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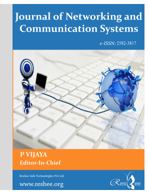

Optimal Positioning of Mobile Sinks in WSN using Hybrid TLBO based Adaptive GOA

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Abstract: The mobile sinks are used by the Wireless Sensor Network (WSNs) in order to collect information from the sensors that are positioned in an environment every so often, so that the hotspot problems, as well as the crisis of energy, are evaded. Via the rendezvous points, the delay in visiting all nodes is identified, which gathers the data from other nodes so that nodes gather data from this end rather than visiting all nodes that store the energy. Nevertheless, mobile sinks' optimal position to visit those rendezvous points is necessary that is identified optimally by exploiting the developed Hybrid Teaching-Learning-Based Optimization (TLBO) based Adaptive Grasshopper Optimization Algorithm (AGOA). Here, the main goal of the developed model is to optimally position the mobile sink for that at first, as uniform-sized cells with Voronoi partitions the wireless sensor environment is divided, and by exploiting the sparse-FCM approach clusters are created. To enable the optimal sink positioning, the main constraints are delay, distance, and nodes energy. The experimentation evaluation shows that the developed model is superior to the conventional techniques with minimum distance, maximum network energy, alive nodes, as well as throughput correspondingly.

Keywords: *Alive Nodes, Distance, Energy, Mobile Station, Voronoi Partitions, WSN.*

Nomenclature

Abbreviations	Descriptions
ABC	Artificial Bee Colony
WSNs	Wireless sensor networks
GA	Genetic Algorithm
sparse-FCM	sparse fuzzy c-means
PSO	Particle Swarm Optimization
VTS	Virtual Tube Storage
TLBO	Teaching-Learning-Based Optimization
UWSN	Unattended WSN
AGOA	Adaptive Grasshopper Optimization Algorithm
SVM	Support Vector Machine
GWO	Grey Wolf Optimization

1. Introduction

WSN comprises numerous multi-functional, minute electronic devices named sensors that are positioned in a region of interest named sensor field. In a wireless model, the sensors communicate with each other to create distributed platforms that encourage the use of WSNs. Every sensor senses its nearby immediacy lying within its sensing range as well as gathered knowledge is transmitted to the neighboring gateway nodes or neighboring sensors named sinks. The transmission of data is probable merely if the sink is in the sensor communication range which is sensing the data. The sensor's energy capacities are restricted and the exchange of the exhausted sensor's batteries is out of choice because of the high amount of positioning sensors and because of the complexity of each sensor. Therefore, energy loads on every sensor ought to be cautiously planned earlier to expand the lifetime of the WSN [14]. The lifetime of the WSN is stated as the time till initial sensor death or time till initial coverage loss in the sensor field [1].

Generally, WSN comprises minute sensors that could collect the data regarding their surrounding environment as well as work together to transmit sensory data to centralized units named base stations for further processing [13]. Traditionally, in order to perform this process, static base stations are used.

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Nevertheless, as all sensory data is forwarded to sinks, sensors positioned in sinks nearby might be compulsory occurs high traffic as well as reduce their energy before than other sensors. This might occur partitioning of the network as well as finally isolation of sink phenomenon. Finally, the dynamic sinks are developed in that the sink positions are updated dynamically after a period of time. In 4 classifications the sink mobility model is categorized as location-restricted mobility, uncontrollable mobility, path-restricted mobility, as well as unrestricted mobility [2].

In WSNs, Target coverage and connectivity are the two most important challenges and significant problems [3]. The previous is to present adequate monitoring quality whereas by sensors all points of interest in the network are covered. The latter is to assure acceptable communicating ability whereas all sensors can link to as a minimum one base station. Under target coverage and connectivity constraints, the node deployment optimization consequently turns out to be a significant problem in WSNs attracting numerous concentrations from the research community [4].

In the state of artwork [15], numerous approaches were presented to optimize node positioning with linked target coverage. Nevertheless, to the finest knowledge, no consideration was paid to the node that is relay nodes and sensors position optimization in WSNs with dynamic base stations. In the meantime, in spite of the reality that numerous attention was paid to WSNs with dynamic base stations, conventional works mostly focal point on the base stations. Especially, numerous studies were conducted for targeting WSNs with dynamic base stations is dedicated to modeling sinks' trajectory sink determinations position or presenting effectual data collection methods to optimize a few performance factors namely the consumption of energy, a lifetime of the network, packet delivery ratio, latency, network throughput [6].

The main reason for this research is to develop a Hybrid TLBO-AGOA optimization algorithm in order to address the MS's optimal positioning to visit the rendezvous points. Here, the developed model uses the fitness measure modeled on the basis the distance and energy. Therefore, the effectual energy conservation is obtained which tends to the network lifetime extension.

This paper is structured as follows: Section 2 summarizes the literature review. Section 3 exhibits the system model and section 4 represents the proposed model. Section 5 summarizes the result and discussion and section 6 demonstrates the conclusion.

2. Literature Review

In 2020, Muhammed Emre Keskin et al [1], worked on three important manners such as a mathematical approach that uses sink travel times for multiple mobile sinks was presented. It was exhibited that taking into consideration sink travel time was significant in particular circumstances. Then, the conditions were demonstrated that the sink travel times were considered appropriate/ inappropriate. An optimization model was designed for WSN applications can pursue particularly for the scenarios where the sink mobility was restricted.

In 2020, Yongbin Yim et al [2], developed a VTS model to aid effectively basic scenarios of mobile sink groups in WSNs. Initially, design principles of data dissemination as well as data storage were presented. Subsequently, a technique was effectually modeled virtual tube storage on basis of the model data storage principle. Subsequently, the process was described to distribute data from a source node to a mobile sink gather through virtual tube storage on basis of the model data dissemination principle.

In 2019, Phi Le Nguyen et al [3], focused on WSNs with dynamic sinks that comprise positions of sinks and multiple sinks that might alter every so often, and researchers showed how to position the least amount of nodes for linked target coverage. Particularly, the issues were classified into two sub-issues and were decomposed. The initial one was the target coverage issue was to position sensor nodes to cover all targets. The next one was called a network connectivity issue was to place the relay nodes to link sensor nodes to sinks. Initially, the target coverage issue was formulated in an integer linear programming approach and proposes a precise approach to ascertain the optimal solution. Subsequently, a constant approximation approach was proposed based on the shifting as well as the partitioning model. Initially, the NP-hardness was proved and subsequently present two approximation approaches for the network connectivity. Initially, the least group Steiner tree was exploited to least positioned relay nodes when the next one was a time effectual approach on the basis of the spanning tree as well clustering methods.

In 2019, A. Pravin Renold and A. Balaji Ganesh [4], dealt with the issue of secure data transmission as well as utilization of balanced energy in a UWSN consisting of a mobile sink as well as multiple static source nodes in the attendance of adversaries. The developed model consists of three stages such as the data collection point’s identification, planning of the path by the mobile sink, as well as safe data transmission. For recognition of data collection points, an energy-aware convex hull approach was exploited for transmission of the data to the mobile sink. From sensor nodes, the transmission of data to adjacent data collection points was carried out by exploiting the multihop communication and from sensor nodes to the mobile sink in a single hop. By exploiting the SVM, the variation in threshold energy and digital signature attained was exploited to ascertain the attendance of malicious nodes in the network.

In 2018, Georgios Tsoumanis et al [5], developed an analytical technique to analyze the obtainable energy in the network. The subsequent step was to analytically technique the general consumption of energy as a k-median capability position issue, its solution similar to the position of k sinks in the network. Following the solution of the preceding ability position issue as analytically exhibited, while k sinks were positioned, subsequently the entire consumption of energy was reduced, ensuing in a superior energy-saving system. Therefore, the stored energy can be additionally used, for instance, to expand the lifetime of the networks and aid the modern replenishing approaches namely battery recharges and energy harvesting.

3. System Model

The optimal positioning of sink nodes improves the performance of the network as well as convenes the energy crisis of WSNs. Fig 1 demonstrates the architectural model of the developed approach to WSN routing. Initially, the WSN environment utilizing battery-operated sensors fed to cell network formation is helped by exploiting the Voronoi partition that carries out optimal partition. Cells are referred to as the partitioned areas which perform numerous sensors with two or additional cells distributed as a sink node. By exploiting the Sparse FCM scheme, energy effectuality is sustained via an effectual CH chosen scheme. At last, the optimal positioning of the MSs is started in the network by exploiting the developed optimization model that uses the fitness measure modeled on the basis of the distance as well as energy. Therefore, the effectual energy conservation is obtained which leads to the extension of the network lifetime [11].

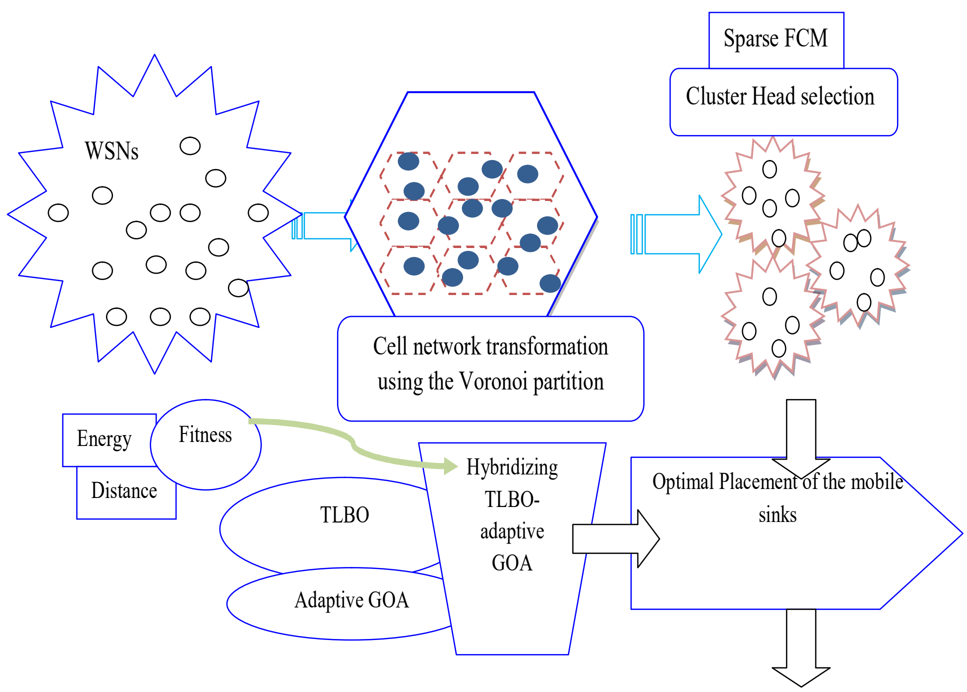

Fig. 1. *Architectural model for the placement of mobile sink using the proposed model*

3.1 Voronoi Partitions for Cell Network Formation

Initially, by exploiting the Voronoi partitioning [6], the WSN environment is transferred to a cell network which sets up WSN environment optimal partitions. Y_U indicates compilation of Voronoi areas; $(1 \le U \le Z)$ which indicates Z the count of cell partitioned areas is present that is produced by exploiting points, $o_1,...,o_Z$. The cell network refers to the partitioned network that is furthermore fed to the selection of CH, whereas the solitary cells distribute a cluster head with further cells in the cell network.

3.2 Sparse-FCM for the Election of Cluster Head

By exploiting the sparse-FCM approach [7], the selection of CH is developed which is the addition of the sparse regularizations on the FCM approach to identify problems related to the high-dimensional data clustering. By exploiting sparse-FCM, the cluster centroids created which are indicated as,

$$c = \{c_1, c_2, \ldots, c_j, \ldots, c_n\} \tag{1}$$

whereas, n indicates the amount of the cluster centroids available in the network. Consider a data matrix $M_d = w^d_{pq} = \Re^{u \times v}$ with u count of data points as well as a total of v attributes; $(1 \le q \le v)$ as well as $(1 \le p \le u)$. The d^{th} data matrix size is $[u \times v]$ as well as it is obvious that $w^d_p \in \Re^v$ and $w^d_q \in \Re^u$ is columns as well as rows in M_d. By exploiting approach clustering is on basis of the minimum distance amid the cluster centroid as well as an individual data point. The steps for the sparse-FCM algorithm are stated as follows:

Step 1: *Initialization:* Initially, the attribute weights are initialized as, $z = z^e_1 = z^e_2 = \ldots = z^e_v = \frac{1}{\sqrt{v}}$.

Step 2: *Updation of partition matrix:* Consider cluster centers O as well as attribute weights z so that $\varepsilon(\Re)$ is reduced while

$$U_{lt} = \begin{cases} \frac{1}{P_t} & ; \quad \text{if } H_{lt} = 0 \text{ and } P_t = \text{card } \{s : H_{lt} = 0\} \\ 0 & ; \quad \text{if } H_{lt} \ne 0 \text{ but } H_{lj} = 0 \text{ for few } j,\ j \ne t \\ \dfrac{1}{\sum_{j=1}^{n} \left(\frac{H_{lt}}{H_{jt}}\right)^{\left(\frac{1}{\hbar - 1}\right)}} & ; \quad \text{Otherwise} \end{cases} \tag{2}$$

wherein, the cardinality of a set N is represented by $\text{card}(N)$. In Sparse-FCM distance is measured using Eq. (3).

$$H_{lt} = \sum_{t=1}^{n} z_s \left(X_{ls} - X_{ts}\right)^2 \tag{3}$$

The distance amid the individual data point as well as the cluster center is computed using the distance measure so that data points with the least distance are gathered in a similar cluster.

Step 3: *Cluster center O updating:* Consider z and $\Re$ be set as well as $\varepsilon(c)$ is reduced if

$$c_{ts} = \begin{cases} 0 & ; \quad \text{if } z_s = 0 \\ \dfrac{\sum_{j=1}^{n} U^{\hbar}_{lt} . X_{ls}}{\sum_{t=1}^{n} U^{\hbar}_{lt}} & ; \quad \text{if } z_s \ne 0 \end{cases} \tag{4}$$

wherein, $t = 1, \ldots, n$ and $s = 1, \ldots, v$, $\hbar$ denotes the weight module which controls membership sharing amid cluster centroids. z_s denotes s^{th} feature contribution to the objective model, and $\Re$ indicates the dissimilarity measure.

Step 4: *Calculate the class:* By means of the membership U as well as fixed clusters $c = \{c_1, c_2, \ldots, c_i, \ldots, c_n\}$, the class value is calculated. On the basis of the below objective, the class E_k is calculated, $\max_z \sum_{k=1}^{v} z_k . E_k$ so that $\|z\|_2^2 \le 1$, $\|z\|_f^f \le \ell$ and attain z^*.

wherein, ℓ indicates tuning parameter as well as $(0 \le f \le 1)$; $\|z\|_f^f = \sum_{k=1}^{v} |z_k|^f$.

Step 5: *Terminate:* Until stopping criteria are obtained iteration is continued. Eq. (5) indicates the stopping criteria,

$$\frac{\sum_{k=1}^{v}\left|z_k^* - z_k^e\right|}{\sum_{k=1}^{v}\left|z_k^e\right|} < 10^{-4} \tag{5}$$

The sparse-FCM results indicate the "cluster centroids" which are stated as in Eq. 1.

3.3 Optimal Positioning of the Sink

In the network, the development model of optimally positioning of sink is described so that the node's energy is minimized as well as network lifetime is maximized. The sink node optimal positioning is done by exploiting the developed optimization algorithm.

Eq. (6) indicates the fitness measure which is calculated by exploiting the distance as well as energy.

$$Q = \frac{1}{2} \times \left[\chi . E + \mu . \partial + \psi . \partial_{\sin k}\right] \tag{6}$$

wherein, ∂ implies distance and E indicates energy.

Energy: In [8] nodes energy is considered as the main constriction gave battery-operated nodes to extend the lifetime of the network which is calculated as follows:

$$E = \frac{1}{n}\sum_{j=1}^{n} E_{loss}^{predict}(j) \tag{7}$$

wherein, $E_{loss}^{predict}(j)$ indicates the energy loss of j^{th} node in the network and n indicates total CHs. Consider E_0 as initial energy in the nodes. During the communication, energy in nodes has vanishes therefore the transmission distance, attendance of the radio electronics as well as power amplifiers in the routing protocols, transmitters, etc. In the nodes the energy dissipation is stated as follows:

$$E_{dis}\left(E_q\right) = E_{elec} \times b_q + E_{pa} \times b_q \times \left\|E_q - h_j\right\|^4 ; \text{if } \left\|E_q - h_j\right\| \geq \Omega_0 \tag{8}$$

wherein, electronic energy is stated as E_{elec}. In the q^{th} node energy dissipation is stated as $E_{dis}\left(E_q\right)$. Consider b_q indicating the total bytes transmitted from q^{th} node as well as E_{pa} indicating power amplifier energy in attendance in the transmitter. The energy dissipation is stated as Ω_0 a parameter that is on the basis of the distance between the j^{th} head and q^{th} sensor node. When the distance between E_q and its head h_j is lesser than Ω_0, the energy dissipation happening in E_q is stated as,

$$E_{dis}\left(E_q\right) = E_{elec} \times b_q + E_{free} \times b_q \times \left\|E_q - h_j\right\|^2 ; \text{if } \left\|E_q - h_j\right\| < \Omega_0 \tag{9}$$

The energy dissipation is on the basis of eq. (13), while the distance goes beyond Ω_0.

$$T_{\Omega_0} = \sqrt{\frac{E_{free}}{E_{pa}}} \tag{10}$$

Wherein, free space energy is represented as E_{free}. The electrical energy is based upon the transmitter as well as data aggregation processes such as filtering, modulation, coding, etc as well as it is stated in eq. (11).

$$E_{elec} = E_{tx} + E_{agg} \tag{11}$$

Wherein E_{agg} indicates data aggregation energy and E_{tx} indicates transmitter energy. $\left\|E_q - h_j\right\|$ indicates distance amid the j^{th} Cluster Head as well as q^{th} node. Conversely, the data bytes attained h_j are stated as follows:

$$E_{dis}\left(h_j\right) = E_{elec} \times b_q \tag{12}$$

In nodes, CHs, as well as energy, are updated at the end of transmission and it is stated in eq. (13) and (14).

$$E_{\tau+1}\left(E_q\right) = E_\tau\left(E_q\right) - E_{dis}\left(E_q\right) \tag{13}$$

$$\varepsilon_{t+1}\left(H_i\right) = \varepsilon_t\left(H_i\right) - \varepsilon_{dis}\left(H_i\right) \tag{14}$$

wherein, $\varepsilon_t\left(H_i\right)$ and $E_\tau\left(N_q\right)$ represents a normal node of CH and normal node energy at an instant τ, $\varepsilon_{dis}\left(H_i\right)$ and $E_{dis}\left(E_q\right)$ indicates the dissipated energies of CH and normal node at a time t. The update ensures till every node are not-alive.

Distance: On basis of eq. (15), the distance measure is stated.

$$\partial = \frac{1}{3}\left[\partial_1 + \partial_2 + \partial_3\right] \tag{15}$$

wherein, ∂_1 indicates distance amid the j^{th} Cluster head as well as sink node that must be minimum.

$$\partial_1 = \frac{1}{n}\sum_{j=1}^{n}\frac{\partial\left(h_j,\$\right)}{\aleph} \tag{16}$$

wherein, $\partial\left(h_j,\$\right)$ indicates distance amid j^{th} Cluster head as well as sink node; and $\$$ denotes normalization factor. The distance ∂_2 is calculated on basis of the distance amid nodes as well as CH in the specific cluster and on distance amid the sink node as well as j^{th} cluster.

$$\partial_2 = \frac{1}{u*n}\sum_{q=1}^{u}\sum_{j=1}^{n}\left[\frac{\partial\left(E_q,h_j\right)+\partial\left(h_j,\$\right)}{\aleph}\right] \tag{17}$$

wherein, $\partial\left(E_q,h_j\right)$ indicates distance amid the q^{th} node as well as j^{th} CH. In the cell network ∂_3 distance denotes on basis of distance amid neighboring cells that are referred to below

$$\partial_3 = \frac{1}{I}\sum_{j=1}^{n}\frac{\partial^{\text{Intra-cell}}\left(h_j,\$\right)}{\aleph} \tag{18}$$

The distance ∂_{sink} is calculated as the distance amid the sink location in the current iteration and the sink node location at present is stated as below:

$$\partial_{\sin k} = \frac{\partial\left(\$_{\tau-1},\$_{\tau}\right)}{\aleph} \tag{19}$$

4. Proposed Hybrid Model

4.1. Conventional TLBO

The conventional TLBO is a population-based optimization approach as well as it imitates in the class as a teacher learning procedure [9]. Here, the two most important stages of the approach are taken into consideration such as the learners and teacher stages. The distribution of teacher's knowledge to all learners is called as teacher stage. Regarding the knowledge, a learner knows from the other learners in the learner stage.

a) Teacher Stage

This approach is the initial part where the learner with maximum marks represents a teacher as well as the teacher's task is to maximize mean marks in class.

In the teacher stage, the update procedure of i^{th} learner is indicated as:

$$Y_{i,new} = Y_i + rn \times \left(Y_{teacher} - T_F \times Y_{ave}\right) \tag{20}$$

wherein, Y_{ave} indicates marks average of all learners, $Y_{teacher}$ indicates the teacher's solution mark, Y_i indicates the solution mark of the i^{th} learner, rn indicates a random number in [0,1], and T_F indicates the teaching factor which determines the mean value to be altered.

The value of T_F can be either one or two one indicates no augment in knowledge level as well as two indicates to whole knowledge transfer that is once more a heuristic step as well as decided arbitrarily with equivalent probability as $T_F = \text{round}\left[1 + rn(0,1)\{2,1\}\right]$. Moreover, a novel solution $Y_{i,new}$ is established merely if it is superior to a preceding solution, it is devised as:

$$Y_i = \begin{cases} Y_{i,new};\ f\left(Y_{i,new}\right) > f\left(X_i\right) \\ Y_i;\ \ \text{otherwise} \end{cases} \tag{21}$$

wherein f indicates fitness model.

b) Learner Stage

The learner stage is known as the next segment of the approach wherein the learner updates its knowledge via communication with other learners.

Here 2 learners assist with Y_m and Y_n in that smarter learner enhances marks of other learners in every iteration. The occurrence is explained as below:

$$Y_{m,new} = \begin{cases} Y_m + rn \times (Y_m - Y_n); f(Y_m) > f(Y_n) \\ Y_m + rn \times (Y_n - Y_m); f(Y_m) \le f(Y_n) \end{cases} \tag{22}$$

The impermanent solution is established merely if it is superior to a preceding solution, and it is devised as:

$$Y_m = \begin{cases} Y_{m,new}; f(Y_{m,new}) > f(Y_m) \\ Y_m; \quad \text{otherwise} \end{cases} \tag{23}$$

4.2. GOA

The GOA is a novel "population-based optimization" approach that imitates grasshopper swarms behavior in nature [10]. Eq. (24) states the stimulation of grasshopper swarming behavior

$$P_p = S_p + G_p + A_p \tag{24}$$

wherein, G_p and S_p indicates gravity force as well as social interaction as well as on P^{th} grasshopper P_p indicates P^{th} grasshopper location and A_p signifies wind advection. In Eq. (24) A_p, S_p and G_p values are computed as below:

$$\begin{cases} S_p = \sum_{q=1 \neq p}^{N} s(d_{pq}) \hat{d}_{pq} \\ G_p = -g\hat{e}_g \\ A_p = u\hat{e}_w \end{cases} \tag{25}$$

wherein $d_{pq} = | P_q - P_p |$ indicates distance amid the $P-th$ grasshopper as well as q^{th} grasshopper. $\hat{d}_{pq} = (P_q - P_p)/d_{pq}$ indicates unit vector to q^{th} grasshopper from P^{th} grasshopper, $\hat{e}_g$ signifies a unity vector to earth center, g indicates gravitational constant, $\hat{e}_w$ implies unity vector in wind direction, as well as u signifies constant drift. $s(\cdot)$ signifies a function to describe the strength of the social forces, it is attained as below:

$$s(r) = f\, e^{\frac{-r}{l}} - e^{-r} \tag{26}$$

wherein, l signifies attractive length scale as well as f signifies attraction intensity. When grasshoppers are communicated substitute A_p, S_p as well as G_p in Eq. (24), this formulation is reformulated as below:

$$P_p = \sum_{q=1 \neq p}^{N} s(| P_q - P_p |) \frac{P_q - P_p}{d_{pq}} - g\hat{e}_g + u\hat{e}_w \tag{27}$$

As grasshoppers speedily arrive at relieve zone as well as swarm does not converge to a particular point. To resolve optimization issues, the eq. (27) cannot be directly exploited; so the ensuing updated formulation is stated as below:

$$P_p^d = \left(\sum_{q=1 \neq p}^{N} c \frac{ub_d - lb_d}{2} s(| P_q{}^d - P^d{}_p |) \frac{P_q - P_p}{d_{pq}} \right) + \hat{T}_d \tag{28}$$

wherein, P_p^d indicates d^{th} dimension value in p^{th} grasshopper $\hat{T}_d$ indicates d^{th} dimension value in target thus the optimal solution is obtained, lb_d as well as ub_d indicates lower and upper bounds in d^{th} dimension. c parameter indicates a minimizing coefficient to minimize ease areas of range, elimination as well as magnetism In the shrinking mechanism, to balance the exploitation and exploration, c is linearly minimized from "1 to 0" against the course of iterations as well as it is computed as below:

$$c = c_{max} - \frac{t(c_{max} - c_{min})}{T} \tag{29}$$

wherein t indicates current iteration, c_{min} and c_{max} indicates the minimum as well as maximum value correspondingly, and T indicates a maximum number of iterations.

a) Adaptive GOA

The GOA searching process is highly complicated parameter c searching scheme, minimizing linearly with a count of iterations does not completely return real searching procedure. Hence, a nonlinear scheme is used to restore the linear model indicating the difference of searching steps in conventional GOA. Moreover, the position updation model of GOA is the same as the PSO. Hence, this work is enthused using inertia weight in PSO approach. The c parameter is computed as below:

$$c = c_{max} - (c_{max} - c_{min})\tan\left(k\frac{t}{T}\pi\right) \tag{30}$$

wherein k indicates a constant. Here, the enhanced parameter c is compared with the original parameter c, as well as analyzed constant value k.

4.3. HYBRID TL-GOA

Balance the exploration and exploitation are critical as adaptive GOA and TLBO be owned by population-based optimization approaches. In a few local areas, local exploitation is to identify an optimal solution on the basis of the preceding knowledge or novel information at the time of the search procedure. The reason for global exploration is to identify a highly capable area in the complete search area. Even though adaptive GOA uses a non-linear scheme on c to enhance the performance of global search as well as evade approach, a similar update method (arbitrary walk) is used for the exploitation as well as exploration. It indicates that the adaptive GOA can always identify the best solution inadequate estimate times; however, this may not assure rapid convergence. Nevertheless, TLBO is not needed at all to set the parameters as well as it possesses evident performance of local exploitation. Hence, a combination of TL-GOA is exploited. In the adopted, initial phase, the adaptive GOA can perform more performance to explore the complete areas and create more solutions to move to the most capable area. In the final phase, TLBO will attain a high chance to exploit a maximum-accuracy solution. Conversely, the proposed model can associate the conflict local as well as global search efficiently [12].

5. Result and Analysis

In this section, the performance evaluation of the adopted model for placement of mobile sink was described it was the performance on the basis of various measures. Moreover, the developed model efficiency was shown by the analysis of various techniques via varying the number of nodes in the environment. Here, the performance of the developed model was evaluated on the basis of the measures like network lifetime, distance, energy, and nodes throughput. The network lifetime is performed on the basis of the total count of active nodes else total count of alive nodes in the experimentation environment as well as the energy of the network indicates the energy residue in the nodes in charge to indicate the network lifetime. The throughput term states the total number of bits transferred. Here, the measures such as distance indicate the sink nodes' travel distance that must be least.

Fig 2 demonstrates the analysis of the adopted technique over traditional models and it is progressed on the basis of the performance measures by exploiting 150 nodes in the experimentation environment. Here, the proposed model is 12% better than the ABC, 14% better than the PSO, 16% better than the GA, and 12% better than the GWO for distance. In terms of alive nodes, the proposed model is 16% better than the ABC, 22% better than the PSO, 13% better than the GA, and 28% better than the GWO. The proposed model is 22% better than the ABC, 24% better than the PSO, 26% better than the GA, and 21% better than the GWO for network energy. The proposed model is 12% superior to the ABC, 15% superior to the PSO, 18% superior to the GA, and 22% superior to the GWO for throughput. From the figure, it is evident in the developed model distance traveled by sink node is minimum with a maximum count of active nodes at end of the iteration.

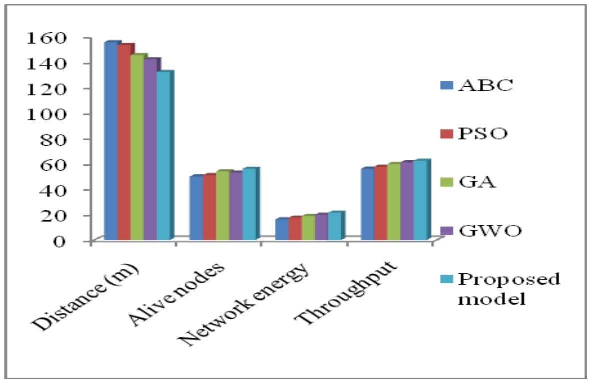

Fig. 2. *Performance analysis of adopted technique over the existing techniques using various metrics*

6. Conclusion

The main aim of this work was to deal with the Mobile Station as well as its optimal positioning via the optimization approach in order to convene the demands to establish the effectual routing in the WSN environment. In the WSN environment, to optimally place the sink node, a technique was developed that was on the basis of the optimization model. In WSN, the developed model set up the effectual routing for that at first, to divide the environment as the cell network, the Voronoi partitions were permitted. By exploiting the sparse FCM approach, the CH was performed after attaining the uniformly sized cells. In the WSN, the sink was optimally positioned by exploiting the optimization algorithm upon the cluster formation. Via the fitness model, the optimal sink node placements were performed by exploiting the metrics such as delay, distance as well as nodes energy in the network. Finally, the experimentation was carried out by exploiting 50, 100 as well as 150 nodes. Here, the experimentation evaluation shows that the developed model was superior to the conventional techniques with minimum distance, maximum alive nodes, network energy, and throughput correspondingly.

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.

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