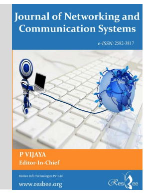
Vol.4 No.1 Jan 2021

Journal of Networking and Communication Systems

Received 19 October, Revised 24 November, Accepted 12 January



Spiral Optimization Algorithm for Lifetime Enhancement of Wireless Multimedia Sensor Networks

Shruti Tambulunde
Sunny Buffalo, New Jersy University, USA
shrutigre@gmail.com

Abstract: The Wireless Sensor Network (WSN) is considered one of the most significant networks due to the participation of both the WMSNs and traditional WSNs in the last few decades. The WSNs are the network that consists of minimum power, low cost, and its size, is small. In addition, by exploiting the multi-hop, the information shared during the communication is handled and it also presents merely easy sensing data namely humidity, temperature, etc. The WMSNs are considered as distributed sensing networks that consist of the sector sensor area. The WMSNs have the ability to transmit, receive and process the video data information that is highly rigorous and by covering with the wireless transceiver. Regarding the characteristics such as directivity and turn ability, the WSNs and WMSNs are varied. Hence, the main contribution of this work is to extend the lifespan of the network with minimized energy utilization by exploiting highly developed optimization techniques. By optimizing the parameters of the system, the optimal transmission radius is attained in order to transfer the information of the sensor to consequential sensor nodes (SNs) that are presented within range. Hence, this work presents a spiral optimization algorithm (SOA) and then the optimal Cluster Head Selection (CHS) is also presented. At last, the developed technique performance is examined and evaluated with the conventional approaches regarding the convergence rate, network energy, and alive nodes.

Keywords: WSN, WMSNs, CHS, Lifetime, Optimization Algorithm

Nomenclature

Abbreviation	Description
WSN	Wireless Sensor Network
IoT	Internet of Things
MIP	Mixed Integer Programming
WMSNs	Wireless Multimedia Sensor Networks
GA	Genetic Algorithm
CS	Compressive s Sensing
PSO	Particle Swarm Optimization
AODV	Ad-hoc On-demand Distance Vector

1. Introduction

Nowadays, WMSNs are very famous because of their numerous application areas and the minimum cost for industrial applications. Here, the most important applications of WMSNs such as circumstance monitoring systems, industrial automation systems, and environment control systems [1]. The WMSNs has been used in many industrial factories for monitoring applications. For example, using the WMSN based early warning systems, in manufacturing process failures can be prevented such as high repair cost. Moreover, by exploiting the WMSNs the industrial devices and machines' performance and usage were controlled and monitored to enhance the efficiency of the system [2].

Generally, the standard WSN was designed and it concentrates by reducing the communication power. Nevertheless, for image transmission, aforesaid schemes were not appropriate in WSNs. The entire network energy utilization was not reduced by the maximal image compression. It happens the image compression occasionally utilizes a large amount of energy than communication [3]. The energy rapidly reduces because in camera-equipped node image compression task rests always.

In conventional surveillance systems, the audio and video recordings are efficiently exploited as balancing models in order to contradict possible threats which might necessitate the participation of law enforcement officials. In many applications [12], attaining high accurate and detailed information is highly probable by means of multimedia sensors participation. In real-time scenarios, present audio and video sensors and few existing sensors are exploited for high precise recognition [4]. WMSNs are represented as the main sources of maximum volume data traffic due to this they offer big data information in urban and smart environments applications from multimedia devices. For bulk volume WMSNs there is a rising demand that creates it inconvenient to manually transport and process the data. Hence, the advantages of effectual and lightweight solutions to manage the data traffic on WMSNs turn out as important for the IoT and big data analytics areas [5].

In the topic of the combination of homogeneous camera-equipped nodes, many of the researchers were interest in order to reduce the image transmission energy. A distributed coding model was developed from the Slepian Wolf coding model to understand the coding gain of correlated data in information theory. Also, on the basis of the Wyner-Ziv theorem, the distributed image and video coding were concentrated by many researchers; this method is an extended version of lossy coding from Slepian–Wolf theorem.

The major contribution of this work is to present a working model of a novel developed Spiral optimization technique that is exploited to extend the WMSN lifetime. It is obtained by choosing the parameter of the optimal system and hence obtains radius of optimal transmission to transmit the information of the sensor to corresponding SN which are within range. Then a selection of optimal Cluster Head is performed using the novel optimization approach.

2. Literature Survey

In 2012, Zhen Zuo *et al* [1], developed a two-hop clustered image transmission model. Here, to compress and forward the image, numerous redirectors were exploited. It was mainly exploited to decrease energy utilization for the CH and a camera-equipped node. In the network, energy utilization of nodes was balanced on basis of the remaining energy of normal SN in the tasks allocation and camera cluster using the camera-equipped node by means of adaptive alteration of the transmission line.

In 2014, Muhammet Macit *et al* [2], developed a new technique for image transmission to locate diverse values of the reliability for image packets in WMSNs. At the time of data transmission, the significant parts of the image were allocated by exploiting the prioritization i.e., high and low priority. Finally, the single and multipath performance was estimated using the developed method, the QoS-aware routing protocols were examined in WMSN.

In 2020, Nazli Tekin and Vehbi Cagri Gungor [3] worked on the diverse data size minimization models like CS, and image compression, the EH techniques, namely thermal, vibration, and indoor solar, on the lifespan of WMSNs in industrial environments. Moreover, to extend the lifespan of the network a novel method called the MIP model was proposed.

In 2020, MUHSIN ATTO *et al* [4], developed a new technique to enhance AODV protocol performance. Finally, for image-based applications, the experimentation outcome revealed that the developed techniques enhance the AODV protocol performance. Moreover, the proposed method increases the lifetime of the networks, maximizes the delivered images, and minimizes the delay, network overhead related by means of offering such images.

In 2019, Murat Koyuncu *et al* [5], worked on the energy effectuality and object classification and recognition in a precise way for the combination of visual-audio multimedia effects and scalar data gathered using the SN in a WMSN. A wireless multimedia sensor node was examined by means of audio and video processing and capturing abilities and conventional scalar sensors. In sleep mode, the multimedia sensors were reserved to store the energy till they were turned on using the scalar sensors that were forever active.

In 2019, Adnan Yazici *et al* [6], developed a combination-based WMSN model which minimizes the number of data that needs to transfer over the network exploiting the intra-node processing. Here, a WMS node was examined and modeled by exploiting the commercially present modules. Here, to detect and classify the objects a technique was exploited to minimize the number of information which needs to transfer the base station. Hence, the lifetime of WMSN was increased. To transmit the gathered information, a novel energy effectual cluster-based routing approach was proposed.

3. Image Transmission Process for Clustering Model

3.1 Network Model

Fig 1 depicts the network model and its theory. In addition, the camera-equipped and normal nodes are the two types of SN which are presented in the network model. To capture image, complete node does not have the capability and also not possible mainly in the enormous and thick WMSNs.

Chiefly, the image which is contained in camera-equipped nodes, and these images, is transferred to the BS that is distant from the sensing area. In addition, the count of Base station in particular areas is distantly minimum from general SN due to higher sensing radii in camera-equipped nodes. Moreover, by SN the radius of the transmission has the ability to be dynamically altered that is presented in the network model. In sensor node, alteration is done in a camera-equipped node based on the irregular remaining energy distribution and the radius of transmission which directs the extension of the network lifetime.

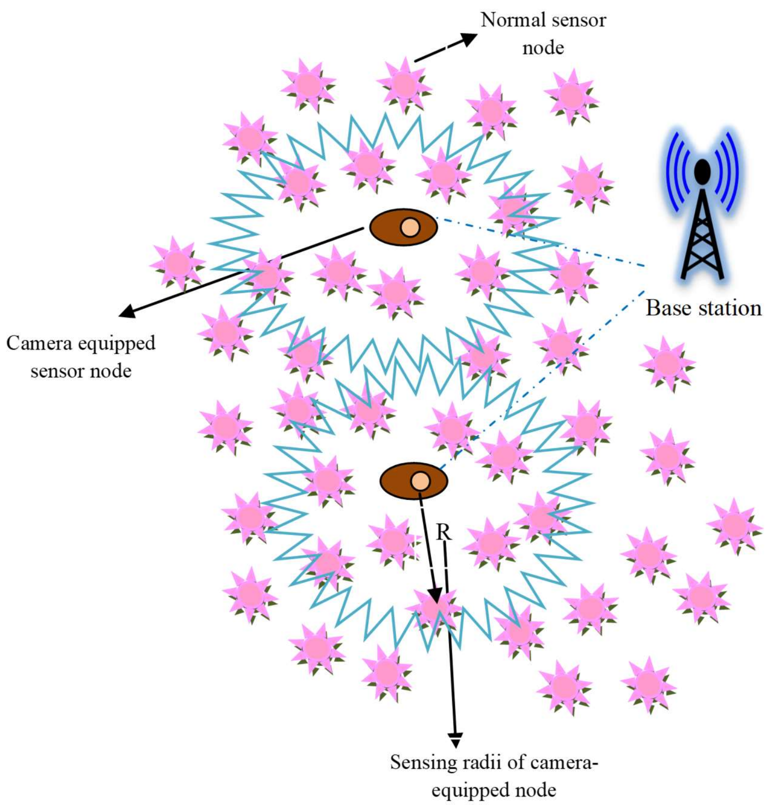


Fig. 1. *Systematic representation of camera-equipped SN*

3.2 Energy Utilization Model

The eq. (1) and (2) explains the energy utilization of both the transmitting and receiving p bit data on distant t.

$$EG_{tm}(p,t)=\begin{cases}EG_{ecl}\cdot p+\varepsilon_{fr}\cdot p\cdot t^2, & t<t_0\\ EG_{ecl}\cdot p+\varepsilon_{mc}\cdot p\cdot t^4, & t\ge t_0\end{cases} \tag{1}$$

$$EG_{rm}(p)=EG_{ecl}\cdot p \tag{2}$$

EG_{ecl} signifies the utilized energy by circuit per bit, t denotes distance amid wireless transmitter and the receiver, amplifier energy is indicated as $\varepsilon_{fr}t^2$ or $\varepsilon_{mc}t^4$.

Based on Eq. (1) and (2), the energy utilization among the sender and receivers is updated. Moreover, energy utilization per bit is explained by eq. (3), whereas the energy depletion for 1 level wavelet transformation per bit is shown as EG_{DWE} for coding required energy is stated by EG_{cod} and wavelet decomposition level is stated by DL_0.

$$EG_{cpt} = EG_{DWE} \cdot \sum_{DL=1}^{DL_0} \left(\frac{1}{4}\right)^{DL-1} + EG_{cod} \quad (3)$$

i) Energy utilization analysis for Camera-Equipped Node

An image $P \times Q$ pixels size based on the Eq. (4) the energy utilization to transfer with 8 bits per pixel are done during camera-equipped node it transfers raw images to near CH.

$$EG_{CA} = EG_{TM}\left(P \cdot Q \cdot 8, t_{CA-CL}\right) \quad (4)$$

By eq. (5), for $X \times Y$ size, the energy utilization with 8 bits per pixel is carried out, if the image transmits is compressed using the camera-equipped node.

$$EG'_{CA} = EG_{cpt} \cdot P \cdot Q \cdot 8 + EG_{TM}\left(P \cdot Q \cdot B_R, t_{CA-CL}\right) \quad (5)$$

ii) Energy utilization analysis for CH

As several rounds, the operation of clustering is calculated.

At first, subsequent to the Cluster Head Selection, the set-up phase is carried out. Then, the steady-state is performed while image data transformation is performed CL from 1 node and on top of the Base Station. Consequently, by representing the camera-equipped node, at steady phase for each node if it works compression over transmitting images, after energy utilization of Cluster Head to increase compressed data and navigates them to the Base Station is stated as in eq. (6).

In eq. (6), the number of obtained images in the round is indicated and the distance between the Base Station and Cluster Head is stated as t_{CH-bt}.

$$EG_{CL} = d \cdot EN_{RM}\left(P \cdot Q \cdot B_R\right) + d \cdot E_{TM}\left(P \cdot Q \cdot B_R, l_{CL-bt}\right) \quad (6)$$

For the received image, energy utilization of CH is stated in eq. (7), which is used to compress them and transfer compressed image to Base Station, while camera-equipped node transfer image to the Cluster Head and if the Cluster Head compress the image.

$$\begin{aligned} EG'_{CL} = {} & d \cdot EG_{RM}\left(P \cdot Q \cdot 8\right) + d \cdot EG_{cpt} \cdot P \cdot Q \cdot 8 + \\ & d \cdot EG_{TM}\left(P \cdot Q \cdot B_R, t_{CL-BT}\right) \end{aligned} \quad (7)$$

3.3 Setup Phase of Cluster Phase

In-camera clusters if Cluster Heads functioned as camera-equipped nodes during a single time, camera cluster set-up phase functions are estimated.

In-camera cluster set-up phase there are three phases and it is described as below:

(i) To declare attendance of camera-equipped node, the message is transmitted using a nonpersistent CSMA MAC protocol by a different radius of transmission TXD_c. Actually, the message is truly a minute message.

(ii) The sensor node is used to state which camera cluster is exploited to concatenate that is based on the message's obtained signal strength from camera nodes. Moreover, in this message, the camera-equipped node ID is considered and the remaining energy is done between its distance and the general cluster is GH.

(iii) By camera-equipped node In order to schedule the camera cluster, the transmission radius is altered. It is performed on the basis of the merged request message achievement and also it decides the image compression task allocation on nodes within the camera groups, it is based on remaining energy. Subsequent to this, TDMA scheduling is performed and it transmits the schedule away.

3.4 Analysis of TXDc

In the camera cluster setup segment, the TXD_c determination is considered significant based on this, two scenarios are presented. (i) In merging the camera cluster, the shortage of node happens while possessing minimum TXD_c, (ii) in the camera cluster the divergence happens while possessing minimum TXD_c. As a result, in the camera-equipped node, the rate of image transmission may superior to the image compression. Hence, the suitable TXD_c is highly effective for a camera-equipped node to establish a camera cluster connection. Moreover, $P \times Q \times 8$ image size is exploited and the camera-equipped node is used to capture the image. The analysis of camera-equipped node's energy utilization is presented by means of raw image transmission is highly efficient, rather than the image compression working when $EG_c < EG'_c$. The eq. (8) comprises the particular restraints and it is satisfied by exploiting the TXD_c.

$$TXD_c < TXD' = \begin{cases} \sqrt{\dfrac{rEG_{cpt}/(txd-1) - EG_{ecl}}{\varepsilon_{fr}}}. & TXD' < t_0 \\ \sqrt[4]{\dfrac{rEN_{cpt}/(txd-1) - EN_{ecl}}{\varepsilon_{mc}}}, & TXD' \geq t_0 \end{cases} \tag{8}$$

Whereas the ratio of the image compression ($r > 1$ and $r = 8/B_R$) is indicated as r. Hence, fixed TXD_c estimation is performed by exploiting the eq. (9), whereas the parameter of the system is linked to normal sensor node density and it is indicated as α, whereas, the value of $\alpha < 1$.

$$TXD_c = \alpha TXD' \tag{9}$$

Assume that density of node in monitoring region as ρ. The computation for the parameter of the system α is exploited by eq. (10).

$$\alpha = \sqrt{\frac{h_0}{\pi\rho}} \Big/ TXD' \tag{10}$$

By eradicating common nodes the lifespan of the network is maximized and the camera-equipped node emerged in a cluster at a similar moment.

Let, total nodes remaining energy is equivalent and it is represented as RE and it is stated in eq. (11), whereas distance among normal nodes to Cluster Head in the general cluster and it is indicated as t_i

$$\frac{RE}{\{EG_{ecl} + (\varepsilon_{fr} \cdot TXD_c^2, \varepsilon_{mc} \cdot TXD_c^4)\} \cdot P \cdot Q \cdot 8} = \frac{h_0 RE}{EG_{ecl} \cdot P \cdot Q \cdot 8 + EG_{cpt} \cdot P \cdot Q \cdot 8 + \{EG_{ecl} + (\varepsilon_{fr} \cdot t_i^2, \varepsilon_{mc} \cdot t_i^4)\} \cdot P \cdot Q \cdot 8/r} \tag{11}$$

Hence, in the camera cluster, the approximate best node counts are represented in eq. (12).

$$h_0 \approx \left[\frac{EG_{cpt} + EG_{ecl}}{EN_{ecl}} \right] + 1 \tag{12}$$

By substituting Eq. (12) in Eq. (10), the system parameter α is attained. Hence, the radius of the fixed transmission is devised.

Hence, the eq. (9) is used to formulate the radius of fixed transmission TXD_c.

3.5 Alteration of Transmission Radius

In Eq. (12) h_0 exploited is not represented as the real optimum value as general sensor node's remaining energy that concatenates camera cluster is unnecessary. By transmitting with TXD_c the join-request messages back h_0 cannot be guaranteed. Hence, using the camera-equipped node the best value α is required to decide.

Let $RE_i, \{i = 1,2,....h\}$ has represented as remaining energy of general SN. Eq. (13) indicates the calculation of normal lifespan of c_i node.

$$\beta_i = \left[\frac{RE_i}{EG_{rm}(P \cdot Q \cdot 8) + EG_{cpt} \cdot P \cdot Q \cdot 8 + EG_{tm}(P \cdot Q \cdot 8/r, t_i)} \right] \tag{13}$$

Whereas, in the normal cluster, the distance between the node c_i and the Cluster Head is indicated as t_i the image compression ratio is represented as r. Here, from the node (camera-equipped) for obtaining an image the node c_i's total dissipated energy is indicated as denominator value. Eq. (14) indicates the usual lifetime of b.

$$\beta_{cam} = \left[\frac{RE_{cam}}{EG_{tm}(P \cdot Q \cdot 8, TXD_c)} \right] \tag{14}$$

To improve the lifespan of the network, the camera-equipped node, and general SN in cluster, possesses to die simultaneously and therefore eq. (15) is obtained.

$$\sum_{t(c_i, b) \leq RXD_c} \beta_i = \beta_{cam} \tag{15}$$

4. Network Lifetime Enhancement

4.1 Objective Function

Conversely, Eq. (15) will not be fulfilled in most of the scenarios. Therefore, the transmission radius adjustments in the cluster need to performed using the camera-equipped node at any cost and it makes sure in eq. (16).

$$\begin{cases} \min & \sum_{t(c_i,b)\le TXD_c} \beta_i \\ & \sum_{t(c_i,b)\le TXD_c} \beta_i \ge \beta_{cam} \end{cases} \tag{16}$$

The eq. (16) is used to state the objective function of the proposed method and thereby the network lifetime rises. To reorganization of the optimal Cluster, the Head is considered as the objective function.

4.2 Spiral Optimization Algorithm(SOA)

The SOA is enthused by spiral phenomena in nature, stated in galaxies in the universe, Nautilidae shells and whirling currents, [7]. The spiral movement of search points that is search agents is stated as follows:

$$x_i(k+1) = x^*(k) + r \times R(\theta) \times \left(x_i(k) - x^*(k)\right) \tag{17}$$

whereas $x_i(k)$ symbolizes the solution related to the ith search point in the kth iteration; $\theta \in (0, \pi)$ symbolizes rotation rate of $x_i(k)$ around a center $x^*(k)$ that is optimal solution decided in current iteration; $r \in (0, 1)$ symbolizes parameter of step rate; and $R(\theta)$ symbolizes composite rotation matrix which is computed using the below equation:

$$R(\theta) = R_{i_1 j_1}(\theta) \times \ldots\ldots \times R_{i_\tau j_\tau}(\theta) \tag{18}$$

In Eq. (17), the variable $\left(x_i(k) - x^*(k)\right)$ comes close to "0", as a search point comes close to the center.

If the center is a local optimum, subsequently all search points come close to the local optimum. Hence, it is probable that optimization only attains a local optimum before global optimum.

At optimum solution, the search point is stationary while the variable $\left(x_i(k) - x^*(k)\right)$ is equivalent to '0'. The variable τ indicates an arbitrary number that might considerably augment the calculation price to compute the composite rotation matrix.

Hypotrochoid SOA

A hypotrochoid SOA is developed in this paper to attain the following objectives:

i) The hypotrochoid spiral motion paths are followed by search points that enable the search points to discover search space more competently and successfully. The complete center neighborhood is explored by search points.

ii) As regards the escape ability, to identify the constraint from local optima, the hypotrochoid spiral optimization search point's stray around 2 center points.

iii) The search points which attain the optimal solutions are moved arbitrarily to shun mislaid the search points.

iv)To control calculation cost and movement of search agents the variable τ is user-defined [8].

For the search points, the hypotrochoid spiral movement is devised as:

$$x_i(k+1) = x^*(k) + r \times R(\theta) \times \left(x_i(k) - x^*(k)\right) \tag{19}$$

$r \in (-1, 0)$ indicates the step rate; $x_i(k)$ signifies the location of the ith search point in k^{th} iteration; $R(\theta)$ indicates composite rotation matrix; and $\theta \in (0, \pi)$ indicates rotation rate of $x_i(k)$ around center of kth iteration $x^*(k)$:

$$x^*(k) = \begin{cases} x_2^*(k) & \text{rand} \le \rho \\ x_1^*(k) & \text{else} \end{cases} \tag{20}$$

$\rho \in (0, 1)$ indicates probability index, and $x_1^*(k)$ and $x_2^*(k)$ correspondingly state first and second center points. The location of the first center $x_1^*(k)$ is computed using:

$$x_1^*(k) = \arg\min\{f(x_i(K))\}, i = 1,\ldots\ldots, np,\ K = 0,\ldots\ldots, k \tag{21}$$

$\arg\min\{f\}$ indicates the solution that minimizes f; np indicates the number of search points and $f(x_i(K))$ states the objective function value of $x_i(K)$.

The location of the second center $x_2^*(k)$ is calculated using the below formulation:

$$x_2^*(k) = \begin{cases} \arg\min\{f(x_i(K))\}, i = 1,\ldots\ldots, np, \ x_1^*(k) = x_1^*(k-1) \\ \arg\min\{f(x_i(K))\}, i = 1,\ldots\ldots, np \sim= c, \ x_1^*(k) \neq x_1^*(k-1) \end{cases} \quad (22)$$

~= indicates the operator which excludes components from an array, c indicates the index of the first center. For instance, A ~= α represents α excluded from the array A.

By equations, (21) and (22), the first center $x_1^*(k)$ indicates the solution by means of the least objective function value. In the current iteration as for the second center $x_2^*(k)$ if the first center is not updated, $x_2^*(k)$ will be optimal solution attained in current iteration; else, if the first center is updated, $x_2^*(k)$ will be the second optimal solution attained.

Subsequently, search points chosen as centers move based on the Eq.(23):

$$x_s(a) = x_s(a) + (ub[a] - lb[a]) \times rn \quad (23)$$

x_s indicates the chosen search point location; a indicates an arbitrarily chosen module of the array x_s; $x_s(a)$ indicates the ath module of x_s; $lb[a]$ and $ub[a]$ indicates the lower and upper bound of ath variable, correspondingly; rand indicates an arbitrary count in the range of (-1, 1). On the basis of Eq. (23), one module is altered to evade misplaced the search points.

5. Result and Discussion

For the network, the simulation setup experimented was stated as follows: there are 100 nodes subsisted in the network, and one of the nodes is a camera-equipped node. A base station was also obtainable in this section. For the experimentation work, the network area was 100×100. The performance of the developed method was evaluated with the other conventional techniques like Firefly [8], GA [9], PSO [10], and Dragonfly [11] regarding several parameters such as network energy, alive node analysis, and normalized energy. This examines developed technique performance with other techniques and therefore establishes superior of this technique.

Table 1: *Performance analysis of proposed and existing models*

Performance analysis	Metrics			
	Delay	Energy	Throughput	Number of alive nodes
FF	0.3696	0.0055	0.5666	31
PSO	0.3999	0.0636	0.5666	32
GA	0.3699	0.0037	0.5666	36
DA	0.3793	0.0369	0.5666	55
Proposed algorithm	0.3636	0.0763	0.6	65

Table 2: *Statistical analysis of proposed and conventional models*

Round	FF	PSO	GA	DA	Proposed method
Best	0.56958	0.56959	0.56958	0.56958	0.56958
Worst	0.02287	0.02802	0.0289	0.02887	0.06071
Mean	0.28672	0.2888	0.28898	0.28876	0.2925
Median	0.22285	0.2259	0.22562	0.22655	0.22268
Standarad	0.28672	0.27075	0.26926	0.26892	0.26956

Table 1 shows the performance analysis of the developed technique over the existing techniques. It is clearly evident that the developed method shows a minimum delay, maximum energy, throughput and alive nodes than any other existing models in turn increases the network lifetime.

Table 2 indicates the statistical analysis of existing and proposed methods regarding their network energy level. From the table 2, the analysis clearly states that the developed method attained larger network energy while comparing with the existing ones. The developed technique hence shows superior performance regarding the maximum energy.

6. Conclusion

A novel approach was developed for CH with a camera-equipped node in this paper. The main idea was to improve the network lifetime by exploiting a highly developed optimization approach. The system parameters optimization was performed, therefore; the optimal transmission radius was attained by the sensor information transmission to equivalent SN that was equipped within the range. A novel optimization approach was introduced named SOA by this the optimal CHS was done. At last, the proposed method performance was evaluated with the existing methods regarding the network energy, alive nodes, and convergence rate.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

References

[1] Zhen ZuoQin LuWusheng Luo,"A two-hop clustered image transmission scheme for maximizing network lifetime in wireless multimedia sensor networks",Computer Communications1 January 2012.
[2] Muhammet MacitV. Cagri GungorGurkan Tuna,"Comparison of QoS-aware single-path vs. multi-path routing protocols for image transmission in wireless multimedia sensor networks",Ad Hoc NetworksAugust 2014.
[3] Nazli TekinVehbi Cagri Gungor,"Analysis of compressive sensing and energy harvesting for wireless multimedia sensor networks",Ad Hoc Networks3 April 2020.
[4] M. Atto, R. J. Mstafa and A. Alkhayyat, "Improving AODV Routing Protocol for Image Transmission Over Mobile Video Sensor Networks," in IEEE Access, volume. 8, page no. 169396-169407, 2020.
[5] M. Koyuncu, A. Yazici, M. Civelek, A. Cosar and M. Sert, "Visual and Auditory Data Fusion for Energy-Efficient and Improved Object Recognition in Wireless Multimedia Sensor Networks," in IEEE Sensors Journal, volume. 19, number. 5, page no. 1839-1849, 1 March1, 2019.
A. Yazici, M. Koyuncu, S. A. Sert and T. Yilmaz, "A Fusion-Based Framework for Wireless Multimedia Sensor Networks in Surveillance Applications," in IEEE Access, volume. 7, page no. 88418-88434.
[6] K. Tamura, K. Yasuda, Spiral dynamics inspired optimization, Journal of Advanced Computational Intelligence and Intelligent Informatics, vol. 15,no 8, pp1116–1122, 2011.
[7] A. Kaveh, S. Mahjoubi, Hypotrochoid spiral optimization approach for sizing and layout optimization of truss structures with multiple frequency constraints, Eng. Comput. vol 35, no 4 pp1443–1462, 2019.
[8] A.H. Gandomi , X.-S. Yang , S. Talatahari and A.H. Alavi, " Firefly algorithm with chaos", Commun Nonlinear Sci Numer Simulat, volume. 18, page no. 89–98, 2013.
[9] JohnMcCall, "Genetic algorithms for modelling and optimisation", Journal of Computational and Applied Mathematics, volume. 184, number. 1, page no. 205-222, 2005.
[10] M.E.H.Pedersen and A.J.Chipperfield, " Simplifying Particle Swarm Optimization", Applied Soft Computing, volume. 10, number. 2, page no. 618-628, 2010.
[11] Mohammad Jafari and Mohammad Hossein Bayati Chaleshtari, " Using dragonfly algorithm for optimization of orthotropic infinite plates with a quasi-triangular cut-out", European Journal of Mechanics A/Solids, volume. 66, page no.1-14, 2017.
[12] Amol V Dhumane,"Examining User Experience of eLearning Systems using EKhool Learners",Journal of Networking and Communication Systems (JNACS), Volume 3, Issue 4, October 2020.