Enhancing the network performance of wireless sensor networks on meta-heuristic approach: Grey Wolf Optimization

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Abstract. The sensing technology has brought all advancements in the human lives. Wireless Sensor Network (WSN) has proven to be a promising solution to acquire the information from the remote areas. However, the energy constraints of the sensor nodes have obstructed the widely spread application zone of WSN. There has been a great magnitude of efforts reported for acquiring the energy efficiency in WSN, these efforts varying from conventional approaches to the meta-heuristic method for enhancing the network performance. In this paper, we have presented a comparative evaluation of state of art metaheuristic approaches that helps in acquiring energy efficiency in the network. We have proposed Grey Wolf Optimization (GWO-P) algorithm with the empirical analysis of the existing methods PSO, GA and WAO that will help the readers to select the appropriate approach for their applications. It is similarly exposed that in different other execution measurements GWO-P beats the contender calculations for length of stability, network lifetime, expectancy, and so on.

Keywords: WSN, Meta-heuristic, Empirical analysis, Gray wolf optimization, Network performance

1. Introduction:

In computing and communication technology, background Intelligence including electric battery driven nano sensors, wireless communication technology is developing a desire for advancement of wireless sensor network. Additionally, nowadays the huge use of wireless sensor system will be the primary target area of investigation Wireless sensor system becoming more and more attractive every day for the potential approach of its in ecological monitoring, natural area monitoring, battle field surveillance, natural attack detection in any obscure and ordinary environments [1]. The event is found by a humongous number of small, affordable and minimal powered devices anytime it can feel virtually any earthy movement (pressure, high heat, sound, areas getting some magnetic qualities, vibration, etc.) [2]. Each one of those devices is known as a sensor node. A WSN is composed of thousands or hundreds of inexpensive sensor nodes which may also use a fixed place or randomly deployed for checking purpose [3]. The relaying of information finishes at a unique node identified as Base Stations (also known as sinks). A Base Station links the sensor system to the next public network as web to disseminate the sensed information for more processing [4].

Apart from sensing as well as transmitting information, you will find a number of restrictions including power management, distance management, real time difficulties, topological issue, design issue, energy usage etc. as well as among them the main restriction is the power usage in terminology of the longevity of WSN due to the irreplaceable and limited battery backup of the sensor nodes [5]. Moreover, the nodes close to the Base Station is the very first one in order to run out of power due to its extra relaying of information of the nodes that are miles away from the BS [6]. To locate an answer of these problems' different studies as radio communication hardware, moderate access management have been studied.

Meta-heuristic optimization algorithms are starting to be increasingly more well known in engineering apps since they: (i) depend on relatively easy ideas and therefore are not hard to implement; (ii) don't need gradient info; (iii) is able to avoid community optima; (iv) may be employed in a broad range of issues covering various disciplines. Nature-inspired meta heuristic algorithms solve optimization difficulties by mimicking physical or biological phenomena [9]. They may be grouped in 3 major categories (see Fig. one): evolution based, physics based, and swarm-based methods. Evolution-based techniques are influenced by the laws of organic evolution. The search process begins with a randomly generated population that is evolved over the following generations. The strength point of these techniques is the fact that the most effective people are constantly coupled together to form the coming generation of individuals. To be able in order to optimize network 's lifetime, this Grey Wolf

Optimization (GWO) [10] Meta-heuristic algorithm for choosing the effective clustering to data transmitting information period from the sensor node to sink and to enhance energy efficiency to maximize network's lifetime. a few scientific studies are recommended to the literature deal with all the optimization issues such as; variant of Particle Swarm Optimization (ICRPSO) [20], variant of Genetic Algorithm (GA-LEACH) [7] and the variant of Whale Optimization Algorithm (WOTC) [8].

Clustering is among the most crucial strategies to enhance the system lifetime in WSNs. Clustering is the procedure of partitioning the whole region into a selection of subregions, known as clusters. Based on the analysis the use and also the optimization of electricity usage by the sensor in the bunch-based network version can be accomplished far more efficiently. For information transmission clustering is among the well-known and simpler mechanism. In simpler language, a pair of nodes produce a team or even cluster. Each cluster communicates with one another and also works towards the targeted objective. Nodes from each cluster could be included as well as taken out of the bunch whenever & of all the nodes one has long been used as a leader, named group head (CH) [7]. All of the collected information is delivered by the sensor nodes to the head of theirs of the group and after that the CHs aggregate the information and also delivered to the sink or maybe base station (BS) indirectly or directly like through some other CHs. Due to several following effective capabilities clustering method gets to be more appealing

1. Sensor nodes take out all irrelevant information and unwanted info before sending information to the CH which enhance the power consumption

2. CHs just conserve the intra cluster path that enhances the scalability of the WSN effectively

The rest of this paper is systematized as follows. In Section 2 the related work is introduced. System model for proposed GWO meta-heuristic methods are in section 3. The comparative analysis and results are discussed in Section 4. Finally, the conclusion is given in Section 5.

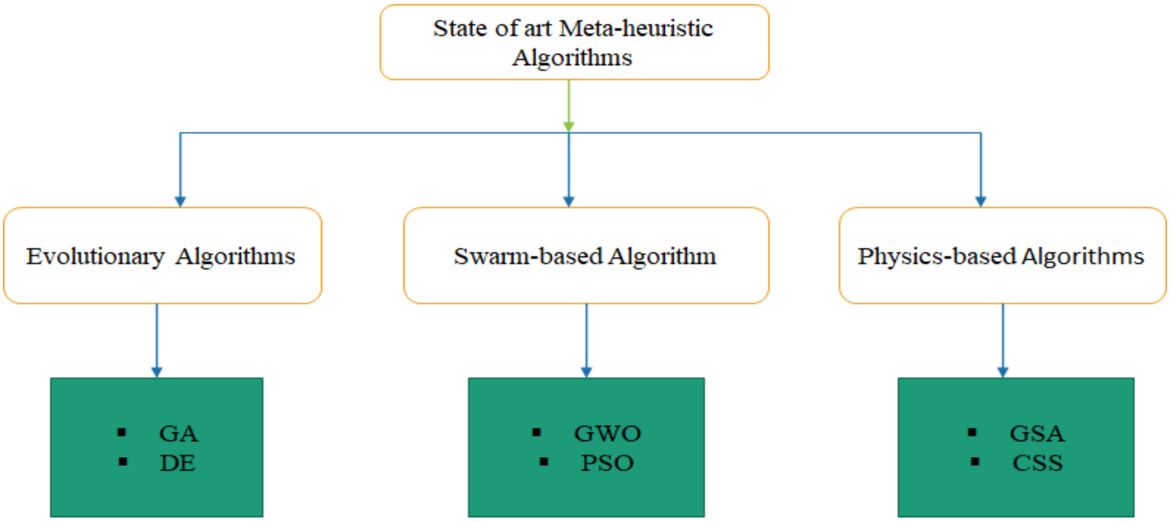

Fig.1. Categorization of Meta-heuristic Algorithms

2. Related Work:

In this literature review, we show several routing methods recommended for cluster head (CH) selection then also highlighted described the limitations and a full awareness on the routing strategies following the different meta heuristic such as PSO, GA, WOA and GWO algorithm are highlighted.

Sahoo et al. [11] proposed PSOECSM protocol directing heterogeneous WSN aimed at enhancing cluster head choice technique in addition to sink mobility remain resolved by means of PSO which reflects the reduced power CH along with closest CH from the moving sink in addition to dimensions of the bunch. PSO-UFC [12] are represent the PSO based strategy to gain the workout perform for inadequate clustering in addition to fault understanding mechanism to balance the intra and also inter cluster energy consumption. Latiff et al. [13] proposed PSOMSB targeting various characteristics specifically, network lifetime, information delivery as well as power use are believed to be to that the distance among the node as well as sink is recognized as. Hu et al. recommended immune orthogonal learning particle swarm optimization algorithm (IOLPSOA) [14]. Nevertheless, the long-haul transmission in this particular strategy eats a great deal of energy.

A different routing technique that are derived from GA are emphasized. Kuila et al. [15] exploited GA for controlling the load balancing of the system. The projected method did not contemplate the CH choice. Jana et al. [16] proposed GACR which involved the distance as well as standard deviation components in the objective function of its directing to obtain improved number of rounds prior to the very first node is dead. Bhola et al. [17] proposed genetic algorithm which shows efficiently consumption of energy in WSNs. This proposed algorithm is actually based on leach protocol. By using hierarchical leach protocol cluster heads are selected and to find out the optimal route GA is used.

Arora et al. [18] projected an Ant Colony Optimization (ACO) which constructed self-organized method for WSNs. This is also introduced for energy consumption in efficient manner [19]. In this algorithm also we have to first choose Cluster heads by maximal residual energy and after that members joining process has been started under the cluster head. Gharaei et al. [20] proposed ICRPSO to Inter and also intra cluster-based routing using PSO. In ICRPSO, inter and intra cluster motion moving sink for grouping by using PSO discussed. ICRPSO deficiency as follows: (a) disregard traffic evidence for the spiral movement of the sink moves; and (b) the arbitrary movement of the sink in the group has a high energy usage.

Mirjalili et al. [21], proposed Whale Optimization Algorithm (WOA) is recognized as among swam smart program which is a novel nature inspired meta heuristic optimization algorithm, humpback whales swim around prey in a shrinking group and along a spiral shaped path at the same time to create distinct bubbles along a group or' 9 ' shaped path.

Sahoo et al. [22] designed and introduced a hierarchical hybrid approach for distributed clustering using GA and PSO algorithm but in broad level WSNs. This is dual levels of clustering where GA is utilized for the cluster that belongs at ground level and for higher level clustering PSO is utilized which provides better convergence. The results prove, introduced approach became successful in reducing the energy consumption effectively which straight away point out towards the increment of network’s lifespan.

Mirjalili et al. [10] Grey Wolf Optimizer (GWO) a leader choice mechanism is recommended grounded on alpha, beta, as well delta wolves to upgrade as well as change the remedies in the archive as well as a power system mechanism continues to be incorporated to GWO to be able to enhance the non-dominated remedies in the archive.

Visu, et al. [23] in their paper proposed “Bio inspired dual cluster heads optimized routing algorithm for wireless sensor networks”. In this paper they describe the clustering and routing strategies. From every cluster data or information is moved forward to their respective CH which assigns as an aggregator and mainstay of the routing system as well. Technically, CH in the cluster consumes the most energy as compare to the further nodes are in same cluster as the aggregated data is need to be transferred to the base station named, sink node through single or else multiple hops communication system. This causes imbalance in energy in the network to resolve this problem, and to optimize the energy consumption by the CHs, a double-cluster based Krill Herd Optimization algorithm is introduced [24]. Routing protocols in wired and wireless network are absolutely different. The conventionally utilized WSN routing techniques are utilized because of its various advantages like energetic routing, on-demand routing, hybrid routing, etc. This examination advances an improvement strategy to manage energy compelled climate and to derive the lopsided utilization of energy, for remote sensor network directing. As indicated by this proposed enhanced steering, at first the hubs which sent in the networks are grouped utilizing the underlying centroid calculation. Then the sensed data got aggregated by the primary centros wids. The secondary centroids help by providing detail of the route trust value aimed at individually route. Kill Herd Optimization helps to figure out the minimize the decision path. Then, the data which are aggregated are moved forward through that established optimized path. The introduced trust-based Krill optimized aggregated data through the given path which square in shape [25]. In wireless sensor networks (WSNs) the technique of gathering the sensor nodes (X), is one of the crucial ways to make the system long last. Gathering of nodes for cluster formation, and the election to elect a node as cluster heads (CH) among them for each cluster is performed.

The proposed method in this particular paper utilizes GWO for the choice of CH. The purpose for picking GWO more than other meta-heuristic strategies would be that the GWO highlights a quicker convergence rate. Additionally, GWO brings about the ceaseless decrease of search space notwithstanding assurance factors are less. Additionally, it stays away from local optima.

3. The Proposed Grey Wolf Optimization Algorithm:

After observing at clustering as a major problem, the only aim is to gain the finest trade-offs among the energy consumption and efficient data transmission. The problem is still on the increment of the number of clusters. As such, we propose a multi objective clustering using grey wolf algorithm to get rid of hierarchy issue. The proposed method will be compared and investigated with existing meta-heuristic algorithm and the well-known benchmarking multi-objective approaches.

This algorithm is influenced by the social hierarchy and hunting mechanism of grey wolf. According to the algorithm it mimics the social hierarchy and hunting strategy of Grey wolves. There are four wolves or layers of the social hierarchy which described in fig.2.

The alpha (α) wolf: indicates the best objective valued solution
The beta (β) wolf: indicates the second best objective valued solution
The delta (δ) wolf: indicates the third best objective valued solution
The omega (ω) wolf: indicates rest of the solutions

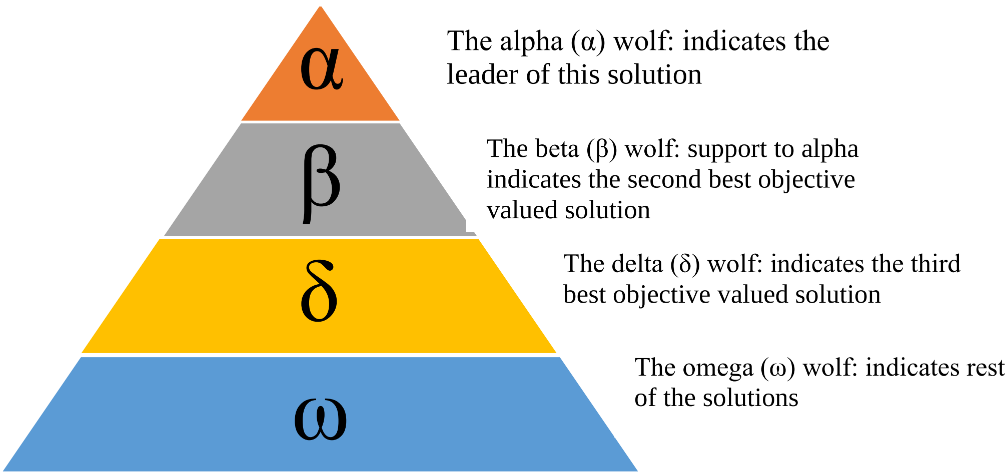

Fig. 2. Hierarchical model of GWO

In the above model the alpha is viewed as the strongest participant of the package. Alpha (α) is in the roof of the hierarchy, and also considered as the strongest prospect of the package. Alpha is generally male wolf but might be female too. Alpha wolves gave the order, and that is adhered to by all of the additional wolfs in the package. Beta wolves are generally accountable to apply the orders of alpha. Alpha wolf additionally looks for the sleeping spot for the pack.

Subsequently, beta grey wolves play an important job in the hierarchy. These're the next most crucial wolves in the package. Alpha wolves take the choices by using beta wolves. The beta wolves additionally coordinate in the responses purpose. Subsequently, delta wolves will come and also categorize as guards, predators, spies and caretaker. Then will be the role of omega wolves. These wolves are believed to be as babysitters and are permitted to consume within the last.

Hence, the primary 3 wolves that denoted as α, β, and δ take responsibility to guide the looking mechanism of the protocol. the remainder of the wolves(ω) are thought-about and ordered to follow them. throughout the hunting, gray wolves follow a collection of well-ordered phases: encircling, hunting then also attacking.

Along with the social leadership, the subsequent formulas have been suggested to be able to mimic the encircling behaviour of grey wolves through hunt (Mirjalili et al. in 2014).

$$\vec{D} = |\, \vec{C} \,.\, \overrightarrow{X_p}\,(t) - \vec{X}\,(t)| \tag{1}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}\,(t) - \vec{A}.\vec{D} \tag{2}$$

$$\overrightarrow{D_\alpha} = |\, \overrightarrow{C_1} \,.\, \overrightarrow{X_\alpha} - \vec{X}\,| \tag{3}$$

$$\overrightarrow{D_\beta} = |\, \overrightarrow{C_2} \,.\, \overrightarrow{X_\beta} - \vec{X}\,| \tag{4}$$

$$\overrightarrow{D_\delta} = |\, \overrightarrow{C_3} \,.\, \overrightarrow{X_\delta} - \vec{X}\,| \tag{5}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha} \tag{6}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta} \tag{7}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \tag{8}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{9}$$

In the above equation 1 and 2, $\overrightarrow{X_p}$ denoted the position vector of the prey and t denoted the current iteration. Where, grey wolf position vector is denoted by $\vec{X}$ and coefficient vectors are $\vec{A}$ and $\vec{C}$.

The coefficient vectors $\vec{A}$ and $\vec{C}$ are evaluated as

$$\vec{A} = 2.\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{10}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{11}$$

In equation 10 and 11, $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are the casual vectors lies between 0 and 1 and the element $\vec{a}$ is reduced linearly after 2 to 0 throughout the iterations.

The last phase of the system of chasing will be the attack. The procedure for assaulting might be mathematically identified utilizing the operators mentioned above. This's accomplished by lessening the valuation of $\vec{D}$ as well as letting down the assortment of contrast of $\vec{A}$ in the number of [-2a, 2a] whereas actually decreased by two to zero till the iterations. In case the standards of $\vec{A}$ invention of [-1,1], the role of the exploration representative determination likely be in among the present place as well as the prey's situation. If |A| <1, the wolves outbreak the target. Consequently, it could remain observed that based on the GWO method, the exploration managers upgrade their places based on the roles of alpha, beta, and delta participants. The hunt for target starts once the wolves deviate from one another to locate the target. This particular research is determined by the roles of the alpha, delta members, and beta. The circumstances for exploration or maybe hit are determined thru the ethics of $\vec{A}$ as follows:

As per the diverge and search, |A| > 1.
As per the converge and attack, |A| < 1.

3.1 Objective Function:

The objective function is the combination of various performance parameters collective to surround a phrase that is usually both maximized or perhaps minimized. Objective characteristic refers to two different settings that choose the ability of the individual. The drive parameters used in the objective function that spoke as follows.

- Objective1 (Average energy of nodes):

$$\mathrm{F}_1 = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \mathrm{E}_{(\mathrm{i})} \tag{12}$$

Where, $E_{(i)}$ symbolize the energy of the i^{th} node along with N stand for the whole nodes of the network in equation (12).

- Objective2 (Residual Energy):

$$\mathrm{F}_2 = 1/\sum_{i=1}^{\mathrm{N}} \left(\frac{\mathrm{E}_{\mathrm{R(i)}}}{\mathrm{E}_{\mathrm{T}}}\right) \tag{13}$$

Where, $E_{R(i)}$ is denoted the summation fraction of remaining energy of i^{th} node and total energy is denoted by E_T in equation (13).

The objective function is the integration of objectives as in single expression is follows in equ. (14)

$$\mathrm{F} = 1/[(\gamma * \mathrm{F}_1) + (\theta * \mathrm{F}_2)] \tag{14}$$

Where, γ and θ are the constant values and $\gamma + \theta = 1$

3.2 Radio Model:

In this energy radio model, the quantity of energy use is determined by the distance among nodes. The power usage for moving the z bit statistics information withinside the distance 'd' is represented by $\mathrm{E}_{\mathrm{tx}}(\mathrm{z}, \mathrm{d})$ besides additionally supplied as follow

$$\mathrm{E}_{\mathrm{tx}}(\mathrm{z}, \mathrm{d}) = z \times \mathrm{E}_{\mathrm{elec}} + z \times \mathrm{E}_{\mathrm{efs}} \times \mathrm{d}^2 \tag{15}$$

The energy required while receiving z- bit of data as follows in equation

$$E_{rx}(z) = z \times E_{elec} \tag{16}$$

Where, E_{elec} and E_{efs} are the required energy intended for transceiver circuitry and energy of free space. $E_{rx}(z)$ is denotes the energy required while receiving the z-bit data.

4. Simulation and Result Analysis:

The simulation options determine the simulation setting wherein the suggested GWO method is designed to use. The MATLAB application model 2019 is placed on a structure through system of 8 GB RAM, 1 TB HD, Intel processor i5 by CPU consecutively on 3.07 GHz in addition Window 10. The exact same sensor system produced arbitrarily is utilized in all of the simulations. It's assumed that nodes spread with the place of 100 X 100 m^2.

Table 1 Simulation parameters.

GWO Parameters	Values
Size of Networks	100 ×100 m^2
Total Nodes (N)	100
Sink node	1
Node energy (in Joules) (E_o)	0.5
E_{elec}	50nJ/bit
Threshold distance (d_o)	87m
(E_{efs})	10pJ/bit/m^2
Inertia weight	0.7
Size of data packets	2000bits
Number of total particles	30
C_1	2
C_2	2
Simulation run	20
Maximum Iteration	150

4.1 Comparative Evaluation:

The effectiveness of the proposed GWO-P method is analyzed with existing state of art algorithms; so as to test the recommended work is better one. For evaluation purpose, we are now analyzing current procedure as WOTC [8], GA-LEACH [7] and ICRPSO [20] methods and the results are evaluated in different metrics like, stability period, network remaining energy and throughput etc.

4.1.1 Stability Period:

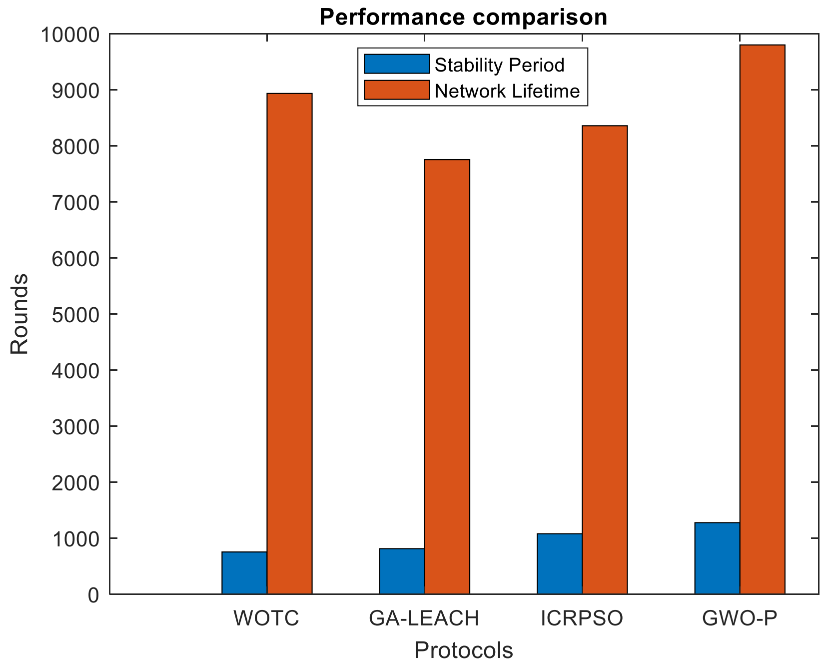

Fig. 3 Comparison of Network Lifetime with Stability Period of GWO-P with existing methods

Results well-known shows that during GWO-P, the primary node is lifeless after 1278 rounds whereas for WOTC, GA-LEACH and ICRPSO, the standards of stability period remain individually 755, 814 and 1080 rounds as shown in Figure 3. The network lifetime of GWO-P is 9801 rounds whereas the WOTC, GA-LEACH and ICRPSO covers 8935, 7754 and 8359 rounds, respectively computed.

4.1.2 Comparison of Network Lifetime of Simulated Methods with Stability Period:

Protocols	FND	HND	LND	Stability Period
WOTC	755	3498	8935	755
GA-LEACH	814	3354	7754	814
ICRPSO	1080	4021	8359	1080
GWO-P	1278	4802	9801	1278

Table 2. Comparison of Network Lifetime of Simulated Methods with Stability Period

Table 2 represents the number of rounds taken for FND, HND and LND along with stability period for simulation methods. Here the improvement of 65.2%, 57% and 18.3% of stability period of GWO-P against the existing methods WOTC, GA-LEACH and ICRPSO respectively and the improvement of 9.6%, 26.3% and 17.2 % of network lifetime of GWO-P against the existing methods WOTC, GA-LEACH and ICRPSO respectively.

4.1.3 Network Remaining Energy:

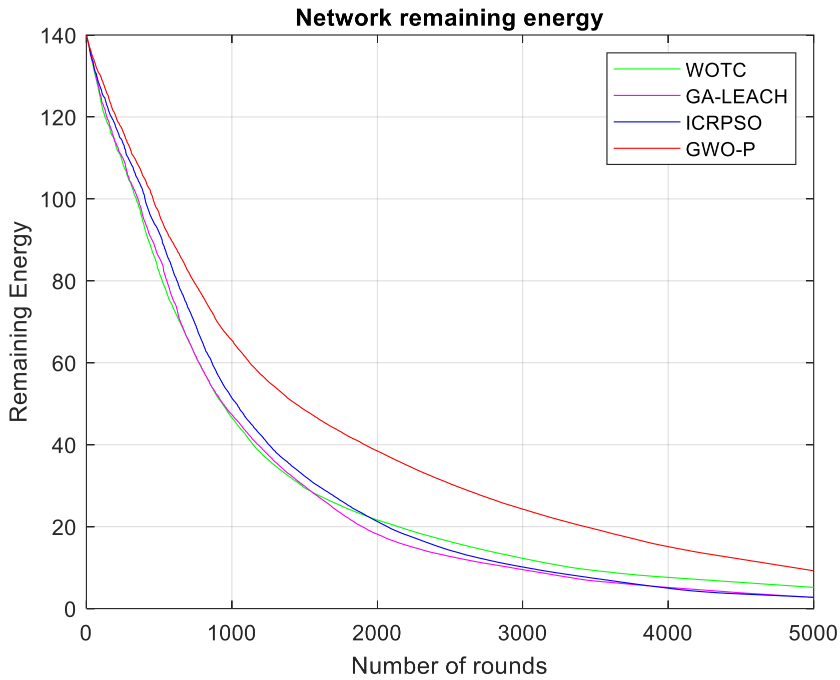

Fig. 4. Comparative analysis of Network's remaining energy GWO-P with existing algorithms

In this metric, when information communication is assumed, the system's vitality begins decreasing. This is very basic to watch the conduct of network's outstanding energy through increment in number of rounds. GWO-P accomplishes better when contrasted with WOTC, GA-LEACH and ICRPSO calculations, individually such that it covers a more prominent numeral of rounds whereas the information communication is in improvement as appeared in Fig 4. The vitality of a hub remains saved on an individually basis round because of the base energy utilization came about because of the vitality effective correspondence.

4.1.4 Throughput:

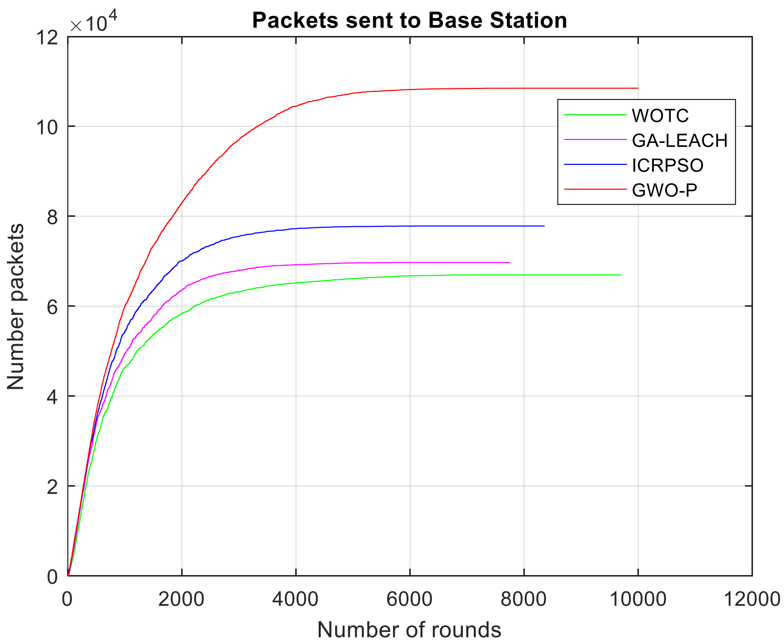

Fig. 5. Comparative analysis of Throughput GWO-P with existing algorithms

The throughput of GWO-P is seen to be increased as the effective transmission of 108487 information packets were finished as shown in Fig. 5. In any case, WOTC, GA-LEACH and ICRPSO sent 66965, 69714 and 77835 packets of information, separately.

5. Conclusion:

The different metaheuristic directing calculations have been reported in the accessible writing so far so as to acquire network stability and life span. The proposed grey wolf optimization for wireless sensor networks is roused from the everyday schedule of grey wolves that utilization four unique positions, portrayed by α, β, δ and ω to attack the prey. These various wolves are utilized to play out the activity of investigation and misuse in the search space. In the proposed strategy, upgraded number of bunches are taken by the assembly of the estimation of α wolf, as α wolfs spans to their best worth. So as to evaluate its presentation, the proposed GWO-P calculation is broadly introduced and reproduced in MATLAB. There is the improvement of 65.2%, 57% and 18.3% of stability period of GWO-P against the existing methods WOTC, GA-LEACH and ICRPSO respectively and the improvement of 9.6%, 26.3% and 17.2 % of network lifetime of GWO-P against the existing methods WOTC, GA-LEACH and ICRPSO respectively. It is likewise discovered that in different other execution measurements GWO-P beats the contender calculations for length of stability, network lifetime, expectancy, and so on. Still, there is always an opportunity to further enhancement of proposed work by extending by numerous clustering methods to cumulative mobile sink nodes efficiently.

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