size that the network should maintain. For different values of Gaussian standard deviation and mean distance, the values of d_{toBS}, d^2_{toBS} and d^4_{toBS} are calculated which are shown in Table 7.

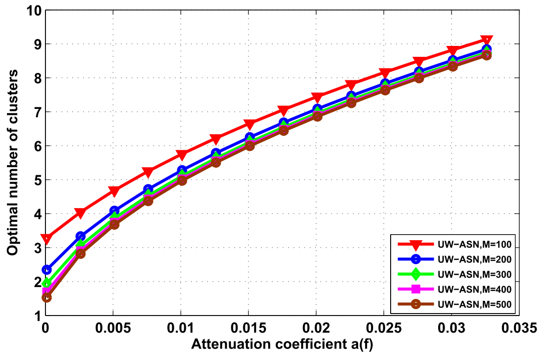

FIGURE 10. Optimal number of cluster versus attenuation coefficient $a(f)$ for acoustic wave based UWSNs (frequency: 1 to 50 KHz).

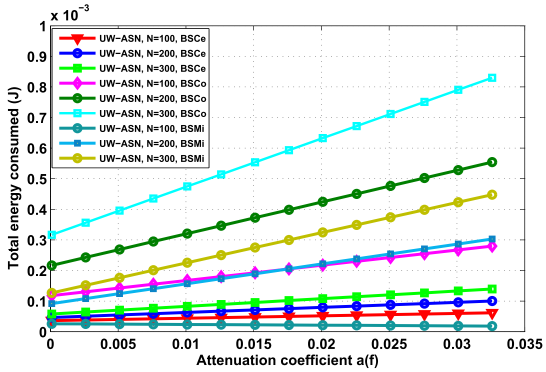

FIGURE 11. energy consumption versus attenuation coefficient $a(f)$ for acoustic wave based UWSNs (frequency: 1 to 50 KHz).

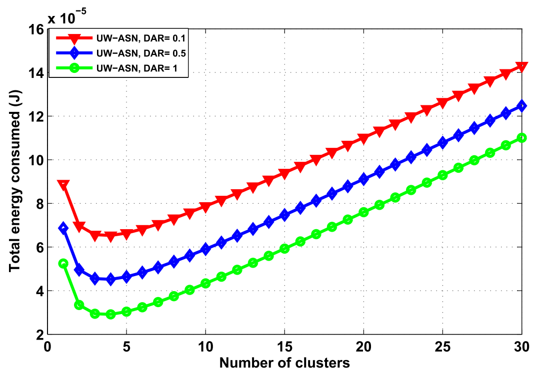

FIGURE 12. Total energy consumption versus optimal number of clusters for acoustic wave based UWSNs (data aggregation ratio value 1, 0.5, 0.1).

A. OPTIMAL CLUSTERING IN UW-ASN

From the closed form expression for the optimal number of clusters; as shown in Table 6, we can say that, in case of acoustic wave communication optimal number of cluster i.e. $(K_{opt})_{Acoustic}$ is the function of $M, N, H, T_b, a(f), E_{elect}, d_{toBS}$.

When the BS is at the center, with nodes varying from 50 to 300, from the plot of optimal number of clusters against number of nodes the optimal number of clusters vary from 2 to 5 which is shown in Fig. 7. For the same above setting, as shown in Fig. 8, Fig. 9, when the BS is located at the corner and at the lateral midpoint of the sensing field, the optimal number of clusters vary from 2 to 5 and from

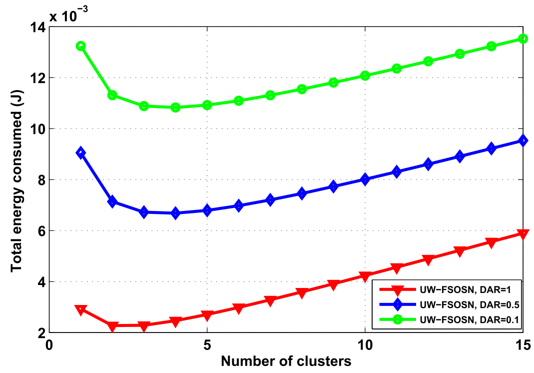

FIGURE 13. Total energy consumption versus optimal number of clusters for FSO wave based UWSNs (data aggregation ratio value 1, 0.5, 0.1).

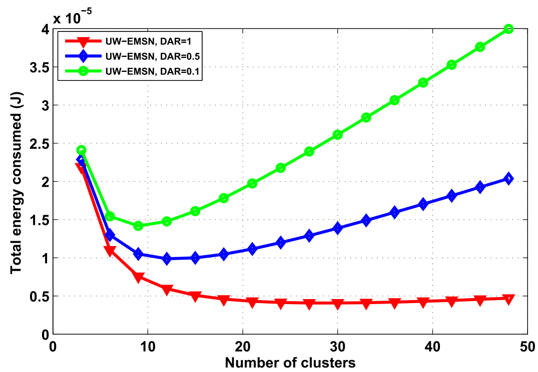

FIGURE 14. Total energy consumption versus optimal number of clusters for EM wave based UWSNs (data aggregation ratio value 1, 0.5, 0.1).

2 to 7 respectively. For the above three BS configurations, the optimal energy consumed is found to be $6.7\times10^{-5}J$, $4.1\times10^{-4}J$, $1.8\times10^{-5}J$, which is shown in Fig. 15(a), Fig. 15(b), Fig. 15(c) respectively. The impact of DAR is shown in Fig. 12, as per which the least energy required for optimal clustering for the DAR values of 1, 0.5, 0.1 is $2.5\times10^{-5}J$, $4.2\times10^{-5}J$, $6.5\times10^{-5}J$ respectively. It can be inferred that the energy consumption will be minimized when the BS is placed at the center of the sensing field.

From the Fig. 10, the impact of attenuation coefficient for a frequency range of 1 to 50 KHz on acoustic wave can be analyzed in terms of total energy consumption and optimal number of clusters. Also, for a given attenuation coefficient, as the sensing field dimensions increase, the optimal number of clusters decreases. When there is a high attenuation of signal in the medium, it requires more optimal number of clusters. From Fig. 11, it can be verified that the total energy consumption increases with an increase of the attenuation coefficient.

B. OPTIMAL CLUSTERING IN UW-FSOSN

Similar to the above study, the optimal clustering in underwater FSO communication depends on $M, N, \alpha(\lambda), P_0, T, E_{elect}, d_{toBS}$. For the same simulation setup, the optimal clusters vary from 4 to 10, 4 to 10, 3 to 8 for the center, corner and lateral midpoint locations of BS respectively. It is shown in Fig. 7, Fig. 8, Fig. 9 respectively. Further,

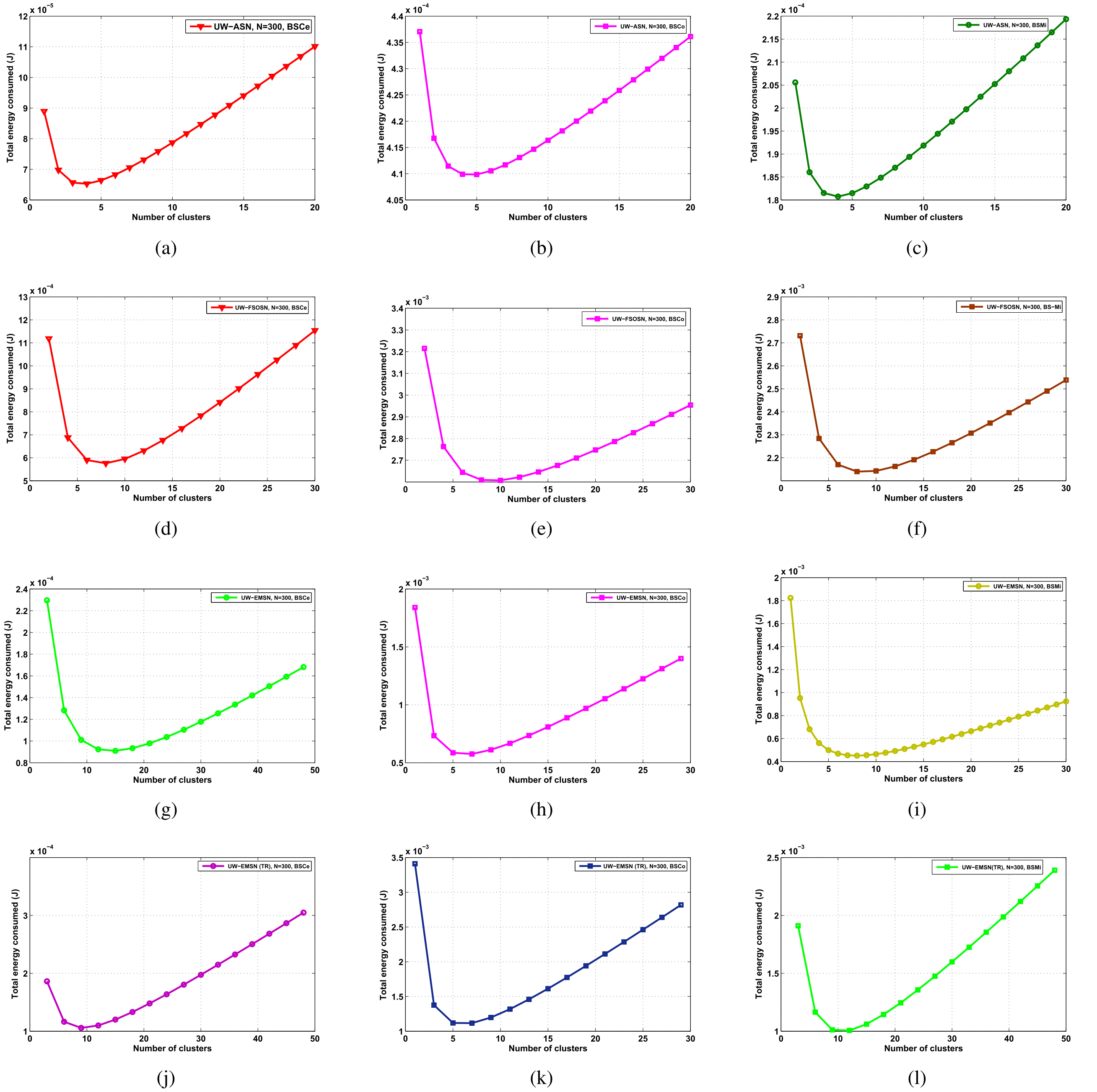

FIGURE 15. **Total energy consumption versus number of cluster for UW-ASN, UW-FSOSN, UW-EMSN, UW-EMSN (two ray). (a) Acoustics wave(when BS is at the center of the sensing field). (b) Acoustics wave (when BS is at the corner of the sensing field). (c) Acoustics wave (when BS is at lateral midpoint of the sensing field). (d) FSO wave (when BS is at the center of the sensing field). (e) FSO wave (when BS is at the corner of the sensing field). (f) FSO wave (when BS is at lateral midpoint of the sensing field). (g) EM wave (when BS is at the center of the sensing field). (h) EM wave (when BS is at the corner of the sensing field). (i) EM wave (when BS is at lateral midpoint of the sensing field). (j) EM wave (two ray) (when BS is at the center of the sensing field). (k) EM wave (two ray)(when BS is at the corner of the sensing field). (l) EM wave (two ray)(when BS is at lateral midpoint of the sensing field).**

the optimal energy consumed for these three different BS configurations is $5.9\times10^{-4}J$, $2.5\times10^{-3}J$, $2.2\times10^{-3}J$ as shown in Fig. 15(d), Fig. 15(e), Fig. 15(f) respectively. As shown in Fig. 13, the optimal energy required for similar above DAR values is $2.2\times10^{-3}J$, $6.5\times10^{-5}J$, $11.5\times10^{-3}J$ respectively.

C. OPTIMAL CLUSTERING IN UW-EMSN

The optimal number of clusters in case of EM wave communication depends on $K_{opt} = f(M, N, \sigma_{uw}, \epsilon_{fs}, E_{elect}, d_{toBS})$. Herein, for both EM two ray and EM direct communication, the optimal clustering behavior is observed to be the same. We considered the above identical simulation setup.

For EM direct communication, the optimal number of clusters vary respectively from 4 to 11, 3 to 8, 4 to 9 for center, corner and lateral midpoint locations of BS, which can be seen in Fig. 7, Fig. 8, Fig. 9. The optimal energy required is $9\times10^{-5}J$, $7\times10^{-4}J$, $5\times10^{-4}J$ respectively as shown in Fig. 15(g), Fig. 15(h), Fig. 15(i). The optimal energy

TABLE 9. Comparative analysis of acoustic, optical and EM of K_{opt} vs number of nodes (N) for different dimension of sensing field.

K_{opt} versus N when BS at the Center																									
		Acoustic wave						FSO						EM wave						EM wave (two ray)					
	M/N	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300
K_{opt}	50	2	3	4	4	5	5	3	4	5	5	6	7	5	7	9	9	11	13	7	11	13	16	17	19
	100	2	3	4	4	5	5	3	3	4	5	5	6	5	7	8	9	11	11	3	4	5	6	7	7
	150	2	3	3	4	4	4	2	3	3	4	5	5	5	6	8	9	11	11	2	3	3	3	4	4
	200	2	3	4	4	5	5	2	3	4	4	5	5	4	7	10	9	10	11	2	2	2	3	3	3
	500	2	3	4	4	4	5	4	6	7	8	9	10	4	6	8	9	10	11	4	6	7	8	9	10
K_{opt} versus N when BS at the Corner																									
		Acoustic wave						FSO						EM wave						EM wave (two ray)					
	M/N	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300
K_{opt}	50	2	3	3	4	4	4	9	12	15	17	19	21	2	3	3	4	4	4	4	5	6	7	7	8
	100	2	3	4	4	5	5	7	9	11	13	14	16	2	3	4	4	5	5	3	5	5	6	7	7
	150	2	3	4	4	4	5	6	8	10	11	13	13	2	3	4	4	4	5	3	5	5	6	7	8
	200	2	3	4	4	5	5	5	7	9	11	11	13	2	3	4	4	5	5	3	5	6	6	7	8
	500	2	3	4	4	5	6	4	6	7	8	9	10	3	5	6	6	7	8	3	5	6	7	7	8
K_{opt} versus N when BS at the lateral midpoint of the sensing field																									
		Acoustic wave						FSO						EM wave						EM wave (two ray)					
	M/N	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300	50	100	150	200	250	300
K_{opt}	50	4	5	5	6	7	8	5	7	9	10	12	13	4	5	6	7	9	9	6	9	11	13	14	16
	100	4	5	5	7	8	8	4	5	7	8	9	10	4	5	6	7	8	9	6	8	9	11	12	13
	150	3	5	6	7	8	8	3	5	6	7	8	9	3	5	6	7	8	9	5	8	9	11	12	13
	200	4	5	6	7	7	8	4	5	6	7	7	8	4	5	6	7	7	9	5	8	9	11	12	13
	500	2	4	5	6	7	7	3	5	6	7	8	8	4	5	6	7	8	9	5	7	9	10	11	12

required for similar above DAR values is, as shown in Fig. 14, $0.5\times10^{-5}J$, $1.0\times10^{-5}J$, $1.5\times10^{-5}J$ respectively.

For EM two ray communication, the optimal clusters are found to vary respectively from 4 to 10, 3 to 8, 5 to 12, which is shown in Fig. 7, Fig. 8, Fig. 9. The optimal energy consumed is $1.1\times10^{-4}J$, $1.2\times10^{-3}J$, $1\times10^{-3}J$, as shown in Fig. 15(j), Fig. 15(k), Fig. 15(l) respectively.

V. CONCLUSION AND FUTURE SCOPE

In this paper, we have investigated the analytical framework to determine the optimal number of clusters for Gaussian distributed underwater sensor networks. The analytical results are listed for different communication techniques like acoustic, optical and EM wave for three positions of BS that is when BS is at the center of sensing area, at one of the corners of sensing area and at the lateral midpoint of the sensing area. In addition, extensive simulations for different network configurations are performed to substantiate our study on the energy efficient cluster size. It has been observed that the analytical results are in-line with the simulation results. From the simulation, the following results can be inferred:

- For a Gaussian distributed UWSNs, with respect to the achievable minimum optimal number of clusters, acoustic waves outperforms EM and FSO communication techniques.
- For any kind of underwater application especially using clustering topology, acoustic communication requires less energy consumption.
- It is known that acoustic underwater communication is characterized by limited available bandwidth. Behavior of optimal clustering is not uniform in the entire bandwidth. At the lower bound of bandwidth, the best optimal number of clusters can be achieved.
- Optimal clustering is affected by the data aggregation ratio. For the perfect data aggregation ratio least optimal number of clusters are achieved.

As a future work, we would like to find the energy dissipation model for underwater Magnetic Induction (MI) communication [4]. Also, we would like to perform the analysis of optimal clustering using the above energy model. This work can be further extended by incorporating realistic sensing models [19].

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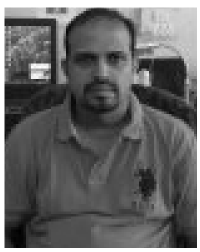

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