Secure and Energy Efficient Distributed Routing protocol using GA-BWO for Large Scale WSNs

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Abstract

Large scale wireless sensor network (LS-WSN)is one of the important parts in modern-day communication that employing low-cost sensor devices with different environmental and physical parameters. The secure communication path between the base station and sensor nodes are built with the help of an efficient routing protocol. In the past years, the existing protocols met few difficulties in terms of higher computational complexity, poor cluster head selection performance, higher energy consumption, lower security, expensive in cluster head selection, scalability management, and uneven load distribution, and so on.In this paper, Secure Energy-Efficient Distributed (SEED) protocol with multiple sink nodes was developed to select the best residual energy. secure path selection using genetic algorithm mutation (GA)with black widow optimization (BWO) approach.The novel routing protocol is named as GA-BWO-SEED. Particularly, the mutation phase of the conventional BWO algorithm is improved with the help of direction average strategy of genetic algorithm. Further, thefuzzy logic system (FLC) selects the most relevant and optima cluster heads. The simulation results shows that the proposed GA-BWO-SEED method demonstrates optimal performance output among all other methods.

Keywords: wireless sensor networks, energy efficiency, security protocols, multiple sink nodes.

1. Introduction

One of the rapid developments in the fled of wireless communication systems and a microelectromechanical system is WSN. The sensor nodes (SN) in the LS-WSN contain the number of small battery-operated devices [1]. Three basic principles such as wireless data transmission, computation on sensed data, and data sense from external surroundings are the basic endow of WSN. The nodes group functioning in the co-ordination to finish the needed task is called as WSN. The physical parameters such as humidity, pressure, and temperature are manipulated by these nodes.The LS-WSNs linked with different kinds of applications such as crisis management, military, defence systems, and so on [2]. Usually, the limited energy with power resources and a huge quantity of nodes are accessible in WSN. The energy-efficient routing protocol is required to impart sensed data packets to the base station. The communication path among sensor nodes and the base station is founded by using a different kind of effective routing protocol [3–7]. Furthermore, the optimal Quality of Service (QoS) parameters are achieved by cross-layer techniques. The replacement information in a non-hierarchical way is combined with different communication protocol layers [8]. According to the network structure, the routing protocols are divided into fat and hierarchical types. Each sensor nodes are to perform a similar role in fat routing protocols and it reduces the network overhead. The nodes are divided into clusters in hierarchical routing protocols [9, 10]. The cluster heads act as a leader and each cluster consists of few sensor nodes. The respective CH receivesthe sensed data send by their sensor nodes. The development of clustering-based energy-efficient protocols faced few issues such as data routing to the base station, cluster maintenance, the optimum number of clusters, and proper secure cluster head selection [11], 12]. In recent years, evolutionary methods [13–15] achieved better performance in engineering applications. The most popular and rapidly developing area of communication is smart antenna systems (SAS). The SAS is working under the principle to elegance different applications in the case of WSN. The smart antenna system maximizes the data exchange efficiency between the network nodes. The smart antenna system plays a vital role in WSN to increase the node lifetime and reduces energy consumption [16]. The WSN capacity becomes harshly limited because of the constraints of interference. The entire capacities of the sensor network with the usage of smart antennas are improved in this way.

In past years, enlarger numbers of clustering protocols are intended to solve these problems. These papers are a very challenging one and are not suitable for both heterogeneous and homogeneous networks [17]. From the past decades, the WSN protocols deliver higher computational complexity, Lower performance of secure cluster head selection, higher energy consumption, expensive in secure cluster head selection, scalability management, uneven load distribution and etc. So, we proposed an efficient routing protocol for both heterogeneous and homogeneous networks. The novel routing protocol is named as GA-BWO-SEED. Here, GA-BWO algorithm is utilized to choose the higher residual energy. The optimal cluster head is selected using the FLC. Hence, the below section summarizes the major contribution of this paper.

- We design the GA-BWO-SEED protocol for actual higher residual energy determination with high security properties.
- We boost up the mutation part of the BWO algorithm into GA based direction average mutation and the newly proposed algorithm is termed as GA-BWO.
- We use the FLC for the searching of optimal cluster head node and it improves the network lifetime.
- We demonstrate different kinds of benchmark functions and existing algorithms for the performance analysis of proposed GA-BWO-SEED.

The rest of the paper is arranged as: Section 2 explains the literary. GA-BWO algorithm is formulated in Section 3. Section 4 explains the proposed work and the results are argued in Sect. 5. Section 6 concludes the paper.

2. Related work

The well-known feature scheming of energy-efficient protocols in LS-WSNs is proved by the clustering procedure. In the past years, the researchers were published a lot of clustering-based protocols. From this, a few of the techniques are discussed in the below section. Singh et al. [10] proposed a routing protocol of adaptive threshold sensitive distributed energy effectivecross layer. The network lifetime improvement and energyefficient cross layers are performed together. The cluster head of the network is assigned by a weighted probability approach. The effective data transmission is performed via both reactive and proactive network. The FLC and ACO-AODV was proposed by Gupta et al. [18], which is used as energy-efficient clustering protocols. Both homogeneous and heterogeneous network modelling was used in WSNs. The authors compared their method with other existing algorithms such as Hybrid Energy-Efficient Distributed clustering (HEED), Improved FLC based HEED (ICFL-HEED), and ACO-AODV. The energy consumption is minimized; also, the network lifetime is improved. The combination of Virtual Grid-based Dynamic Routes Adjustments (VGDRA) and energy effective algorithms were proposed by Saini et al. [19]. Less number of loops with more chance of better result created using an optimization algorithm. The simulation works are performed by NS2 software. The VGDRA with a genetic algorithm delivered low energy consumption with a better network lifetime. Vinitha et al. [20] proposed Taylor based hybrid optimization algorithm, which is used as an energy-aware and safe multi-hop routing protocol in WSN. They used the cat slap swarm algorithm (C-SSA) as the hybrid optimization method. For effective data transmission, the low energy adaptive clustering hierarchy (LEACH) protocol and Taylor C-SSA is utilized to choose both energy efficient CH and optimal hop. The K-means clustering algorithm with Zone-based Energy-Aware Data Collection (ZEAL) was proposed by Allam et al. [21]. This approach used to improve the energy consumption and data delivery performance of WSNs. The comparison results shown optimal Quality of Service parameters like energy, lifetime, throughput, and end-to-end delay results. Anand et al. [22] proposed an enhanced routing scheme in data transmission with the Ad-hoc On-Demand Distance Vector (AODV) routing protocol. It provided better packet transmission quality and enhanced the battery power in MANET. The combination of modified Gabriel Graph (GG) and Optimized Power Control (OPC) for transmission of an optimal power node was proposed by Chaudhry et al. [23]. The network delay, node energy consumption and transmission power parameters are tested using OPC. The comparison results outperformed better scalability and power transmission results. Yu et al. [24] suggested an energy-aware distributed unequal clustering (EADUC) protocol that considers the cluster size as unequal. Note that, various energy resources are present in the nodes and the energy hole problem is solved by using unequal cluster sizes. The EADUC yields maximize network lifetime and energy efficiency compared to LEACH. But the dense area has redundant data that is never denoted in EADUC, which creates unnecessary energy consumption. Park et al. [25] proposed the K-means algorithm to select the cluster head and improves the network lifetime. According to the Euclidian distance, the k clusters partition the network and it determines each cluster centre. From the experimental analysis, the EADUC provides better network lifetime but it yields higher energy consumption. The fuzzy logic (FL) was proposed by Kim et al. [26] that select the cluster head. In each round, the tentative CH is chosen depending upon the random number. The entire network provides higher energy consumption and also the CH selection process is more expensive. From the survey analysis, the existing methods attain few drawbacks in case of higher energy consumption, higher computational complexity, expensive in secure cluster head selection, scalability management, and so on.

3. GA-BWO

3.1 Black widow optimization algorithm

The black widow is one kind of spider in the order of Araneae and it has eight legs. The Latrodectus subfamily of a spider consists of infamous and renowned black widows. The black widow is the suite of species in Latrodectus. The black widow spins her web at day and night and the female widow survives in a similar place for the majority of her adult days. The female one marks a few spots to attract the male in her web when the female black widow desires mate. The Black Widow Optimization algorithm (BWO) is working under the principle of reproduction style and cannibalism of black widows. The potential solution is represented by each spider. During or after mating, the female widow consumes the male subsequent to that she stores the sperm in her thecae [29, 30]. The egg sacs are released from the stored sperms. The spiderlings came out into egg sacs. The overall process of the BWO algorithm steps is explained in the below section.

3.1.1 Population initialization

The black widow spider considers the potential solution (widow) to each problem. The problem variables values are shown by each black widow spider. Here, the structure should be considered as an array in order to solve benchmark functions. The dimensional optimization issue is defined as Mv and the matrix population MP. The problem solution represents a widow (W) is an array of Mv and the array are represented as below:

$$W = [y_1, y_2, y_3, \cdots, y_M] \quad (1)$$

The floating-point number of each variable values are$[y_1, y_2, y_3, \cdots, y_M]$ and the widow fitness is denoted as F.

$$F = F([y_1, y_2, y_3, \cdots, y_M]) \quad (2)$$

The initial population (P) of the spider with the candidate matrix size (MP × Mv) is made to start the optimization problem.

3.1.2 Procreate

In order to reproduce the new generation, they start to mate since the pairs are independent of each other. In each mating, nearly 1000 eggs are produced, but few stronger babies only survived. The random numbers with widow array are created by this algorithm; then the array is known as beta. The beta produces an ofspring and it is explained as below.

$$\begin{cases} x_1 = \beta \times y_1 + (1-\beta) \times y_2 \\ x_2 = \beta \times y_2 + (1-\beta) \times y_1 \end{cases} \quad (3)$$

where the parents are denoted as y1 and y2 as well as the offspring are represented as x1 and x2. Repeat the process at Mv⁄2 times and the randomly selected numbers are never copied. Add the mom and children to the array and the fitness value is stored. Then, add a few best individuals to the newly generated population according to the cannibalism rating.

3.1.3 Cannibalism

The cannibalism has three types. (i) During or after mating, the female black widow eats her husband (i.e., sexual cannibalism). The fitness value recognizes the male and female. (ii) The weaker siblings are eaten by strong siblings (i.e., sibling cannibalism). The fitness values are calculated according to the number of survivors and set the rating of cannibalism RC. (iii) Sometimes, the mother spider is eaten by the baby spiders. Here, the strong and weak spiderlings are determined with the help of fitness values.

3.1.4 Mutation

The mutepop number of individuals as the population is randomly selected in this stage. Exchange two elements from the array and every solution is randomly selected. The mutation rate is to calculate the mutepop.

3.2 GA mutation (direction average strategy)

According to mutation rules, the mutant or donor vector VJ i is generated. In the BWO algorithm, the mutation rule is more important to produce optimal convergence speed. In any local extreme, the mutation rule is used to avoid trapping and boost up the convergence fast. Three basic ingredients are helpful in building up the mutation rules. (a) The Jth generation with the current individual in the population YJ i, (b) Jth generation with the best individual in the population YJ b , and (c) Jth generation with randomly selected individuals YJ R. While the last one is stochastic, the former two ingredients are deterministic [31]. Additionally, the new ingredient such as the (J − 1) generation with a current individual in the population YJ−1 i is added. The new mutation rule is formed with the help of this new ingredient with an average of some selected individuals. While compared to the (J − 1) generation, the surviving individual in the J generation contains at least or better comparable fitness value. The mutation rule embeds the "direction" informationthat provides efficient determinism and more definite. Therefore, the averaged mutation rule with devised direction is explained in Eq

$$V_i^J = Y_i^J + F_1 \cdot (Y_{avg}^J - Y_i^{J-1}) + F_2 \cdot (Y_{r_1^i}^J - Y_{r_2^i}^J) \tag{4}$$

$$V_i^J = Y_{r_3^i}^J + F_0 \cdot (Y_{r_4^i}^J - Y_{r_5^i}^J) + F_0 \cdot (Y_{r_6^i}^J - Y_{r^i}^J) \tag{5}$$

Few mutual exclusive random integers chosen from {0, 1, . . ., PN} are represented using the subscripts ri 1, …, ri 7 or (such that (ri 1, …, ri 7 = random mi [0, PN])). The interval range [0.5, 1] is used to fx the parameters such as F0, F1, and F2. Based on our tests, the planned set S in the range is [0.1 × PN, 0.4 × PN].

4. Proposed protocol

The existing protocols attain some complexities due to computational complexity, higher energy consumption, minimum network lifetime, uneven load distribution, and lower performance of secure cluster head selection. Here, we formulate the proposed GA-BWO algorithm for better secure cluster head selection and FLC for optimal CH node searching. The below sub-sections explain the proposed GA-BWO-SEED method.

4.1 GA-BWO-SEED protocol

In this section, the three clustering parameters of each sensor node such as residual energy, distance to the base station, and node density is used to enhance the selection of cluster head (CH). At the initial specific round, the total node energy defines the residual energy of the node N1. Due to data feature transmission, data processing, and data sensing, the residual energy of the node reduces in every round once network executed.

- The amount of sensor nodes N1 calculates the density of the sensor node Nj. The entire number of sensors in the network is expressed as SNN. Where, 2 ≤ j ≤ SNN.
- At the beginning of the network, the beacon message BEmessage is transmitted with a base station to determine the distance to the base station parameter. The signal strength received of this message calculates each distance to the base station and sensor nodes on the receiving BE message. In the selection of a total amount of CH, the network contains a pre-determined limit (Cprobability).
- At the initial protocol execution, this constraint only works and it never assurance the number of last selected cluster heads. The cluster head probability CHprobability is applied to each uncovered sensor nodes and the mathematic calculation is shown as below:s

$$CH_{probability} = \left(C_{probability} \times \frac{E_{resisual}}{E_{\max imum}}, P_{\max imum} \right) \tag{6}$$

Therefore, the sensor node with residual energy Eresidual and the maximum allocated energy is to the sensor node Emaximum. The pre resolute threshold value is Pminimum. According to the residual energy parameter, the higher residual energy with a set of tentative cluster heads (GtCH) is selected with the help of the GA-BWO algorithm.

4.1.1 Residual energy and secure path selection using GA-BWO

This GA-BWO algorithm is utilized to choose higher residual energy. In the network, the superior residual energy sensor nodes are searched with the help of widows (W). In the network feld, set the widow to move from node to node for higher energy search. At Jth generation, the sensor node energy cost is signified as E (W, i). Procreate and cannibalism steps are used in better energy node searches for the selection of tentative cluster heads. At some SNs, randomly select the sensor nodes with probability using the specific iteration rounds. All the sensor nodes are visited using the widow population during searching for better energy. For i=1, the surviving individual in the Jth generation contains at least or better comparable fitness value using average direction strategy (mutation). In the network feld, apply the GA-BWO algorithm, then the widow population is capable of identifying optimal sensor nodes also choose the tentative cluster heads. The advertisement message broadcast each tentative CH. Therefore, the higher residual energy with the optimal cluster head is obtained. Hence, the optimal residual energy selection is demonstrated in Figure 1.

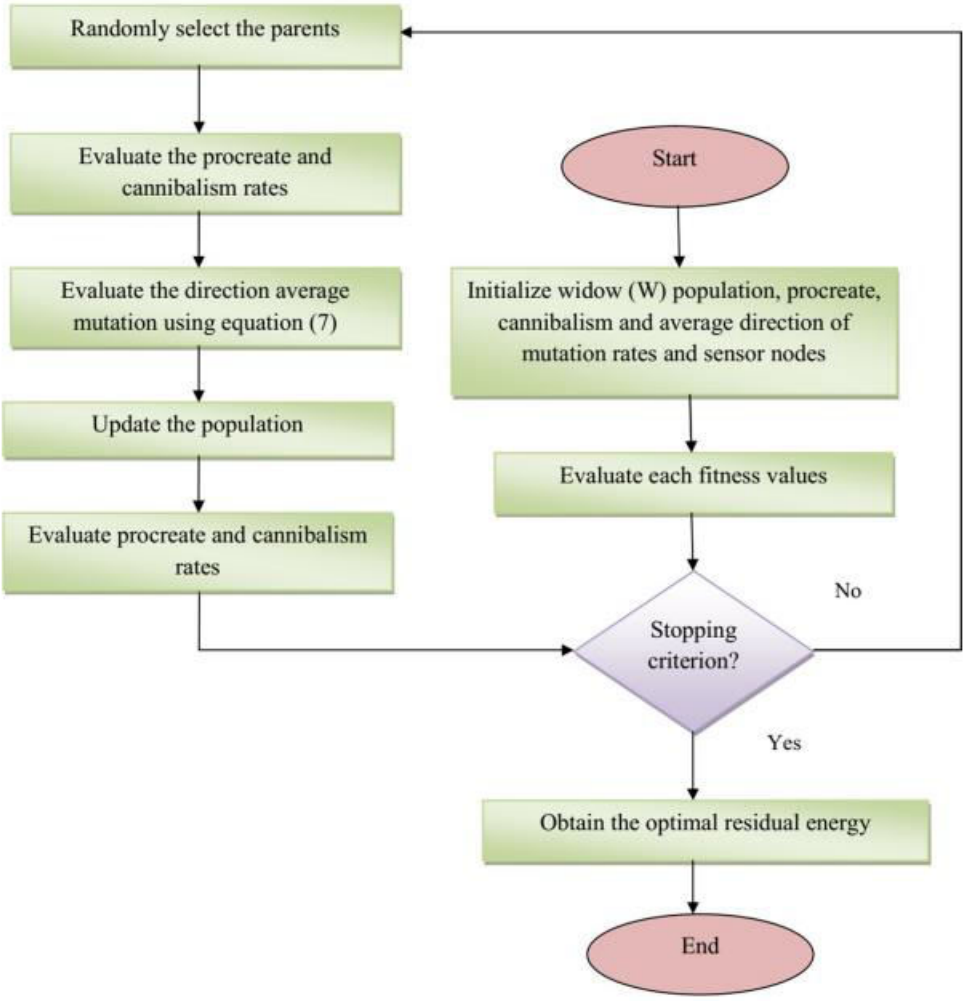

Fig. 1 Flowchart representation of GA-BWO algorithm

While more than one message from various cluster head is obtained using a sensor node. The better probability function selects the cluster head. The FLC module [32] density generates the probability outcome. The better cluster selection node used the input parameters such as distance to the base station. For functioning, the FLC has a fuzzifier, defuzzifier, rule base, and inference engine. The suitable fuzzy linguistic variables are the conversion of inputs such as crisp values. The inputs of the fuzzy inference engine as the (fuzzified values) and set the IF–THEN as fuzzy rules. The crisp output value is the conversion of fuzzy output to defuzzifier. Here, we use the Mamdani model as the inference engine in FLC. Here, the input parameters such as node density and distance to the base station. The output is probably also Fig. 2 explains the working mode of FLC for GA-BWO-SEED. The probability function is represented in Eq.

$$Prob = \frac{\phi_{nd} \times R_{nd} + \phi_q \times (N_q - R_q)}{\phi_{nd} \times N_{nd} + \phi_q \times N_q} \quad (7)$$

The current levels are indicated by Rnd and Rq also the values for node density is Nnd and Nq. The node densitymembership functions (Mfns) have a minimum, intermediate and maximum values. The membership functions (Mfns) of distance to the base station have certain conditions such as greater (4), greater than (3), equal (2), less than (1), and less (0). The fifteen membership function rules such as Very Poor (VP), Poor (P), Rather Weak (RW), Weak (W), Very Weak (VW), Low (L), Very Good (VG), Below Average (BA), Above Average (AA), Average (A), Little Strong (LS), Good (G), Strong (S), Very Strong (VS) and Excellent (E) are the probability outcomes. Hence, the fifteen probability outcomes are shown in Fig. 2. Table 1 explains the outcome of distance to the base station, node density, and the probability that signifies A, B and C. Hence, the If/ Then fuzzy rules are explained as follows:

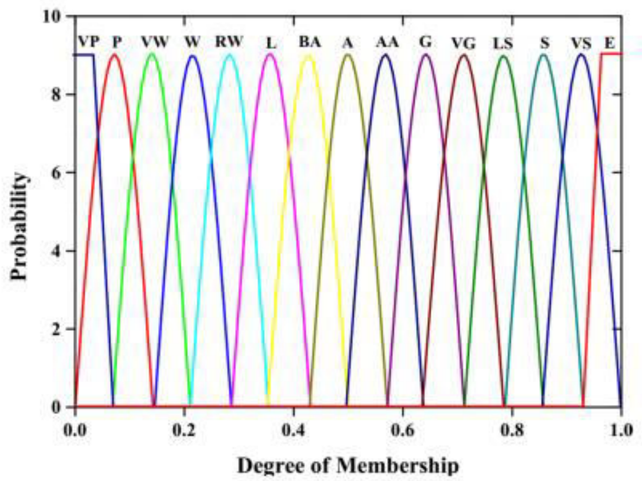

Fig. 2 Fuzzy rule set for the probability output

For Minimum (A)

- If node density A is 4 then the probability distance to the base station is very poor.
- If node density A is 3 then the probability distance to the base station is poor.
- If node density A is 2 then the probability distance to the base station is very weak.
- If node density A is 1 then the probability distance to the base station is weak.
- • If node density A is 0 then the probability distance to the base station is rather weak.

For Intermediate (B).

- If node density B is 4 then the probability distance to the base station is low.
- If node density B is 3 then the probability distance to the base station is below average.

- If node density B is 2 then the probability distance to the base station is average.
- If node density B is 1 then the probability distance to the base station is above average.
- If node density B is 0 then the probability distance to the base station is good.

For Maximum (C).

- If node density C is 4 then the probability distance to the base station is very good.
- If node density C is 3 then the probability distance to the base station is a little strong.
- If node density C is 2 then the probability distance to the base station is strong.
- If node density C is 1 then the probability distance to the base station is very strong.
- If node density C is 0 then the probability distance to the base station is excellent.

Table 1. Membership functions of node density and distance to the base station with probability output

Node density		Distance to the base station (BS)	Probability
A	Minimum	$> (4)$	Very Poor (VP)
		$\geq (3)$	Poor (P)
	Minimum	$= (2)$	Very Weak (VW)
	Minimum	$\leq (1)$	Weak (W)
		$< (0)$	Rather weak (RW)
B	Intermediate	$> (4)$	Low (L)
		$\geq (3)$	Below Average (BA)
	Intermediate	$= (2)$	Average (A)
	Intermediate	$\leq (1)$	Above Average (AA)
		$< (0)$	Good (G)
C	Maximum	$> (4)$	Very Good (VG)
		$\geq (3)$	Little Strong (LS)
	Maximum	$= (2)$	Strong (S)
	Maximum	$\leq (1)$	Very Strong (VS)
		$< (0)$	Excellent (E)

Moreover, the current level values 0 or 1 considered Rnd and Rq . Set 2 as a maximum value for Nnd and Nq. The parameters of node density and distance to the base station provided equal weightage values. For secure cluster head selection, use the node density parameter and the even-sized clusters are generated by the GA-BWO-SEED method. The GA-BWO-SEED is able to choose neared sensor nodes to base stations by applying the distance to base station parameters for the selection of cluster head. During data transmission as of CH to base stations reduces energy consumption and it improves the network lifetime. Every sensor node doubles its probability (CHprobability). The GA-BWO-SEED algorithm is used to start the recognition of new tentative cluster heads also add it to the tentative cluster heads such as (GtCH). The probability (CHprobability) of each sensor node reaches 1 means the process is stopped (i.e.,Final CH). For the specific round, this accomplishes the cluster formation and it provides at the smallest amount of one sensor node active in the LS-WSN. All sensor nodes sense the environmental surroundings, gather the data, and passed it to the particular cluster head in single-hop subsequent to the formation of the cluster in each round. The cluster members send the receptions of the data packets but every cluster head confused about its individual data with the conventional packets. Then, use the single hop to transmit it to the base stations directly.

5. Result and discussion

The proposed GA-BWO-SEED presentation is estimated in this section. The proposed work is implemented in the NS2 software. The homogeneous, secondary, and tertiary level heterogeneous performance of GA-BWO-SEED is analysed in this section. Moreover, the novel algorithm of MB-BWO performance is analysed using different kinds of benchmark functions. Finally, the state-of-art comparison is carried out and the proposed GA-BWO-SEED algorithm performance is evaluated in the below section. The parameters required in support of the proposed work are tabularized in Table 2.

Table 2. Parameter settings of proposed GA-BWO-SEED

Parameter	Ranges
Size of message (K)	2000 bits
Size of WSN field (F× F)	$100 \times 100m^2$
Base station location	(25, 25)
Distance of threshold D_0	50 m
Sensor nodes	50
Energy needed for data fusion	5 nJ/b/m

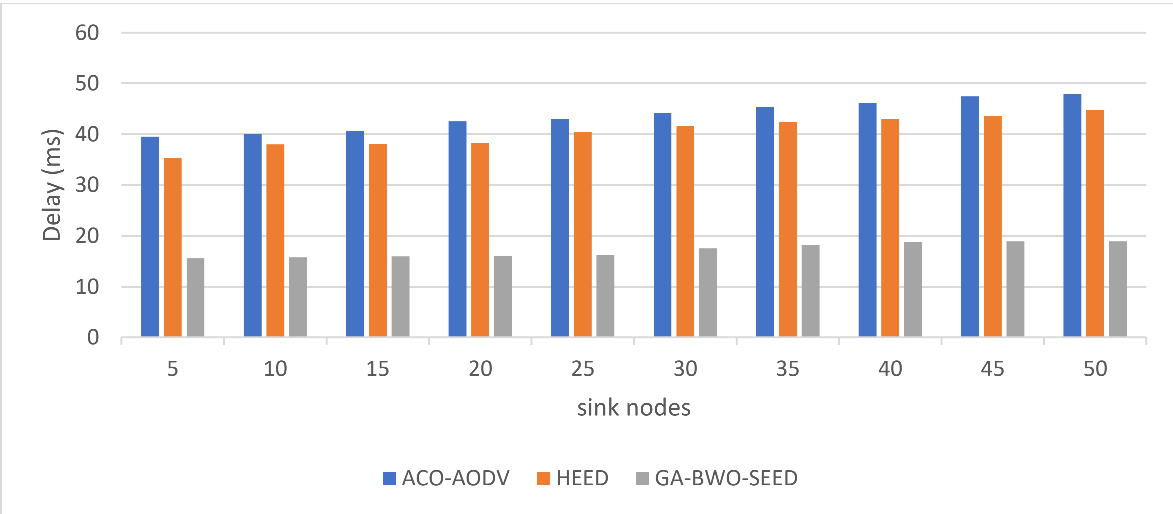

Figure 3. Delay performance estimation.

Figure 3 presents the delay performance estimation of various routing protocols, where the proposed GA-BWO-SEED approach resulted in reduced performance as compared to HEED [18], ACO-AODV [19].

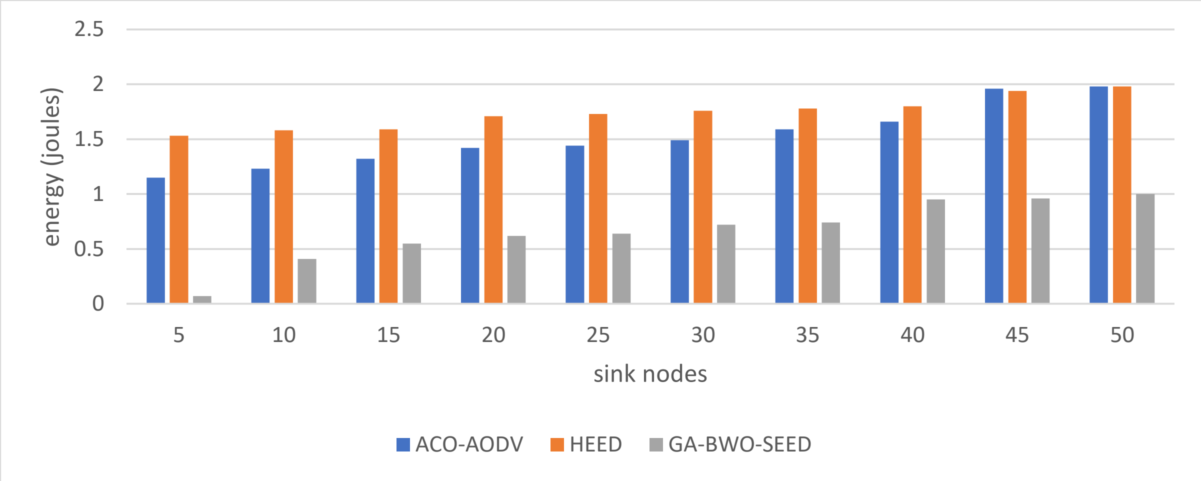

Figure 4. Energy performance estimation.

Figure 4 presents the energy performance estimation of various routing protocols, where the proposed GA-BWO-SEED approach resulted in reduced performance as compared to HEED [18], ACO-AODV [19].

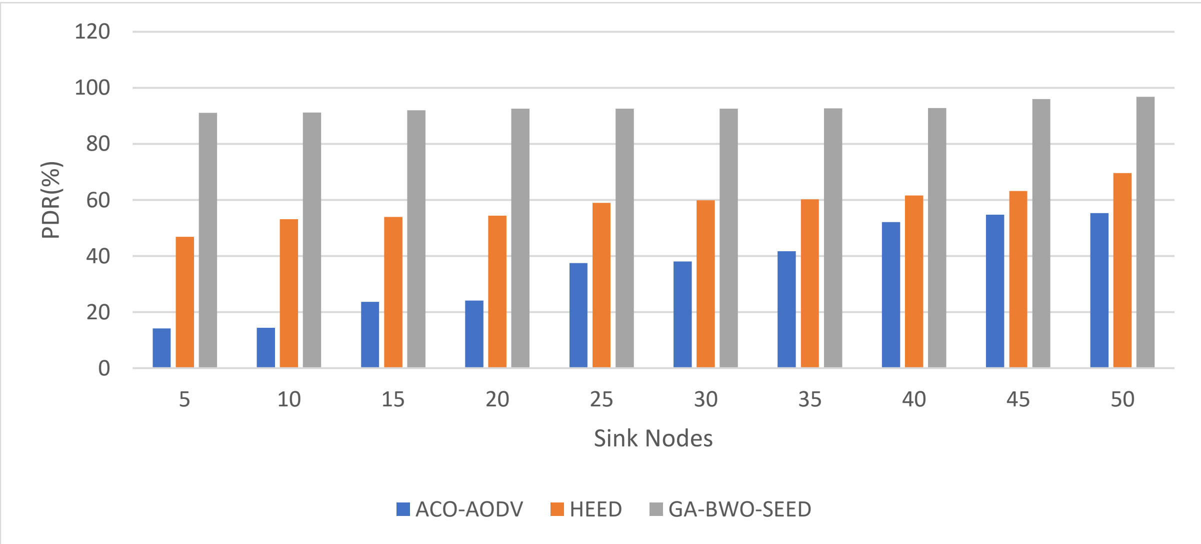

Figure 5. PDR performance estimation.

Figure 5 presents the packet delivery ratio (PDR) performance estimation of various routing protocols, where the proposed GA-BWO-SEED approach resulted in increased performance as compared to HEED [18], ACO-AODV [19].

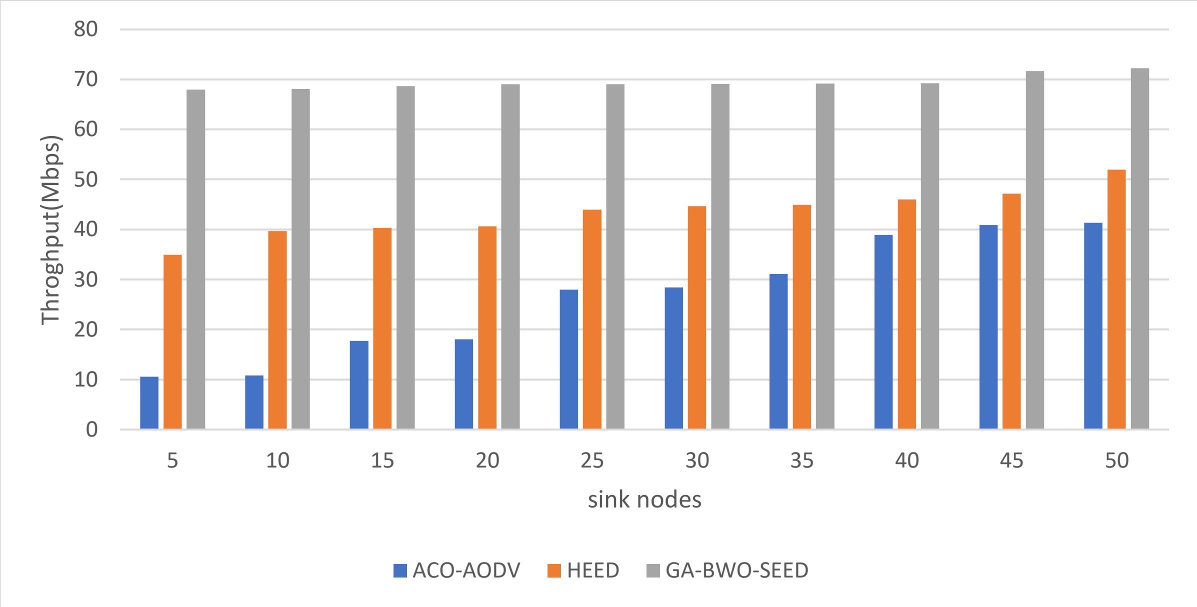

Figure 6. Throughput performance estimation.

Figure 6 presents the Throughputperformance estimation of various routing protocols, where the proposed GA-BWO-SEED approach resulted in increased performance as compared to HEED [18], ACO-AODV [19].

6. Conclusion

This paper proposed GA-BWO with fuzzy logic-basedSEED protocol (GA-BWO-SEED). The proposed work is executed under the platform of NS2. The proposed GA-BWO delivers higher convergence performance among all other methods. The homogenous, secondary and tertiary level heterogeneous in WSN with the proposed method provides optimal residual energy and sensor node performance. The proposed GA-BWO-SEED method is evaluated using existing algorithms namely HEED, ACO-AODV and ICFL-HEED. Finally, the proposed GA-BWO-SEED provides higher residual energy and a better network lifetime

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