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Towards Enabling Fault Tolerance and Reliable Green Communications in Next-Generation Wireless Systems

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Abstract: Green communications have witnessed significant attention being paid to the next generation of wireless systems research and development. This is due to growing use of sensor- and battery-oriented smart wireless devices. The related literature in green communications for next-generation wireless systems majorly relies on transmission and sensing power management, but lacks a fault-tolerant centric approach. In this context, this paper presents a fault-tolerant and reliable green communications framework for next-generation wireless systems (FRGNWS). Firstly, maximum node-disjoint routes from all source nodes to the base station are identified based on the hybrid adapted grey wolf sine cosine optimizer. Secondly, a fault-tolerant and reliable route is selected from the maximum disjoint routes for each sensor node to the base station based on the hybrid adapted grey wolf whale optimizer. The performance of our proposed green communications framework is assessed by simulation experiments considering a realistic implementation scenario and different metrics. Simulation results clearly validate the efficacy of the proposed green communications framework as compared to the state-of-the-art techniques.

Keywords: green communication; wireless sensor network; energy harvesting; whale optimization algorithm; grey wolf optimization; sine cosine optimization

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1. Introduction

The excellent advancements in the field of IoT help in applying the latest smart technologies of wireless communications towards agriculture, grids, smart homes, smart industry revolution, military, etc. Currently, researchers are focusing on designing optimal energy-efficient wireless sensor networks (WSNs) consisting of a large number of tiny sensor nodes for monitoring/sensing/detecting particular events, which are operated primarily by limited-capacity batteries [1]. Tiny sensor nodes (SNs) are also known by the name source nodes (SNs). The main applications of WSNs typically occur in very harsh environments and due to these circumstances, the battery of SNs drains out very fast. Therefore, the main reason for node failure in WSNs is due to their deployment in a harsh environment [2]. Energy harvesting (EH) is the prominent solution for providing an alternative source of energy to tiny nodes for resolving energy issues but sometimes fluctuations occur in harvested energy due to environmental conditions and energy optimization again needed for effective utilization in this case [3]. The concept of duty cycle (DC) is also used for energy efficiency but in the case of an energy-harvesting wireless sensor network (EH-WSN), the SNs require a heterogeneous and dynamic DC [4].

Whenever a specific SN involved in routing a data packet to base station (BS) becomes dead, then this data packet is unable to reach the BS and other SNs are selected to route this data packet to the BS; now, these other SNs are taking extra load and their battery is more likely to deplete fast due to the overloaded mechanism and thereby a greater number of SNs becomes dead. Further, this situation creates multiple network partitions [5]. A disjointed, partitioned network may be created due to this type of inherent limitation of EH-WSN. In general terms, this situation is termed as the problem of disjointed networks. If the network partition condition arises, then, in this case, the communication mechanism happens only between the SN and those other SNs that belong to that specific respective partition only; for the remaining part of the network, they are totally cut off [6]. For resolving this condition and maintaining effective connectivity in the partitioned network, we require the placing of a special type of node, called a relay node (RN) [7]. Further, they may be different from traditional SNs in terms of the power of the battery, having the capability of movement, etc.; also, their uniqueness lies in the fact that, first, they collect data packets from the SNs, and then they forward the data packets to neighboring RNs, and in this way data packets finally reach the sink node [8]. Relay nodes contribute towards enhancing the network life span since they relive the overloaded SNs by distributing their loads [9]. The only limitation in deploying relay nodes is related to increments in the budget of the network since they may be costly compared with traditional SNs. The relay nodes (RNs) can be placed by using two approaches, namely, the random approach or pre-determined approach [10]. The pure random approach is relatively complex since it requires distributed algorithms as well as a routing framework with self-organizing capabilities [11]. It should be noted that a controlled random approach with non-uniform nature is the best solution for the deployment of relay nodes (RNs) [12]. Therefore, for optimal performance with cost-effectiveness for the EH-WSN, we should place the minimum number of relay nodes at appropriate optimal positions. Again, this requirement forms the NP-hard problem, where the relay node optimization problem is having a discrete type nature and a discrete solution is needed for this NP-hard problem [13].

Next, fault-tolerant routing with awareness of the quality of routing is the only solution for the optimal performance of EH-WSN. Towards enabling fault-tolerant routing, the first step is to establish the multi-node/link disjoint routes, comparing these with the previous route as well as all other alternative routes. In this mechanism, the failure in the previous route due to the breakdown of any or all nodes/links has no impact on the alternative routes; this since, in the energy-harvesting environment, the time-varying, unstable, and random nature of harvested energy may compel the nodes to fail. Furthermore, due to this random nature of harvested energy, the nodes' lifecycle frequently switches between alive and dead, which results in dynamic changes in the quality of the routing. The designing of effective fault-tolerant routing in EH-WSN is a hard nut to track since it constitutes the NP-complete problem.

For providing faut tolerant routing, a few research articles recently were published; e.g., Belkadi et al. [14] proposed a fault-tolerant routing scheme utilizing clustering for WSN; Abdulrab et al. [15] presented a multipath routing model with features such as increased reliability, minimum latency, and cost-effectiveness. In the proposed model, there exists a backup node in each route. The backup node is responsible for storing the data from the parent node for maintaining the continuity in case of failure. Hao et al. [16] also proposed an energy-efficient routing scheme based on a greedy strategy. In the proposed scheme, an energy evaluation model is constructed first for identifying the energy state of the node. Further, a range judgment framework was designed, and these two schemes were combined for designing a reception state adjustment scheme.

Researchers are using various techniques based on approximations, heuristics, etc., for providing the appropriate solution for the relay node optimization problem, as well as to solve the NP-complete problem of fault-tolerant routing in EH-WSN. Metaheuristics are used currently for providing the solution to these non-deterministic polynomial time (NP)-hard and NP-complete optimization problems, respectively. The major reason for using metaheuristics for solving these problems is that these frameworks are efficient in handling NP-hard as well as NP-complete optimization problems, having non-linear characteristics. As compared with heuristic algorithms, metaheuristic algorithms have added advantages since metaheuristic algorithms are intelligent enough and also have adaptability features; in turn, heuristic algorithms are mainly problem dependent. The two main pillars of stochastic algorithms are a deterministic component and a random component. Further, the local optimum can be found by a deterministic component, on the other hand, with the help of a random component; metaheuristic algorithms also can adopt various forms by considering random walk and random sampling.

In this research article, a novel framework is proposed, namely, a framework enabling fault-tolerant and reliable green communication in next-generation wireless systems (FRGNWS), considering a single-tiered EH-WSN with constrained RNs deployment. The proposed novel framework consists of two phases. In the first phase of the proposed novel framework, maximum node-disjoint routes from all SNs to BS using minimum RNs are explored based on a hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework, the HA-GWSCO framework also discovers k-node-disjoint routes from each SN to BS with $k \geq 2$, which enhances the fault tolerance capability in EH-WSN. In the second phase of the proposed novel framework, out of the k-node-disjoint routes from each SN to BS with $k \geq 2$, the best appropriate reliable route is selected for routing, which enhances the reliability in routing for EH-WSN based on the hybrid adapted grey wolf whale optimizer (HA-GWWO).

The salient contributions of this proposed novel research are listed below in a point-wise fashion.

1. The proposed novel research effectively handles both the NP-hard (relay node optimization) as well as NP-complete (fault-tolerant reliable routing) problems, challenging optimization problems simultaneously in EH-WSN. This salient feature of the proposed novel research distinguishes it from other existing literature.
2. The first phase of the proposed novel framework (FRGNWS) is dedicated for exploring the maximum approximate number of node-disjoint routes from all SNs to BS utilizing the least number of RNs in EH-WSNs based on the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO).
3. The first phase of the proposed novel framework (FRGNWS) also provides a novel approach for discovering k-node-disjoint routes from each SN to BS with $k \geq 2$ in EH-WSN.
4. The second phase of the proposed novel framework (FRGNWS) is dedicated for finding the best appropriate reliable route from each SN to BS out of the available k-node-disjoint routes from each SN to BS in EH-WSN based on the hybrid adapted grey wolf whale optimizer (HA-GWWO).
5. To assess the effectiveness of the proposed novel framework in EH-WSN, we have considered five metrics, namely, the energy consumption, lifetime of the network, throughput, delay, and delivery ratio, and analyzed the results by comparing the proposed novel framework with other metaheuristic frameworks. The simulation results attest to the claim that the performance of the proposed novel framework is optimal, and this approach can be adopted for enhancing the capability towards fault tolerance and reliable green communication in next-generation WSN.

The proposed novel research article is organized into six sections. The research article is introduced in Section 1; this section briefly narrates the various details, including the salient contributions, of this research article. Next, all similar works from the literature are illustrated in Section 2; this section is named Related Works. Further, the proposed novel research is well explained in Section 3; this section describes both the phases of the proposed novel framework in detail, and is named The Proposed Approach. The validation of the effectiveness of the proposed novel framework is carried out in Section 4; this section analyzes and explains the evaluated results and is named Results and Discussion. Finally, in Section 5, a summary of the proposed novel framework is provided, with future research directions, and this section is named Conclusions.

2. Related Work

There are two types of relay node placement strategies for EH-WSNs, namely, constrained and unconstrained approaches. The constrained approach sets specific objectives, namely, enhancing the network life, improving the coverage, and specific location restrictions, etc. The unconstrained approach for relay node placement focuses on generalized objectives such as connectivity and fault tolerance in EH-WSN. We will first discuss the unconstrained strategies for relay node placement. The objective of fault tolerance in single-tiered (ST) as well as two-tiered (TT) EH-WSNs can be achieved by providing k-connectivity with $k \geq 2$. Further, if k = 1, then ultimate objective is internode reachability, with a focus on generating fully connected EH-WSN. Next, Lloyd et al. [17] have presented an M1tRNP scheme, which is known as the minimum 1-tiered relay node placement scheme. For single-tiered (ST), the proposed scheme utilized polynomial-time 7-approximation and on the other hand for two-tiered networks, $5 + \varepsilon$ ($\epsilon > 0$). Here, Kruskal's algorithm is used for constructing the MST. The sensing radius of the relay nodes is utilized for placing the RNs on the edges of the tree.

Liu et al. [18] proposed an approximation framework for one connected network with polynomial time ($6 + \varepsilon$) and two connected networks with ($24 + \varepsilon$). The Steiner minimum tree is utilized for determining the minimum number of RNs, covering the entire set of SNs for one connected network. Next, the scheme is further extended for two connected networks; here, extra relay nodes are deployed for each relay node in one connected network. Next, we will discuss the constrained strategies for relay node placement. Xu et al. [19] have addressed the objective of reducing the cost of a network with improvement in network life span. This problem is NP-hard, also known as the minimum set covering problem. In the proposed recursive scheme, the divide and conquer strategy is utilized. In the proposed scheme, the relay nodes are deployed in the locations where the SNs' ranges intersect. In [19], the focus is on deploying the minimum number of relay nodes for a two-tiered architecture with the objective of achieving the load balancing. The locations are identified where ranges of relay nodes intersect for extra relay node deployment and the focus is on achieving k-connectivity. Next, there are four classifications of relay node optimization strategies, namely, algorithm-based frameworks, approximation algorithm-based frameworks, frameworks based on heuristics, and frameworks based on metaheuristics. We will illustrate each strategy one by one starting from algorithm-based frameworks.

Senturk et al. [20] have proposed two efficient frameworks for the positioning of the distributed RNs. These two frameworks are aimed at reducing the cost of movement of the RNs for guaranteed recovery of the network. The first proposed framework focused on the movements of RNs based on virtual force on the other hand the second proposed framework utilized the concept of Game Theory among the partitions of the network. Next, Chang et al. [21] have proposed an efficient framework for jigsaw-based placement of RNs for indoor WSNs. They aimed at constructing the WSNs, with the minimum number of RNs and SNs in an indoor space with obstructions. Further, Nitesh et al. [22] have proposed an enhanced framework for the placement of RNs. They aimed at optimizing the overall cost by utilizing the least possible RNs. The enhanced framework ensures optimal k-coverage and s-connectivity with respect to SNs and RNs within the network. The next paragraph will illustrate the approximation algorithm-based frameworks for relay node optimization.

Mishra et al. [23] have conducted extensive studies for the constrained RN placement problem (CRNPP) with prior knowledge for candidate locations regarding the potential of energy harvesting. Further, they have presented the NP-hard problems of connectivity and survivability in EH-WSNs. They aimed at achieving connectivity or survivability in EH-WSNs by utilizing the least number of RNs. Next, they proposed the polynomial-time O(1)-approximation frameworks for solving NP-hard problems of connectivity and survivability in EH-WSNs. The proposed approximation frameworks are having low approximation ratios. Next, Ma et al. [24] have presented an efficient local search approximation framework for providing the solution to the problem of a RN single cover. The proposed connectivity-aware approximation framework for the placement of RNs aimed at reducing the system overhead. Further, Liu et al. [25] have conducted studies for the RN placement problem. They aimed at achieving the optimal connectivity in ST-WSN by deploying the least possible RNs. First, they construct the neighbor components by utilizing the Voronoi Graph and Delaunay Triangle. Next, they utilized the Steiner heuristic with the Spanning tree for optimizing the placement algorithm. In the latter, all these components are combined for maintaining effective connectivity. The next paragraph will illustrate the heuristics-based frameworks for relay node optimization.

Han et al. [26] have proposed frameworks for maximizing the fault tolerance in ST-WSNs. In the proposed frameworks they assumed sensors having different ranges. Next, Misra et al. [27] have proposed an efficient framework for achieving effective connectivity in ST-EH-WSNs. They aimed at deploying the least possible RNs at a subspace of candidate areas. Further, the constrained deployment RNs constitute the constrained RN placement problem. Further, Nigam et al. [28] have proposed an efficient framework for deploying the least possible RNs in ST-WSNs known as the branch-and-cut framework. In the proposed framework, they assumed a bound of predefined delay in between the SNs and BS. Furthermore, Izadi et al. [29] have proposed an effective coverage scheme for mobile SNs in ST-WSNs, which are randomly deployed. The proposed effective self-healing coverage scheme is based on fuzzy logic. The proposed effective scheme is aimed at reducing the coverage hole. First, the proposed effective coverage scheme explores the uncovered areas of the sensing. In the next step, the coverage hole issue is effectively handled by selecting the best mobile SNs. Besides, Sitanayah et al. [30] have proposed dual efficient frameworks known as Greedy-MSP and GRASP-MSP for providing the solution to placement problems related to multiple sinks. Further, the two proposed frameworks are also used for providing the solution to the problem of RNs' deployment, with the ultimate aim of reducing the cost of deployment. Next, the proposed frameworks assure the double-coverage of each SN. Moreover, Bagaa et al. [31] have proposed an efficient framework for providing the solution to constrained RN placement problems in ST-WSNs by effectively handling the deployment of RNs in ST-WSNs. The proposed framework aimed at reducing the outage probabilities during the construction of the routing tree with the addition of the least possible RNs for effective connectivity. Also, Djenouri et al. [32] have proposed an effective heuristic scheme for enhancing the life of the network. The proposed effective heuristic scheme provides the solution to the constrained RN placement problem. In the proposed heuristic scheme, the life of the network in ST, as well as TT-WSNs, has been significantly enhanced with the deployment of extra SNs and RNs. The next paragraph will illustrate the frameworks based on metaheuristics for relay node optimization.

Zhao et al. [33] have conducted extensive studies for understanding the problem of optimal deployment. They proposed the framework utilizing the particle swarm algorithm for integer planning. In the proposed framework, the relay nodes are deployed optimally and therefore the proposed framework achieves significant energy efficiency in ST-WSNs by reducing the average length of the route. Next, Perez et al. [34] have proposed a multi-objective model in ST-WSNs. The proposed multiobjective model focused on optimizing the RNs as well as energy dissipation simultaneously. Further, they proposed a hybrid evolutionary framework consisting of two local searches for providing a solution to the constrained RN placement problem. Further, Gupta et al. [35] have proposed excellent dual frameworks for RN placement. The proposed frameworks provide k-connectivity of the SNs. In the proposed dual frameworks, the Genetic Algorithm (GA) is utilized in the first framework while the greedy approach is used in the second proposed framework. Furthermore, George et al. [36] have proposed an optimal framework utilizing a modified genetic algorithm for the placement of RNs in ST-WSNs. In this constrained RN placement approach, the proposed framework aimed at deploying the least possible RNs with effective connectivity. Further, the proposed framework assures fault tolerance in ST-WSNs. Besides, Yu et al. [37] have conducted extensive studies for optimal deployment of RNs in ST-WSNs. They focused on optimizing the two important metrics, namely, the average consumption of energy as well as average reliability of the network simultaneously. They utilized three metaheuristics, such as Archive-Based hYbrid Scatter Search, Particle Swarm, and Non-dominated Sorting Genetic Algorithm, for addressing this multiobjective optimization problem. The metaheuristics that are utilized employ varied evolutional policies. Moreover, Ma et al. [38] have proposed an efficient RN placement framework. The proposed framework supports network reconfiguration. The proposed framework is based on Differential Evolution (DE)-based algorithms. Further, the proposed framework assures a deterministic approximation ratio along with tight time complexity. Rao et al. [39] also have proposed an optimal RN placement framework that is based on the multiobjective Firefly Algorithm. The proposed framework aimed at deploying the least possible RNs with consideration of three constraints, namely, energy, connectivity, and coverage.

Few articles recently have been published for contributing towards fault-tolerant routing: Chanak et al. [40] proposed a fault-tolerance routing framework for improving the QoS in WSNs. In the proposed scheme, faulty nodes are identified, and partial faulty nodes are used to handle the faults in WSN. Sharad et al. [41] presented a multipath fault-tolerant routing framework utilizing clustering for WSN. In the proposed framework, an enhanced version of elephant herding optimization is proposed for selecting the multiple routes. Next, Gurupriya et al. [42] proposed a multipath fault-tolerant routing framework for WSN. In the proposed framework, clustering is performed by using a modified teaching–learning optimization scheme. Further, pigeon optimization based on a nonlinear regression is used for computing the backup node for increasing the fault tolerance. Finally, the optimal path was calculated using a deep Kronecker neural network. Furthermore, Mansour et al. [43] presented a fault-tolerant routing scheme in WSN. In the proposed scheme, clustering was performed using moth flame optimization. Further, the optimal routes were selected using social spider optimization (SSO) in WSN.

Finally, we have selected two existing frameworks, namely, the artificial bee colony-based framework and the genetic algorithm-based framework, to compare the effectiveness of our proposed framework (FRGNWS) against them. In the next paragraph, we briefly provide the features of these two existing frameworks.

Hashim et al. [44] have proposed the framework for placing the RNs between CHs and the sink. In the proposed framework, two phases exist, namely, first-phase RNs and second-phase RNs. In the first phase of the proposed framework, known as first-phase RNs, connections were established by RNs among the CHs and sink. Further, in the second phase, extra RNs were deployed randomly and in a dense way for achieving the desired connectivity level. In the second phase, the aim of the Artificial Bees Colony (ABC) algorithm is to find the optimal location for further deployment of RNs. This framework shows effectiveness, but there are few points that need to be highlighted, such as the constraints, namely, the coverage, energy, and energy-harvesting environment have not been considered in the proposed framework. Next, Gupta et al. [35] have proposed a framework for providing k-connectivity of the SNs. They also proposed the Genetic Algorithm (GA)-based framework for k-connectivity. However, GA is suffering from the problem of convergence, and extra computational complexity is created to solve the hierarchical problem.

3. Proposed Approach: Fault Tolerance and Reliable Green Communications in Next-Generation Wireless Systems (FRGNWS)

In EH-WSNs, the routing framework should use some specific strategies, such as node-disjoint routes with shorter route characteristics, for maintaining the QoS requirements in high-traffic scenarios. In these scenarios, multipath routing is the best-suited alternative compared with the single route between each SN and BS. Even with the multipath routing framework, there is a strict requirement of node-disjoint routes so that RN can serve in one particular route and not others.

Node-disjoint routes in EH-WSNs possess two unique properties, namely, not having any common SN nor link among all the detected routes. The main advantage of these characteristics lies in the fact that failure of any SN or link in a group of these routes can affect the particular route in that when a failure of any SN or link occurs the other routes are not affected. The second advantage of node-disjoint routes in EH-WSNs is related to maximizing aggregated network resources. These two advantages make node-disjoint routes in EH-WSNs a preferred choice as compared with link-disjoint and partially disjoint routes. Also, it should be noted that it is always a challenging task to explore the large set of node-disjoint routes between SNs and BS since SNs are usually deployed randomly. On the other hand, several common SNs may occur in link-disjoint routes but no shared link is allowed between the routes is the main unique property of these types of routes. Therefore, any SN failure in these types of routes may affect (deactivate) multiple routes, since a failed SN may be shared with multiple routes. Furthermore, partially disjoint routes can be easily constructed since these types of routes have multiple routes in which several links or SNs between the distinct routes may be shared. Therefore, in these types of partially disjoint routes, failure of any link or SN in a group of these routes may have an impact on multiple other routes. For the performance requirements, the density of the network for the particular application is the key factor in taking the best decision for selecting the particular category of disjoint routes.

Furthermore, the minimum delay is another requirement for optimal performance of EH-WSNs that can be achieved with the help of the shortest route, since it uses the minimum hops. Further, the routing routes should be as short as possible in EH-WSNs since shorter routing routes result in lower consumption of energy; also, packets delays are always minimum in shorter routing routes, and consequently the lifetime of the network as well as data-delivery ratio will be enhanced. In a multipath routing framework with multiple sources, the density of the RNs should be high towards the BS side compared to the SN side. Therefore, there is a need for careful selection of the distribution strategies for RNs, as the most appropriate distribution strategy for RNs is a controlled random distribution strategy with a non-uniform nature.

The proposed novel framework utilized three metaheuristic optimization algorithms, namely grey wolf optimizer, sine cosine optimizer, and whale optimizer. It should be noted that metaheuristic algorithms are considered a specific category of stochastic algorithms and the unique features of these algorithms are that they are problem-independent techniques. The names of the two pillars of stochastic algorithms are exploration or diversification, and exploitation or intensification. Further, the exploration or diversification component aims at exploring the search space while the exploitation or intensification component aims at searching a near-optimal solution. These are the main powerful attributes of these metaheuristic algorithms. There are three classifications of metaheuristics algorithms, such as swarm intelligence algorithms, physics-based, and evolutionary algorithms. In the stage of exploration, the complete solution space is covered by the search agents with the help of their unique style of random walk. Next, at the stage of exploitation, a local search is carried out with a focused approach for candidate position by covering only a particular part of the solution space. There does not exist any predefined way in which these algorithms can work and therefore their approach is similar to the black-box approach in which we do not have awareness of the internal structure; instead, we give input and get output. Metaheuristic algorithms such as Ant Colony Optimization (ACO), Moth Flame Optimization (MFO), Interior Search Algorithm (ISA), Tabu Search (TS), Whale Optimization Algorithm (WOA), Simulated Annealing (SA), Plant Propagation Algorithm, Genetic Algorithm (GA), Firefly Algorithm, Grey Wolf Optimization (GWO), Cuttlefish Algorithm, Bat Algorithm, Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Cuckoo Search (CS), Sine Cosine Algorithm (SCA), and Intelligent Weeds Optimization (IWO), etc., have a discrete nature, and therefore these metaheuristics algorithms are suitable for solving discrete-type NP-hard as well as NP-complete optimization problems.

Next, Figure 1. illustrates the phases of the proposed novel framework with steps taken in each phase. The proposed novel framework comprises two phases. In the first phase of the proposed novel framework, maximum node-disjoint routes from all the SNs to BS using minimum RNs are explored based on the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework, utilizing the properly designed efficient fitness function, and this HA-GWSCO framework also discovers k-node-disjoint routes from each SN to BS, with $k \geq 2$, which enhances the fault-tolerance capability in EH-WSN. The first phase starts by initializing the EH-WSN. Next, RNs are deployed by adopting the strategy of a controlled random distribution with non-uniform nature. The efficient fitness function is designed and then the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework is applied. The output of this hybrid framework is the maximum number of node-disjoint routes from all SNs to BS in EH-WSN using the least number of RNs and k-node-disjoint routes from each SN to BS. This output is given as input to the second phase of the proposed novel framework. The aim of the second phase is to discover the most appropriate reliable route out of k-node-disjoint routes from each SN to BS. In the second phase of the proposed novel framework, out of k-node-disjoint routes from each SN to BS, with $k \geq 2$, the most appropriate, reliable route is selected from each SN to BS for routing, which enhances the reliability in routing for EH-WSN based on hybrid adapted grey wolf whale optimizer (HA-GWWO). Utilizing a novel and efficient fitness function covering multiple objective functions, the newly designed efficient fitness function consists of six objective functions, namely, the remaining available energy of the SNs, the distance of the edge, the energy consumption of the edge, delay in communication for the node, relay hops, and also the reliability index.

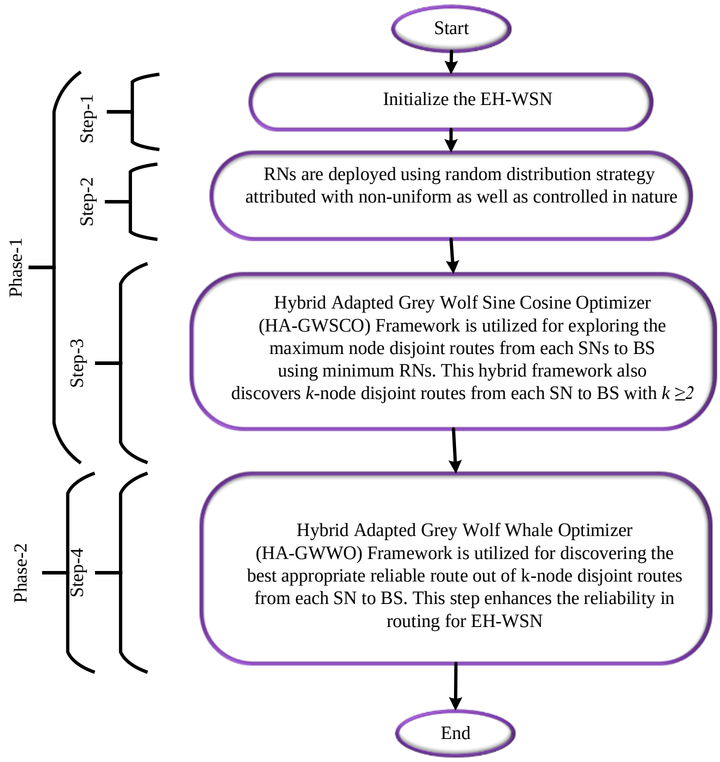


Figure 1. A proposed framework consisting of two phases.

3.1. System Modelling

There are various advantages to deploying the relay nodes between SNs in EH-WSNs, namely, network life enhancement by reducing energy consumption, reduced latency, optimal connectivity, optimal load distribution by relieving the overloaded SNs, etc. Further, optimal connectivity can be ensured by verifying the inter-node reachability, particularly in the disjoint segments of the EH-WSNs. The ultimate aim of deploying the relay nodes is to enable or improve the reachability in the EH-WSNs, where relay nodes perform the designated task by relaying the data collected by the SNs. Next, we will discuss the various components in the system model in pointwise fashion. Table 1 depicts the various symbols used in the system modeling along with their descriptions.

Table 1. Symbols with descriptions.

SN_{set}	It represents the set of SNs in $EH-WSN$ where SNs stands for source nodes/sensor nodes and $SN_{set} = \{SN_1, SN_2, \ldots\ldots\ldots SN_c\}$
$\lvert SN_{set}\rvert$	The number of SNs in EH-WSN
$R_{SN_{set}}$	The set of node-disjoint routes which are existing between all the SNs and BS.
$\lvert R_{SN_{set}}\rvert$	The number of $node-disjoint$ routes in $EH-WSN$. Also, $\lvert R_{SN_{set}}\rvert = \lvert SN_{set}\rvert * k$ with $k \geq 2$.
RN_{set}	It represents the set of relay nodes and $RN_{set} = \{RN_1, RN_2, \ldots, RN_d\},\ d < c$
$\lvert RN_{set}\rvert$	The number of RNs in EH-WSN
SN_i	One of the sensor node/source node in SN_{set}
BS	Sink Node/Base Station in EH-WSN
RN_{CL}	A set representing candidate locations for RNs placement
$Energy_{harvest}^{max}$	Maximum harvested energy by the RN
$Weight_{RN}^{CL}$	It represents the weight of RN for a particular candidate location and $CL \in RN_{CL}$
SN_{state}	The state information of all the sensor nodes/source nodes in EH-WSN
$R_{set(SN_i,\ BS)}$	The set of all the $node-disjoint$ routes between sensor node/source node SN_i and BS
$\left\lvert R_{set(SN_i,\ BS)}\right\rvert$	The number of $node-disjoint$ routes between sensor node/source node SN_i and BS and $\left\lvert R_{set(SN_i,\ BS)}\right\rvert \leq k$
k	k is an integer and $k \geq 2$, $node-disjoint$ routes between each sensor node/source node SN_i and BS
$R_j(SN_i, BS)$	The jth $node-$ disjoint route between sensor node/source node SN_i and BS and $(1 \leq i \leq \lvert SN_{set}\rvert),\ (1 \leq j \leq k)$
SN_e	A sensor node in $R_j(SN_i, BS)$ and $SN_e \in R_j(SN_i,\ BS)$
l	The direct edge between any two adjacent sensor nodes in $R_j(SN_i, BS)$ and $l \in R_j(SN_i,\ BS)$
$RN_{(BS)}$	Base Station neighboring relay nodes
$A(RN_{(BS)})$	The approximate number of base station neighboring relay nodes
$RN_{(SN_i)}$	Source Node/Sensor Node (SN_i) neighboring relay nodes
$A\left(RN_{(SN_i)}\right)$	The approximate number of source node/sensor node (SN_i) neighboring relay nodes
CL	Candidate Location
$Energy^{CL}$	Energy harvested at particular candidate location
$Range_{SN}$	Range of sensor node
$Range_{RN}$	Range of relay node
$CM_{(SN_i,\ SN_j)}$	Connectivity matrix between ith sensor node SN_i and jth sensor node SN_j
RE_{Avl}	Remaining available energy
$Energy\_Consumption_l$	Energy
$hop_{(R_j(SN_i,BS))}$	The hop counts in jth $node-disjoint$ route between ith source node SN_i and BS
$hop_{(R_{set(SN_i,\ BS)})}$	The hop counts in the set of all the $node-disjoint$ routes between ith source node SN_i and BS
$delay(SN_e)$	Delay in communication for the sensor node $SN_e,\ SN_e \in R_j(SN_i, BS)$
$delay(SN)$	Delay in communication for the sensor node $SN,\ SN \in R_{set(SN_i,\ BS)}$
RI	Reliability Index
$Reliability_l$	Link Reliability
BSRI	Best Suitable Route Index

The EH-WSN is deployed in a two-dimensional area and the single-tiered network topology is considered for deploying EH-WSN. The collector node/sink node or base station is placed at predetermined location in EH-WSN. The positions of the SNs are also fixed in EH-WSN; we are trying to get the optimal locations by deploying the relay nodes. Consider RN_{CL} for representing the set of candidate locations for RN placement, and where $Energy^{max}_{harvest}$ represents the maximum energy that RN can harvest. Further, we need to find the weight of RN ($Weight^{CL}_{RN}$) considering the particular candidate location (CL) for optimal placement, as represented by Equation (1).

$$Weight^{CL}_{RN} = \frac{Energy^{max}_{harvest} - Energy^{CL}}{Energy^{max}_{harvest}} + 1 \tag{1}$$

Here, $CL \in RN_{CL}$, $0 \leq Energy^{CL} \leq Energy^{max}_{harvest}$, $Weight^{CL}_{RN} \in [1,2]$, and $Energy^{CL}$ represent the energy harvested at the selected candidate location (CL)

The candidate locations having a higher potential for harvesting the energy should have lower weights and these candidate locations are selected for optimal placement of the RNs. Further, the collector node/sink node or base station is designated for accessing the complete network information through a centralized mechanism, such as the node's position, executing the algorithm for finding the optimal locations of the relay nodes, etc. The deployed EH-WSNs become disjoint after a certain period, and this situation can be announced after analyzing the aggregate data collected at the BS. $Range_{SN}$, $Range_{RN}$ are the sensing range of the SN and RN, respectively, with the condition of $Range_{RN} = 2* \ Range_{SN}$.

Let SN_{set} denote the set of SNs that are deployed in a two-dimensional area and $SN_{set} = \{SN_1, SN_2, \ldots\ldots\ldots SN_c\}$. Similarly, RN_{set} represents the set of relay nodes and $RN_{set} = \{RN_1, RN_2, \ldots, RN_d)$ that are required for maintaining effective connectivity in the EH-WSN, with $c > d$.

The Euclidean distance ($euclidean\_distance$) between the two sensor nodes (SN_i, SN_j) can be calculated by using the following equation:

$$euclidean\_distance_{(SN_i,\ SN_j)} = \sqrt{\left(SN_i - SN_j\right)^2 + \left(SN_i - SN_j\right)^2} \tag{2}$$

Furthermore, it is considered that the sensor nodes SN_i *and* SN_j are connected if

$$euclidean\_distance_{(SN_i,\ SN_j)} \leq Range_{SN} \tag{3}$$

$Range_{SN}$ represents the range of sensor node.

Similarly, it is considered that sensor node SN_i is connected to relay node RN_j and $d < c$, if

$$euclidean\_distance_{(SN_i,\ SN_j)} \leq Range_{RN} \tag{4}$$

$Range_{RN}$ represents the range of relay node.

Next, the connectivity matrix (CM) can be represented as

$$CM_{(SN_i,\ SN_j)} = \begin{cases} 1,\ if\ SN_i,\ SN_j\ are\ coonected\ and\ i \neq j \\ 0, \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{5}$$

$CM_{(SN_i,\ SN_j)}$ represents the connectivity matrix between the *ith* sensor node SN_i and *jth* sensor node SN_j.

3.2. Phase 1: Exploring the Maximum Node-Disjoint Routes from All SNs to BS Using the Least RNs Based on the Hybrid Adapted Grey Wolf Sine Cosine Optimizer (HA-GWSCO) in EH-WSN

In the proposed scheme, we have assumed a controlled random approach that is used for deploying the sensor nodes in the two-dimensional area, and the locations of deployment are decided on by collector node (CN), also known as the sink node or base station (BS). Whenever one or more SN(s) is/are unable to maintain proper communication with the BS through intermediate SNs, due to the dead conditions, then the RNs come to the picture, which are deployed by adopting a control random approach with a non-uniform nature to maintain the proper flow of data by maintaining the optimal connectivity. In the first phase of the proposed scheme, we have used two metaheuristic optimization algorithms, namely, the grey wolf optimizer and sine cosine optimizer, for designing the hybrid framework, named the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO), for exploring the maximum node-disjoint routes from all SNs to BS in the EH-WSN; this hybrid framework also discovers k-node-disjoint routes from each SN to BS, with $k \geq 2$, which enhances the fault-tolerance capability in EH-WSN. This hybrid framework utilizes the fitness function as described by Equation (6) below.

In EH-WSN, the maximum approximate number of node-disjoint routes $max\{A(|R_{SN_{set}}|)\}$ that exists between all the SNs $(|SN_{set}|)$ and BS utilizing the least number of RNs can be determined by Equation (6).

$$max\{A(|R_{SN_{set}}|)\} \geq min\left\{A(RN_{(BS)}),\ \sum_{i=1}^{|SN_{set}|} A\left(RN_{(SN_i)}\right)\right\} \tag{6}$$

subject to

$$\begin{cases} A\left(RN_{(SN_i)}\right) \geq k\ if\ all\ the\ SNs\ are\ having\ same\ number\ of\ \ k-node\ disjoint\ routes \\ A(RN_{(BS)}) \geq A\left(RN_{(SN_i)}\right) * (|SN_{set}|) \end{cases} \tag{7}$$

Equation (6) is assumed as the fitness function for exploring all possible maximum approximate number of node-disjoint routes $max\{A(|R_{SN_{set}}|)\}$ that exists between all the SNs $(|SN_{set}|)$ and BS utilizing the least number of RNs.

Now, we will illustrate the role of the adapted GWO and adapted SCO metaheuristic optimization algorithms. The natural hunting procedure, as well as the leadership hierarchy of grey wolves, are the two main pillars of the population-based grey wolf optimization (GWO) algorithm. In this proposed research, the hybrid framework, having GWO and SCO, is used for solving the relay node optimization problem, which is considered an NP-hard optimization problem. This hybrid optimization framework enhances the convergence performance of the adapted grey wolf optimizer. Further, by boosting the exploitation stage, the best optimal solution can be found.

The results of this hybrid optimization framework represent excellence in terms of robustness and ability to solve the NP-hard relay node optimization problem. The hybrid optimization framework considers the three best candidate solutions as alpha (∝) (representing the first candidate solution), beta (β) (representing the second candidate solution), and delta (δ) (representing the third candidate solution) in the course of the exploitation phase. The positions of the other search agents are modified to conform to alpha (∝), beta (β), and delta (δ), which are assumed as the positions of the best search agents. In the subsequent sections, we explain the adapted grey wolf optimizer, sine cosine optimizer, and then the hybrid version in detail.

3.2.1. Adapted Grey Wolf Optimizer

The natural hunting behavior and leadership hierarchy of grey wolves are the sources of inspiration for the adapted grey wolf optimization framework [2,45]. This optimizer was originally proposed by Mirjalili [46].

The mathematical model of the adapted grey wolf optimization framework has five main components, namely, the leadership hierarchy of grey wolves, method of the prey's encircling, the procedure of searching the prey, mechanism of attacking the prey, and finally the hunting mechanism. We will explain each component one by one in the next paragraph.

The leadership hierarchy of grey wolves consists of three main categories of grey wolves: the first category is known as alpha (∝), the next category is known as beta (β), and delta (δ) is known as the third category. Further, the wolves represented as alpha (∝) are considered as the leaders of the grey wolf community. The beta (β) wolves are designated as the second-level leaders of the grey wolves, while the delta (δ) wolves are the third-level leaders.

Grey wolves adopted the mechanism of encircling the prey for hunting, and the following equations mathematically represent this scenario.

$$\vec{Z} = \left| \vec{Y}.\vec{W}_{prey}(t) - \vec{W}(t) \right| \tag{8}$$

$$\vec{W}(t+1) = \vec{W}_{prey}(t) - \vec{O}.\vec{Z} \tag{9}$$

In the above equation, the position vector of the prey, as well as the grey wolf, is represented by $\vec{W}_{prey}$ and $\vec{W}$, respectively; also, in the mathematical model, t represents the current iteration.

The following equations are used to find the value for two vectors $\vec{O}$ and $\vec{N}$.

$$\vec{O} = 2\vec{g}.\vec{random}_1 - \vec{g} \tag{10}$$

$$\vec{Y} = 2.\vec{random}_2 \tag{11}$$

Here, the random vectors in the range [0, 1] are represented by $\vec{random}_1$ and $\vec{random}_2$; also, parameter $\vec{g}$ is linearly decreased from 2 to 0.

Further, the hunting procedure of the grey wolves is mathematically modeled in the below equations.

$$\vec{Z}_{\propto} = \left| \vec{Y}_1.\vec{W}_{\propto} - \vec{W} \right|,\ \vec{Z}_{\beta} = \left| \vec{Y}_2.\vec{W}_{\beta} - \vec{W} \right|,\ \vec{Z}_{\delta} = \left| \vec{Y}_3.\vec{W}_{\delta} - \vec{W} \right| \tag{12}$$

$$\vec{W}_1 = \vec{W}_{\propto} - \vec{O}_1.\vec{Z}_{\propto},\ \vec{W}_2 = \vec{W}_{\beta} - \vec{O}_2.\vec{Z}_{\beta} / \vec{W}_3 = \vec{W}_{\delta} - \vec{O}_3.\vec{Z}_{\delta} \tag{13}$$

$$\vec{W}(t+1) = \frac{\vec{W}_1 + \vec{W}_2 + \vec{W}_3}{3} \tag{14}$$

Next, the condition for attacking the prey is $\left|\vec{O}\right| < 1$. Now, the grey wolves start moving to attack the prey. The condition for searching the prey is $\left|\vec{O}\right| > 1$. Now, the grey wolves start moving away from the prey to search for more competent prey.

3.2.2. Adapted Sine Cosine Optimizer (SCO)

The adapted sine cosine optimizer (SCO) is based on sine and cosine functions [47]. This optimizer was originally proposed by Mirjalili [48]. It is basically applied in global optimization functions for phases of exploitation and exploration. Initially, it generates multiple random solutions and these random solutions show fluctuations, either outwards or towards the best possible solution. This complete mechanism utilized the sine and cosine functions-based mathematical model, as shown by Equations (15) and (16).

$$\vec{W}_i(t+1) = \vec{W}_i(t) + \varphi_1 * \sin(\varphi_2) * \left| \varphi_3 * l_i(t) - \vec{W}_i(t) \right| \tag{15}$$

$$\vec{W}_i(t+1) = \vec{W}_i(t) + \varphi_1 * \cos(\varphi_2) * \left| \varphi_3 * l_i(t) - \vec{W}_i(t) \right| \tag{16}$$

The current position is represented by $\vec{W}_i(t)$; $\varphi_1,\ \varphi_2$, and φ_3 are random numbers $\in [0,1]$, and the targeted global optimal solution is represented by l_i. The conditions $0.5 \leq \varphi_4 < 0.5$ are also used in Equations (15) and (16) for representing the phases of exploitation and exploration, respectively.

$$\vec{W}_i(t+1) = \begin{cases} \vec{W}_i(t) + \varphi_1 * \sin(\varphi_2) * \left| \varphi_3 * l_i(t) - \vec{W}_i(t) \right|, \ \varphi_4 < 0.5 \\ \vec{W}_i(t) + \varphi_1 * \cos(\varphi_2) * \left| \varphi_3 * l_i(t) - \vec{W}_i(t) \right|, \varphi_4 \geq 0.5 \end{cases} \tag{17}$$

3.2.3. Hybrid Adapted Grey Wolf Sine Cosine Optimizer (HA-GWSCO) Framework for Finding the Maximum Node-Disjoint Routes from All SNs in EH-WSN

The main characteristics of these optimizers, namely, the adapted GWO and SCO, are the efficient accuracy. These optimizers usually show efficient performance in providing solutions to various optimization problems when compared with well-known other swarm intelligence optimization frameworks. Further, various pieces of literature attest to this claim. The only limitations of these optimizers belong to the fact that these are somehow not suitable for handling highly complex functions; also, the second limitation belongs to the phenomenon of getting trapped in local optima. For effectively handling these limitations, a hybrid version [49] is required. The hybrid version enhances the overall searching capability of the framework and consequently can provide the best optimal solutions to complex optimization problems. Now, this hybrid framework is called the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO).

In the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework, the sine cosine optimizer plays a major role in improving the movement of the alpha (∝) wolves of the grey wolf optimizer since for the grey wolves community, these wolves are assumed as the leaders. The beta (β) wolves are designated as the second-level leaders of the grey wolves, while the delta (δ) ones are the third-level leaders. Therefore, the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework has achieved robust search capabilities, and consequently the mechanism behind the global convergence, exploration, and exploitation is enhanced.

From the above discussion, it is clear that the ultimate aim of the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework is to replace the worst results in finding a new population based on an individual approach, since this hybrid framework results in efficient accuracy. There are mainly three procedures (see Equations (18) and (19)) responsible for enhancing the capability of the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework for finding the efficient solution of maximum node-disjoint routes utilizing the minimum RNs from SNs to BS. Next, Figure 2 illustrates Phase 1 of the proposed framework consisting of HA-GWSCO.

Consider the position update equation (Equation (17)) of the adapted SCO; this position update equation is applied in enhancing the position, speed, and convergence accuracy of the alpha ($\propto$) grey wolves of the adapted SCO. This step is taken for maintaining an effective balance between the phases of exploration and exploitation. Further, this step also helps in extending the convergence performance of the adapted grey wolf optimizer framework. The following equations are developed for updating the positions of the alpha ($\propto$) grey wolves.

$$\vec{Z}_\propto = \begin{cases} \varphi_5 * \sin(\varphi_5) * \left| \vec{Y}_1 * \vec{W}_\propto - \vec{W} \right|, \ \varphi_5 < 0.5 \\ \varphi_5 * \cos(\varphi_5) * \left| \vec{Y}_1 * \vec{W}_\propto - \vec{W} \right|, \varphi_5 \geq 0.5 \end{cases} \tag{18}$$

$$\vec{W}_1 = \vec{W}_\propto - \vec{O}_1 * \left(\vec{W}_\propto \right) \tag{19}$$

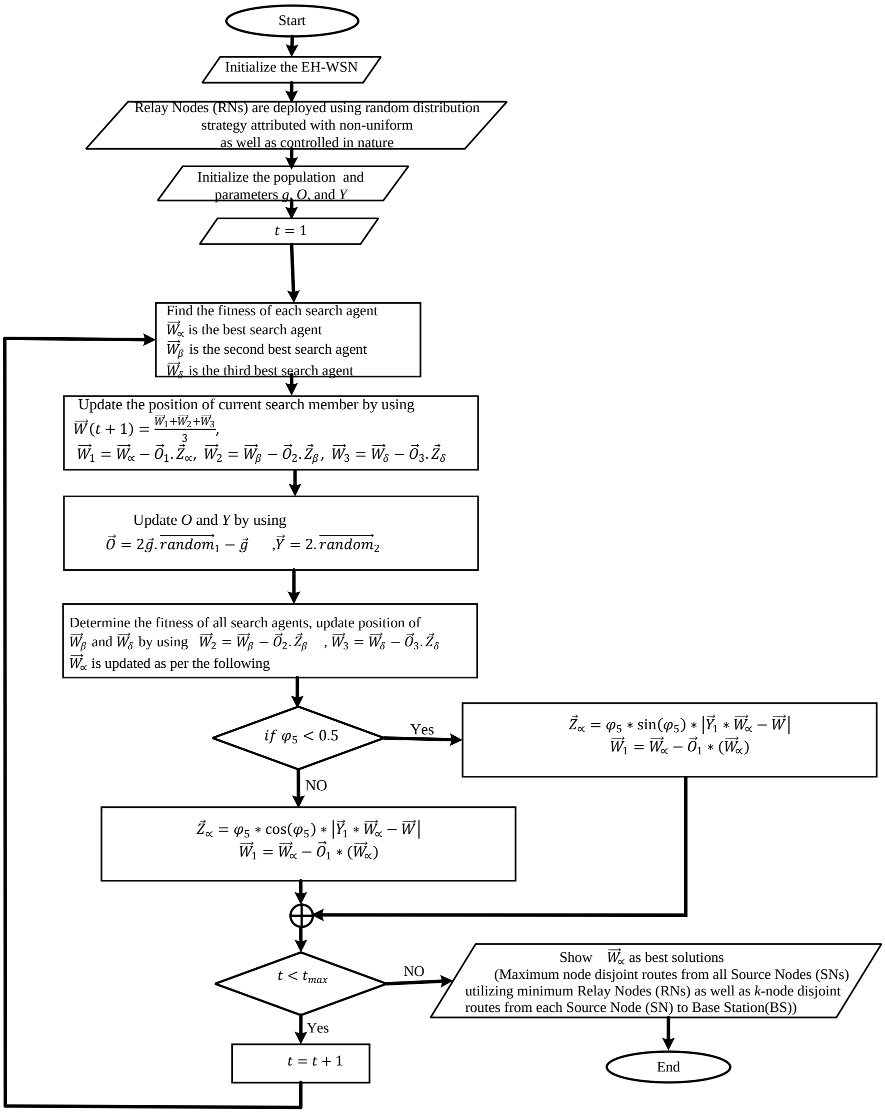


Figure 2. Phase 1 of the proposed framework consisting of the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework.

3.3. Phase 2: Discovering the Most Appropriate and Reliable Route from the k-Node-Disjoint Routes between Each SN to BS Based on the Hybrid Adapted Grey Wolf Whale Optimizer (HA-GWWO) Framework

A sustainable and energy-efficient wireless system is the need of the hour for next-generation green communication since sensors are mainly suffering from limited energy availability caused by limited battery capacity. Prolonging the network lifetime has been an evergreen research area for researchers from the last few decades, and efforts are still ongoing to design energy-efficient frameworks for routing in wireless systems. Energy harvesting techniques have emerged as a solution for handling energy scarcity issues of sensors. In this technique, energy is harvested from RF, vibration, thermal, and solar, etc., by utilizing an energy-harvesting component. In the energy-harvesting wireless sensor networks (EH-WSNs), the dead nodes become alive and resume their operation with the help of harvested energy; in this way the life of the network can be extended without bound. It is a fact that during real-time applications, many unavoidable incidents may occur due to difficult environmental conditions, which results in the breakdown of communication links, malfunctioning of sensor nodes, and partitioning of the network. Therefore, the network functions can be severely disrupted. In these real-time scenarios, the success of green communications majorly depends on the fault-tolerance feature, which has become a critical issue for next-generation wireless systems. Further, in the energy-harvesting environment, the time-varying, unstable, and random nature of the harvested energy may compel the nodes to fail. Furthermore, due to this random nature of the harvested energy, the nodes' lifecycle frequently switches between alive and dead, which results in dynamic changes in the quality of the routing. Fault-tolerant routing with awareness of the quality of routing is the only solution for the optimal performance of EH-WSN. Towards enabling fault-tolerant routing, the first step is to establish the multi-node/link disjoint routes, comparing these with the previous route as well as all other alternative routes. In this mechanism, the failure in the previous route due to the breakdown of any or all nodes/links has no impact on the alternative routes. In the proposed framework, we are maintaining the *k*-node-disjoint routes from each SN to BS by applying the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework in the first phase of the proposed framework. Furthermore, in the second phase, we have designed the enhanced fitness function, named the best suitable route index (BSRI), to select the most reliable node-disjoint route from each SN_i to BS out of available *k*-node-disjoint routes by utilizing the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework. The fitness function consists of various effective objective functions, namely, the first function, representing the remaining available energy of each node in a particular route from SN_i to BS; the second function, representing the distance of the edge between the adjacent nodes; the third function, representing the energy consumption of the edge between the adjacent nodes; the fourth function, representing the delay in communication for the node; the fifth function, representing relay hops for the packet in each route; and, finally, the sixth function, representing the reliability index of the particular route from SN to BS. The route with the higher best suitable route index (BSRI) is selected for routing from each SN to BS out of the available *k*-node-disjoint routes utilizing the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework. In the proposed framework, we have estimated the quality of the route by effectively designing the fitness functions, covering the all-important metrics for assessing the route suitability for routing that rarely have been considered in the literature for EH-WSN.

Next, we are going to explain the six objective functions one by one, as below.

The objective function representing the remaining available energy of each node in the node-disjoint route $R_j(SN_i, BS)$ from SN_i to BS $\left(f_{Energy^{R_j(SN_i,BS)}_{(RE_{Avl})}}\right)$ is represented by (f_1) in Equation (21).

$$f_{Energy^{R_j(SN_i,BS)}_{(RE_{Avl})}} = \frac{\sum_{SN_e \in R_j(SN_i,BS)} Energy^{SN_e}_{(RE_{Avl})}}{\sum_{SN \in R_{set(SN_i,\ BS)}} Energy^{SN}_{(RE_{Avl})}} \tag{20}$$

Here, RE_{Avl} shows the remaining available energy, $R_j(SN_i, BS)$ represents the *jth* node-disjoint route between the *ith* source node SN_i and BS, $R_{set(SN_i,\ BS)}$ reflects the set of all the node-disjoint routes between the *ith* source node SN_i and BS, SN_e is one of the sensor nodes in the *jth* node-disjoint route $R_j(SN_i, BS)$, i.e., $SN_e \in R_j(SN_i, BS)$, and SN is one of the sensor nodes in the set of all the node-disjoint routes between the *ith* source node SN_i and BS, i.e., $SN \in R_{set(SN_i,\ BS)}$.

$f_{Energy^{R_j(SN_i,BS)}_{(RE_{Avl})}}$ is the ratio of the remaining available energy ($Energy^{SN_e}_{(RE_{Avl})}$) of each node $SN_e \in R_j(SN_i, BS)$ in route $R_j(SN_i, BS)$ from SN_i to BS to keep the remaining available energy ($Energy^{SN}_{(RE_{Avl})}$) of each node $SN \in R_{set(SN_i,\ BS)}$ in the set of all node-disjoint routes from SN_i to BS.

$f_{Energy^{R_j(SN_i,BS)}_{(RE_{Avl})}}$ should be maximum for improved life of the wireless system.

Hence,

$$f_1 = f_{Energy^{R_j(SN_i,BS)}_{(RE_{Avl})}} \tag{21}$$

Next, the second objective function representing the distance of the edge $distance(l)$ between the adjacent nodes in the node-disjoint route $R_j(SN_i, BS)$ from SN_i to BS $\left(f_{distance(l)^{R_j(SN_i,BS)}}\right)$ is represented by (f_2) in Equation (23).

$$f_{distance(l)^{R_j(SN_i,BS)}} = \frac{\sum_{l \in R_j(SN_i,BS)} distance(l)}{\sum_{l \in R_{set(SN_i,\ BS)}} distance(l)} \quad (22)$$

Here, $l \in R_j(SN_i, BS)$ reflects the edge in the *jth* node-disjoint route between *ith* source node SN_i and BS, $l \in R_{set(SN_i,\ BS)}$ represents edge in the set of all the node-disjoint routes between *ith* source node SN_i and BS, $distance(l)$ shows the distance of the edge.

$f_{distance(l)^{R_j(SN_i,BS)}}$ is the ratio of the distance of the edge $distance(l)$ between adjacent nodes in the route $R_j(SN_i, BS)$ from SN_i to BS to the distance of the edge $distance(l)$ between adjacent nodes in the set of all node-disjoint routes $R_{set(SN_i,\ BS)}$ from SN_i to BS.

$f_{distance(l)^{R_j(SN_i,BS)}}$ should be the minimum for optimal performance of the wireless system.

Hence,

$$f_2 = \frac{1}{f_{distance(l)^{R_j(SN_i,BS)}}} \quad (23)$$

Further, the third objective function representing the energy consumption of the edge l ($Energy\_Consumption_l$) between adjacent nodes in the node-disjoint route $R_j(SN_i, BS)$ from SN_i to BS ($f_{Energy\_Consumption_l^{(R_j(SN_i,BS))}}$) is represented by (f_3) in Equation (25).

$$f_{Energy\_Consumption_l^{(R_j(SN_i,BS))}} = \frac{\sum_{l=1}^{hop_{(R_j(SN_i,BS))}} Energy\_Consumption_l}{\sum_{l=1}^{hop_{(R_{set(SN_i,\ BS)})}} Energy\_Consumption_l} \quad (24)$$

Here, $hop_{(R_j(SN_i,BS))}$ represents the hop counts in the *jth* node-disjoint route between the *ith* source node SN_i and BS, and $hop_{(R_{set(SN_i,\ BS)})}$ reflects the hop counts in the set of all the node-disjoint routes between the *ith* source node SN_i and BS.

$f_{Energy\_Consumption_l^{(R_j(SN_i,BS))}}$ is the ratio of the energy consumption of the edge ($Energy\_Consumption_l$) between adjacent nodes in the node-disjoint route $R_j(SN_i, BS)$ from SN_i to BS to the energy consumption of the edge ($Energy\_Consumption_l$) between adjacent nodes in the set of all node-disjoint routes $R_{set(SN_i,\ BS)}$ from SN_i to BS.

$f_{Energy\_Consumption_l^{(R_j(SN_i,BS))}}$ should be minimum for optimal performance of the wireless system.

Hence,

$$f_3 = \frac{1}{f_{Energy\_Consumption_l^{(R_j(SN_i,BS))}}} \quad (25)$$

Furthermore, the fourth objective function representing delay in communication for the node $SN_e \in R_j(SN_i, BS)$ in the route $R_j(SN_i, BS)$ from SN_i to BS $\left(f_{delay_{SN_e}^{R_j(SN_i,BS)}}\right)$ is represented by (f_4) in Equation (27).

$$f_{delay_{SN_e}^{R_j(SN_i,BS)}} = \frac{\sum_{SN_e \in R_j(SN_i,BS)} delay(SN_e)}{\sum_{SN \in R_{set(SN_i,\ BS)}} delay(SN)} \quad (26)$$

Here, $delay(SN_e)$ represents a delay in communication for the sensor node SN_e, $SN_e \in R_j(SN_i, BS)$, since SN_e is the sensor node in the *jth* node-disjoint route between the *ith* source node SN_i and BS. Similarly, $delay(SN)$ reflects a delay in communication for the sensor node SN, $SN \in R_{set(SN_i,\ BS)}$, since SN is the sensor node in the set of all the node-disjoint routes between the *ith* source node SN_i and BS.

$f_{delay_{SN_e}^{R_j(SN_i,BS)}}$ is the ratio of delay in communication for the node $SN_e \in R_j(SN_i, BS)$ in the route $R_j(SN_i, BS)$ from SN_i to BS to the delay in communication for the node $SN \in R_{set(SN_i,\ BS)}$ in the set of all node-disjoint routes $R_{set(SN_i,\ BS)}$ from SN_i to BS.

$f_{delay_{SN_e}^{R_j(SN_i,BS)}}$ should be minimum for optimal performance of the wireless system.

Hence,

$$f_4 = \frac{1}{f_{delay_{SN_e}^{R_j(SN_i,BS)}}} \tag{27}$$

Furthermore, the fifth objective function representing relay hops for the packet in the route $R_j(SN_i, BS)$ from SN_i to BS $\left(f_{hop^{R_j(SN_i,BS)}}\right)$ is represented by (f_5) in Equation (29).

$$f_{hop^{R_j(SN_i,BS)}} = \frac{hop\left(R_j(SN_i, BS)\right)}{\sum_{j=1}^{k} hop\left(R_j(SN_i, BS)\right)} \tag{28}$$

$f_{hop^{R_j(SN_i,BS)}}$ is the ratio of the relay hops for the packet in the route $R_j(SN_i, BS)$ from SN_i to BS to the hops for the packet in the set of all node-disjoint routes $R_{set(SN_i,\ BS)}$ from SN_i to BS.

$f_{hop^{R_j(SN_i,BS)}}$ should be minimum for optimal performance of the wireless system.

Hence,

$$f_5 = \frac{1}{f_{hop}} \tag{29}$$

The sixth objective function representing the reliability index (RI) of the particular route $R_j(SN_i, BS)$ from SN_i to BS $\left(f_{RI^{(R_j(SN_i,BS))}}\right)$ is represented by (f_6) in Equation (31).

$$f_{RI^{(R_j(SN_i,BS))}} = \frac{\sum_{l=1}^{hop_{(R_j(SN_i,BS))}} Reliability_l}{\sum_{l=1}^{hop_{(R_{set}(SN_i,BS))}} Reliability_l} \tag{30}$$

Here, $hop_{(R_j(SN_i,BS))}$ represents the hop counts in the *jth* node-disjoint route between the *ith* source node SN_i and BS, and $hop_{(R_{set(SN_i,\ BS)})}$ reflects the hop counts in the set of all the node-disjoint routes between the *ith* source node SN_i and BS.

$f_{RI^{(R_j(SN_i,BS))}}$ is the ratio of the link reliability $(Reliability_l)$ in the route $R_j(SN_i, BS)$ from SN_i to BS to the link reliability $(Reliability_l)$ of the set of all node-disjoint routes $R_{set(SN_i,\ BS)}$ from SN_i to BS.

Here, link reliability $(Reliability_l)$ is expressed in terms of the signal-to-noise ratio (SNR) and f_{RI} should be maximum.

Hence,

$$f_6 = f_{RI} \tag{31}$$

Finally, the best suitable route index (BSRI) of the particular route $R_j(SN_i, BS)$ from SN_i to BS $\left(R_j(SN_i, BS)_{BSRI}\right)$ is represented by Equation (32).

$$R_j(SN_i, BS)_{BSRI} = \left(\frac{\psi_1 * f_1 + \psi_2 * f_2 + \psi_3 * f_3 + \psi_4 * f_4 + \psi_5 * f_5 + \psi_6 * f_6}{6}\right) \tag{32}$$

Further, the best suitable route index (BSRI) of the particular route $R_j(SN_i, BS)$ from SN_i to BS is represented as $R_j(SN_i, BS)_{BSRI}$, which is the maximum for the node-disjoint route, and which is selected as the best suitable node-disjoint route for routing out of k-node-disjoint routes from SN_i *to* BS.

Here,

$$\psi_1 = 0.25,\ \psi_2 = 0.10,\ \psi_3 = 0.20,\ \psi_4 = 0.10,\ \psi_5 = 0.10,\ \text{and}\ \psi_6 = 0.25 \tag{33}$$

are weight factors.

Furthermore,

$$(\psi_1 + \psi_2 + \psi_3 + \psi_4 + \psi_5 + \psi_6) = 1 \tag{34}$$

Finally, we can define the fitness function (ff) as shown by Equation (35) below.

$$ff = \sum_{i=1}^{|SN_{set}|} \left\{ \sum_{j=1}^{k} \max\left(R_j(SN_i, BS)_{BSRI}\right) \right\} \tag{35}$$

3.3.1. Adapted Whale Optimizer

The natural social activity of humpback whales is the source of inspiration for the adapted whale optimization framework [50]. Wales have a unique hunting procedure known as bubble-net attacking. In this procedure, distinctive bubbles are created along a circle. This optimizer is originally proposed by Mirjalili [51].

The mathematical model of the adapted whale optimization framework has three main components, namely, the mechanism of encircling the prey, a unique attacking mechanism known as the bubble-net method, and the procedure of searching for prey. We will explain each component one by one in the next paragraph.

The humpback whales start encircling their prey and update their position for finding the best optimal solution during iterations. This is mathematically modeled by the following equations.

$$\vec{Z} = \left| \vec{Y}.\vec{W}_{prey}(t) - \vec{W}(t) \right| \tag{36}$$

$$\vec{W}(t+1) = \vec{W}_{prey}(t) - \vec{O}.\vec{Z} \tag{37}$$

Further, the humpback whales adopted a bubble-net attacking procedure for attacking the prey, and this procedure is represented by two approaches in the below paragraph, which are named the procedure of shrinking encircling and position updating through spiral movement.

Next, the procedure of shrinking encircling can be achieved by reducing the value of a in the below equation.

$$\vec{O} = 2\vec{g}.\overrightarrow{random}_1 - \vec{g} \tag{38}$$

$$\vec{Y} = 2.\overrightarrow{random}_1 \tag{39}$$

The position-updating mechanism of humpback whales through a helix-shaped spiral movement can be modeled mathematically by Equation (40).

$$\vec{W}(t+1) = \vec{Z\prime}.e^{fh}.\cos(2\pi h) + \vec{W}*(t) \tag{40}$$

$$\vec{Z\prime} = \left| \vec{W}*(t) - \vec{W}(t) \right| \tag{41}$$

Here, $h \in [-1, 1]$ is a random number, the logarithmic spiral shape is defined by the constant f, and the position vectors of the prey as well as the humpback whales are represented by $\vec{W}^*$ and $\vec{W}$, respectively. The humpback whales start swimming around the prey. In this swimming event, the humpback whales swim within the shrinking circle with a spiral path.

There exists a probability of 50% for selecting these methods and this can be mathematically formulated by the equation below.

$$\vec{W}(t+1) = \begin{cases} \vec{W}^*(t) - \vec{O}\vec{Z} & if\ q < 0.5 \\ \vec{Z\prime}.e^{fh}.\cos(2\pi h) + \vec{W}^*(t) & if\ q > 0.5 \end{cases} \quad (42)$$

Here, $q \in [0, 1]$ is the random number.

The condition for searching the prey is $|O| > 1$; also, it should be noted that the random approach is adopted by the humpback whales for searching the prey. This is mathematically modeled by the following equations.

$$\vec{Z} = \left|\vec{Y}.\vec{W}_{random} - \vec{W}\right| \quad (43)$$

$$\vec{W}(t+1) = \vec{W}_{random} - \vec{O}\vec{Z} \quad (44)$$

3.3.2. Hybrid Adapted Grey Wolf Whale Optimizer (HA-GWWO) Framework

The second phase of the proposed framework aimed at selecting the best reliable node-disjoint route out of k-node-disjoint routes available from each SN_i to BS in EH-WSN. The hybrid adapted grey wolf whale optimizer (HA-GWWO) framework was used for discovering the best reliable node disjoint route. Six effective parameters are considered while designing the efficient fitness function, namely, the first function, representing the remaining available energy of each node in a particular route from SN_i to BS; the second function, representing the distance of the edge between adjacent nodes; the third function, representing energy consumption of the edge between adjacent nodes; the fourth function, representing a delay in communication for the node; the fifth function, representing the relay hops for the packet in each route; and, finally, the sixth function, representing the reliability index of the particular route from SN_i to BS. The hybrid adapted grey wolf whale optimizer (HA-GWWO) framework consists of both the adapted grey wolf optimizer as well as the adapted whale optimizer. There exist certain salient features of both optimizers, motivating us to use them. The basic principle of the grey wolf optimizer is simple in nature with easy realization; it has the optimal seeking capability with efficient search precision. The grey wolf optimizer, which has high research value, can be combined with the large number of distinct engineering problems that exist in the real world. In the grey wolf optimizer, all the three solutions comprehensively assessed the position of the best solution during the searching mechanism, since in the grey wolf optimizer, the leadership hierarchy of the wolves is maintained. This unique property of the grey wolf optimizer distinguishes it from other swarm intelligence algorithms in which only a single solution takes the lead for searching the best solution and therefore the grey wolf optimizer can efficiently handle the issue of trapping in the local optimum and the probability of being premature is much less. On the other hand, the whale optimizer has unique characteristics compared with other existing optimization algorithms in terms of having fewer adjustment parameters along with simple operation. The whale optimizer also effectively handles the issue of the local optimum by maintaining the efficient balance between exploitation and exploration capabilities. Therefore, the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework is capable enough for optimally discovering the most-reliable node-disjoint route out of the available k-node-disjoint routes between each SN_i to BS. Further, this hybrid framework utilized the newly designed efficient fitness function. Next, Figure 3 illustrates the integrated view of the proposed optimization framework, consisting of Phase 2.

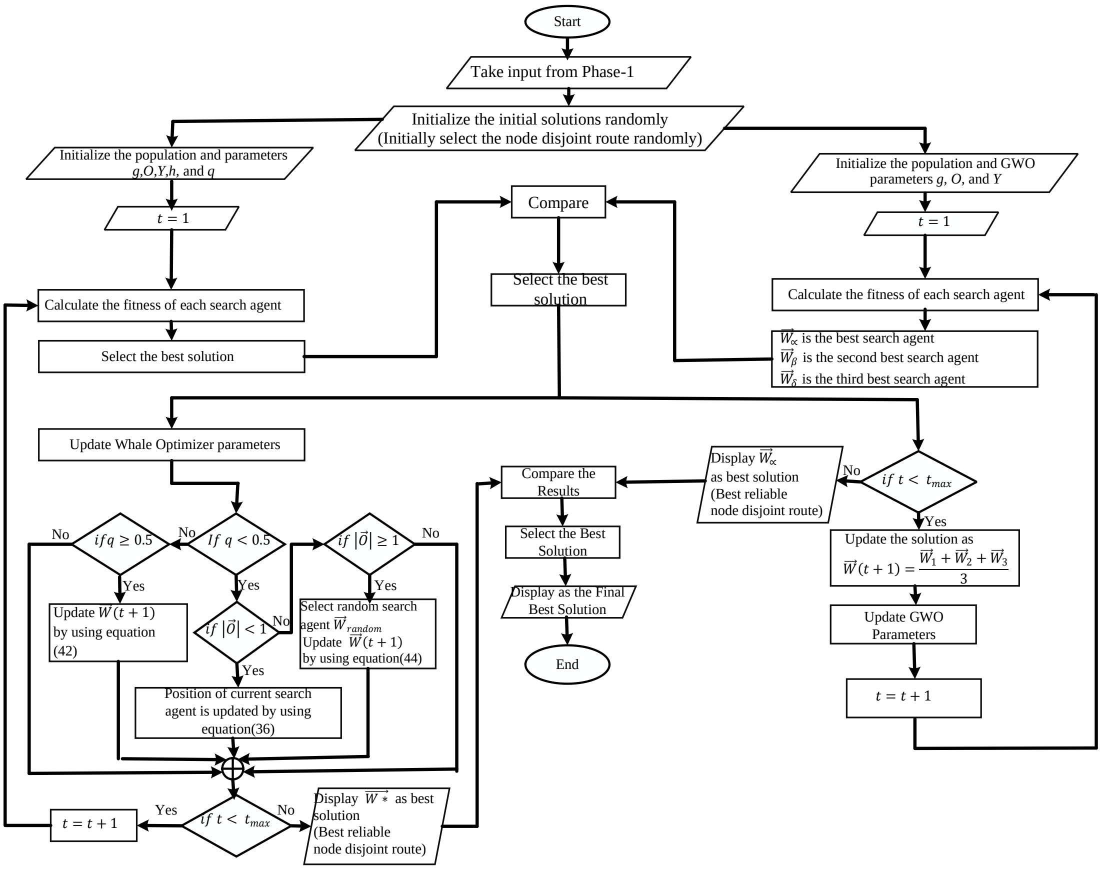


Figure 3. Integrated view of the proposed optimization framework, consisting of Phase 2.

In the EH-WSN, the total number of SNs is $|SN_{set}|$. Each source node is represented by SN_i and BS represents the destination node. The hybrid adapted grey wolf whale optimizer (HA-GWWO) framework discovers the best reliable node-disjoint route between each SN_i to BS in the EH-WSN out of the available k-node-disjoint routes. Further, $S = \{1, 2, \ldots\ldots\ldots, m\}$ is assumed as the solution vector of the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework. Furthermore, $m = |SN_{set}| * k$, with $k \geq 2$, where m is the total number node-disjoint routes from all SNs to BS; the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework discovers the most-reliable route from each SN_i to BS in the EH-WSN out of the available k-node-disjoint routes based on an estimation of the effectively designed fitness function.

In the next paragraph, we explain the detailed working of the hybrid adapted grey wolf whale optimizer (HA-GWWO) framework for selecting the most-reliable node-disjoint route from each SN_i to BS in the EH-WSN.

The hybrid framework starts with the initialization of random solutions. $W_j = \{S_1, S_2, \ldots, S_j, \ldots, |SN_{set}|)$, S_j is the jth random solution vector, and $|SN_{set}|$ represents the total number of random solution vectors.

Next, the fitness of each solution is determined by using the fitness function (35). The solution that has a fine fitness value (maximum best suitable route index (BSRI)) is assumed as the best search agent, which is going to be used in the next optimization step.

- Position update based on exploration and the exploitation mechanism.

In the hybrid framework, two optimizers are integrated, namely, the adapted grey wolf optimizer and the adapted whale optimizer. During each iteration, the best optimal solutions are determined simultaneously from both optimizers, and these solutions are further compared to select the best solution. This best solution is again given to both the optimizers to produce new better solutions as compared to previous solutions obtained. The cycle is repeated again in the same way.

- The best search agent update.

During each iteration t, the solution vector gets updated. Next, the fitness of each solution is determined by using the fitness function (35). The solution that has a fine fitness value (maximum best suitable route index (BSRI)) is assumed as the best search agent, which is going to be used in the next iteration.

- Termination

When the maximum iterations are achieved (t_{max}), the best optimal reliable node-disjoint route from each SN_i to BS is discovered in the EH-WSN. If the maximum iterations are not achieved, then the cycle is again repeated for finding the better solutions.

From the solution vector, the best solution in terms of the most-reliable node-disjoint route is selected after several iterations, simultaneously comparing solutions from both optimization algorithms, namely, the whale optimization and grey wolf optimization algorithms. The best solution is one of the solutions from the available solutions in the solution vector, fulfilling all criteria as per the fitness function.

3.3.3. Complexity Analysis

The time complexity of the proposed green communication framework FRGNWS mainly depends upon three parameters, namely, initialization of the sensor node population size $|SN_{set}|$ in the network, the fitness calculation time t_{max} for green route identification, and finally updating the disjoint routes in the sensor node population $|SN_{set}|$. Therefore, the complexity of the FRGNWS framework can be represented as O$(|SN_{set}| + t_{max}\text{x}|SN_{set}| + |SN_{set}|\text{x}d)$. Here, $|SN_{set}|$ denotes the total sensor population size, d presents the dimension of the maximum node-disjoint route problem, and t_{max} is the maximum number of iterations in the green route identification. Further, the time complexity of the proposed framework described in [35] is O$(SN_{set}(|SN_{set}| + t_{max}\text{x}|SN_{set}| + |SN_{set}|\text{x}d))$. From a comparison point of view, it can be clearly deduced that the complexity of the proposed framework is SN_{set} times lower than the considered literature technique.

4. Results and Discussion

In this section, we are illustrating a set of simulation experiments conducted for evaluating the efficacy of our proposed novel framework. In the simulation experiments, we have used network simulator (NS) version 2.34. For illustrating the outstanding performance of our proposed novel framework, we present a detailed comparative analysis with existing schemes, namely, the ABC-based framework [44] and GA-based framework [35]. The detailed setup for the simulation experiments is presented in Table 2.

Next, Figure 4 illustrates the central methodology adopted for conducting the set of experiments. Broadly, we have divided the set of experiments into four categories, namely, based on varying the number of SNs, varying the network size, variations in the supply of harvested energy, and also varying the number of RNs. We have used a total of five metrics for assessing the effectiveness of our proposed novel framework, namely, the lifetime of the network, throughput, average hop distance, end-to-end delay, and lastly the energy consumption. Further, in the first category of experiments, we conducted four simulation experiments, covering the number of RNs vs. variations in the number of SNs; the lifetime of the network vs. variations in the number of SNs; the throughput vs. variations in the number of SNs; and the average hop distance vs. variations in the number of SNs. Furthermore, in the second category of experiments, we again conducted four simulation experiments, covering the number of RNs vs. variations in the size of the network; the lifetime of the network vs. variations in the size of the network; the throughput vs. variations in the size of the network; and the average hop distance vs. variations in the size of the network. Next, in the third category of experiments, we conducted two simulation experiments, covering the lifetime of the network vs. variations in the supply of harvested energy (uniform); and the lifetime of the network vs. variations in the supply of harvested energy (random). Furthermore, in the fourth category of experiments, we conducted two simulation experiments, covering the end-to-end delay vs. variations in the number of RNs; and the energy consumption vs. variations in the number of RNs.

Table 2. The parameters along with their respective values used in the simulation.

Simulator Used and Its Version	**Network Simulator Version 2.34**
Variations in the number of SNs (N)	25, 35, 45, 55, and 65
Variations in size of network (L)	400 × 400, 600 × 600, 800 × 800, 1000 × 1000, and 1200 × 1200 (m^2)
SNs distribution strategy in EH-WSN	Uniform random distribution
Type of Antenna	Omni Directional
Propagation model of Radio	Two-ray ground
Communication Model	Bidirectional
Interface (Queue Type)	Drop tail
RNs distribution strategy in EH-WSN	Controlled random non-uniform distribution
Location of Sink Node	Centrally placed in the network area
Transmission Range (R)	1/5 ofnetwork area (meter)
Rate of Data (K)	125 kbps
Type of Traffic	CBR (Constant Bit Rate)
Size of Packet $(Packet_{size})$	512 bytes
Variations in Harvested Energy Supply (Uniform) $\left(E_{uniform}^{harvest}\right)$	0.4, 0.8, 1.2, 1.6, and 2.0 mW
Variations in Harvested Energy Supply (Random) $(E_{random}^{harvest})$	0.3, 0.5, 0.8, 1.0, and 1.5 mW
SNs′ initial energy (E_o)	2 J
Energy required for transmission (E_{send})	92 mJ/packet
Energy required for reception $(E_{receive})$	45 mJ/packet
Energy consumption in sleep state (E_{sleep})	15 µJ
Generated voltage every 15 s $(V_{generate})$	1.2 V
For RN activation energy $(E_{activation})$	5.2 V
Inactivity of RN start below	3.5 V
Total time required to charge full (T)	150 s

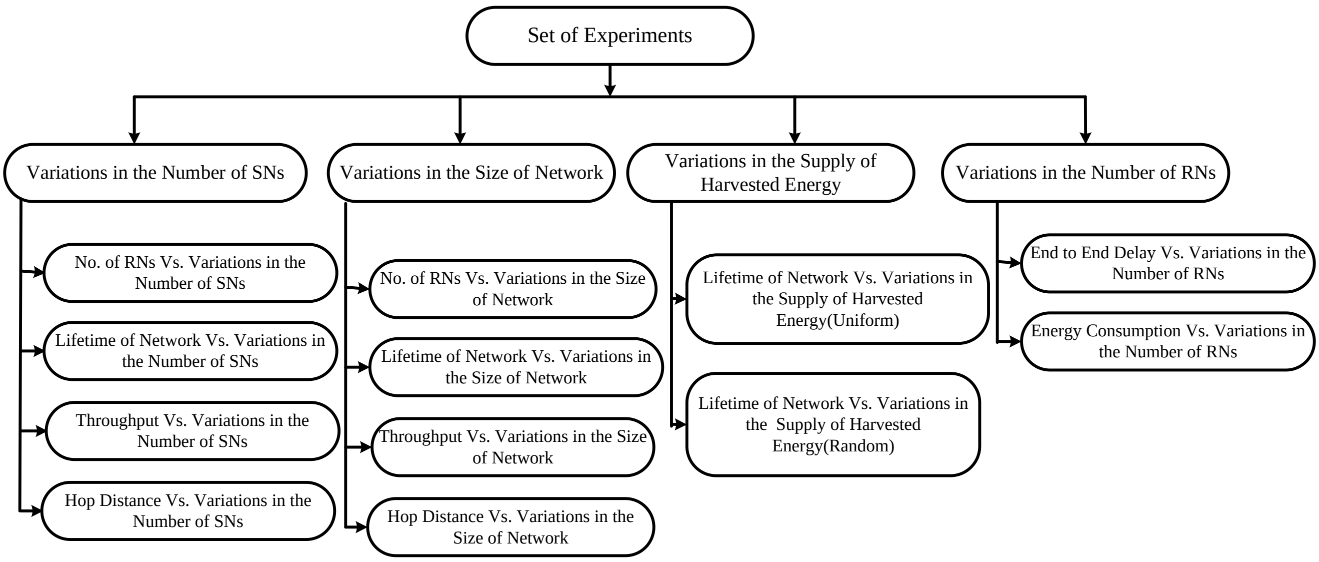


Figure 4. Methodology adopted for conducting the set of experiments.

Category 1: The first set of simulation experiments were carried out under this category. We varied the number of SNs and recorded the outcomes on the number of RNs, the lifetime of the network, throughput, and, finally, the average hop distance to sink. Next, Figure 5a–d illustrate the efficacy of the proposed novel framework (FRGNWS) with existing frameworks, namely, the ABC-based framework and GA-based framework. Further, Tables 3–6 give more clarity on the effectiveness of the proposed novel framework by providing the average % effectiveness with existing frameworks, considering each metric one by one, namely, the number of RNs, the lifetime of the network, throughput, and, finally, the average hop distance to the sink.

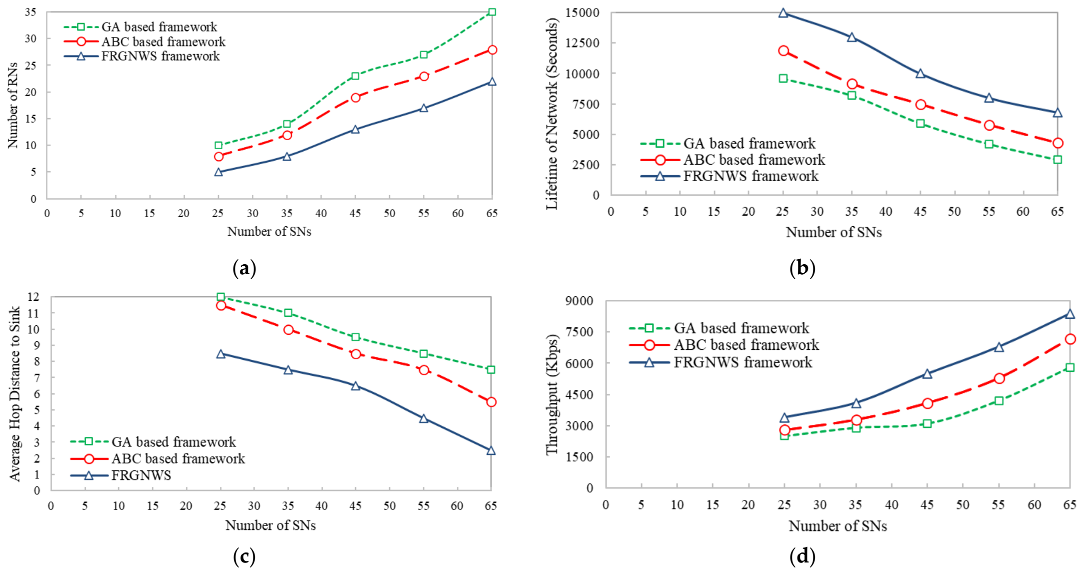


Figure 5. The outcomes of the set of simulation experiments conducted with variations in the number of SNs: (**a**) number of RNs with variations in the number of SNs; (**b**) lifetime of the network with variations in the number of SNs; (**c**) average hop distance to the sink with variations in the number of SNs; and (**d**) throughput with variations in the number of SNs.

Table 3. The average % effectiveness of the proposed novel framework for the number of RNs metric with variations in the number of SNs.

No. of RNs with No. of SNs				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of SNs ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
25	10	8	5	37.50	50.00
35	14	12	8	33.33	42.86
45	23	19	13	31.58	43.48
55	27	23	17	26.09	37.04
65	35	28	22	21.43	37.14
	Avg. % Effectiveness→			29.99	42.10

Table 4. The average % effectiveness of the proposed novel framework for the lifetime of the network metric with variations in the number of SNs.

Lifetime of Network (Seconds) with No. of SNs.				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of SNs ↓	GA-Based Framework	ABC-Based Framework	FRGNWS Framework	% Effectiveness of FRGNWS Framework with ABC-Based Framework	% Effectiveness of FRGNWS Framework with GA-Based Framework
25	9600	11,900	15,000	20.67	36.00
35	8200	9200	13,000	29.23	36.92
45	5900	7500	10,000	25.00	41.00
55	4200	5800	8000	27.50	47.50
65	2900	4300	6800	36.76	57.35
Avg. % Effectiveness→				27.83	43.76

Table 5. The average % effectiveness of the proposed novel framework for the average hop distance to the sink metric with variations in the number of SNs.

Avg. Hop Distance to the Sink with No. of SNs				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of SNs ↓	GA-Based Framework	ABC-Based Framework	FRGNWS Framework	% Effectiveness of FRGNWS Framework with ABC-Based Framework	% Effectiveness of FRGNWS Framework with GA-Based Framework
25	12	11.5	8.5	26.09	29.17
35	11	10	7.5	25.00	31.82
45	9.5	8.5	6.5	23.53	31.58
55	8.5	7.5	4.5	40.00	47.06
65	7.5	5.5	2.5	54.55	66.67
Avg. % Effectiveness→				33.83	41.26

Table 6. The average % effectiveness of the proposed novel framework for the throughput metric with variations in the number of SNs.

Throughput (Kbps) with No. of SNs				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of SNs ↓	GA Based Framework	ABC Based Framework	FRGNWS Framework	% Effectiveness of FRGNWS Framework with ABC-Based Framework	% Effectiveness of FRGNWS Framework with GA-Based Framework
25	2500	2800	3400	17.65	26.47
35	2900	3300	4100	19.51	29.27
45	3100	4100	5500	25.45	43.64
55	4200	5300	6800	22.06	38.24
65	5800	7200	8400	14.29	30.95
Avg. % Effectiveness→				19.79	33.71

Further, considering Figure 5a, it was deduced from the figure that the proposed novel framework outperformed the existing frameworks for the metric number of RNs with variations in the number of SNs. It is a fact that whenever the number of SNs starts increasing in the network then the number of RNs also starts increasing, since the RNs are assisting the SNs in transmitting the sensed data properly to the BS. RNs also cover the entire network gradually and after achieving a good connectivity level there is no need of deploying extra RNs in the network and therefore the RN count becomes constant after a particular level of connectivity. Table 3 depicts the average % effectiveness of the proposed novel framework, compared to the ABC-based framework and GA-based framework, at 29.99% and 42.10%, respectively.

Now, we will explain the reason for this outstanding performance of the proposed novel framework. The proposed novel framework utilized a hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework with a properly designed objective function aimed at exploring the maximum number of node-disjoint routes from all SNs to BS using the minimum number of RNs. The proposed novel framework also ensures k-node-disjoint routes from each SNs to BS with $k \geq 2$. The ABC-based framework considers the two factors, namely, cost and connectivity. However, this framework lacks consideration of the energy depletion rate. Therefore, the ABC-based framework results in more RNs when compared with the proposed framework since additional RNs are required in the case of disconnected SNs due to energy-depleted RNs. On the other hand, the GA-based framework considers the connectivity factor, but this framework lacks a consideration of the energy level along with coverage issues. Hence, the GA-based framework also results in more RNs, since covering all SNs require more RNs.

Furthermore, considering Figure 5b, we can infer from the figure that there is a gradual decrement in the lifetime of the network with an increase in SNs. The reason for this gradual decrement is that, whenever the increase in SNs occurs in the network, there are a few specific activities that also start increasing in the network that consume lots of energy, namely, the retransmission of packets, synchronizations, and high traffic between nodes. These activities result in a high energy depletion rate of the nodes and, consequently, the lifetime of the network suffers. Again, the proposed novel framework surpasses the existing frameworks. Table 4 shows the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 27.83% and 43.76%, respectively.

The proposed novel framework has two phases: the first phase discovers the maximum node-disjoint routes from all SNs to BS using the minimum RNs having k-node-disjoint routes from each SN to BS, therefore providing fault-tolerant capabilities; the second phase is aimed at selecting the best reliable route out of the available k-node-dis joint routes from each SN to BS, hence enhancing reliability in the network, and therefore the possibility of selecting the faulty route is low. Moreover, the routes from each SN to BS utilized the lowest number of RNs, and therefore less consumption of energy as compared with existing frameworks, resulting in an efficient lifetime of the network. Further, the ABC-based framework does not consider the energy-depletion rate of the nodes; the GA-based framework also does not consider the energy factor, instead focusing on the connectivity factor. Further, the existing frameworks do not have the capabilities of energy harvesting, so if the level of energy of the nodes is below a particular level, then network failure will start.

Considering Figure 5c, this figure reflects the efficacy of our proposed novel framework for the average hop distance to the sink metric with existing frameworks. It is a fact that if we are going to increase the SNs in the network, then there occurs a gradual decrement in the average hop distance to the sink. Here also, our proposed novel framework outrun the existing frameworks. Next, Table 5 shows the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 33.83% and 41.26%, respectively.

Minimum RNs are utilized in the proposed novel framework for exploring the maximum number of node-disjoint routes with k-node-disjoint routes from each SN to BS. Since the average hop distance to the sink metric depends on the number of RNs, our proposed framework shows an efficient, steady performance compared to existing frameworks. The existing frameworks require a higher number of RNs, resulting in a higher average hop distance to the sink.

Considering Figure 5d, this figure illustrates the fact that throughput increases with an increase in SNs. The reason is obvious: more SNs in the network try to send the sensed data to the BS using RNs as far as possible. In this entire mechanism, the existence of RNs plays a major role. The proposed novel framework outperforms the existing frameworks. Next, Table 6 shows the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 19.79%, and 33.71%, respectively.

The proposed framework utilized the control random strategy with a non-uniform nature for deploying the RNs in EH-WSN. The minimum number of RNs is utilized in discovering the maximum node-disjoint routes in the network from all SNs to BS. Further, the most-reliable node-disjoint route is selected from each SN to BS. The proposed framework efficiently utilized the RNs and relieved the burden of SNs; in this environment, the energy level of the nodes does not deplete fast, which results in high throughput. The existing frameworks show poor results for the throughput metric. First, the existing frameworks do not have energy-harvesting capabilities. Second, the energy depletion rates of the nodes are higher in the existing frameworks.

Category 2: The second set of simulation experiments were carried out under this category. We varied the network size and record the outcomes on the number of RNs, the lifetime of the network, throughput, and, finally, the average hop distance to the sink. Figure 6a–d illustrate the efficacy of the proposed novel framework (FRGNWS) with the existing frameworks, namely, the ABC-based framework and GA-based framework. Further, Tables 7–10 give more clarity on the effectiveness of the proposed novel framework by providing the average % effectiveness compared to the existing frameworks, considering each metric one by one, namely, the number of RNs, the lifetime of the network, throughput, and, finally, the average hop distance to the sink.

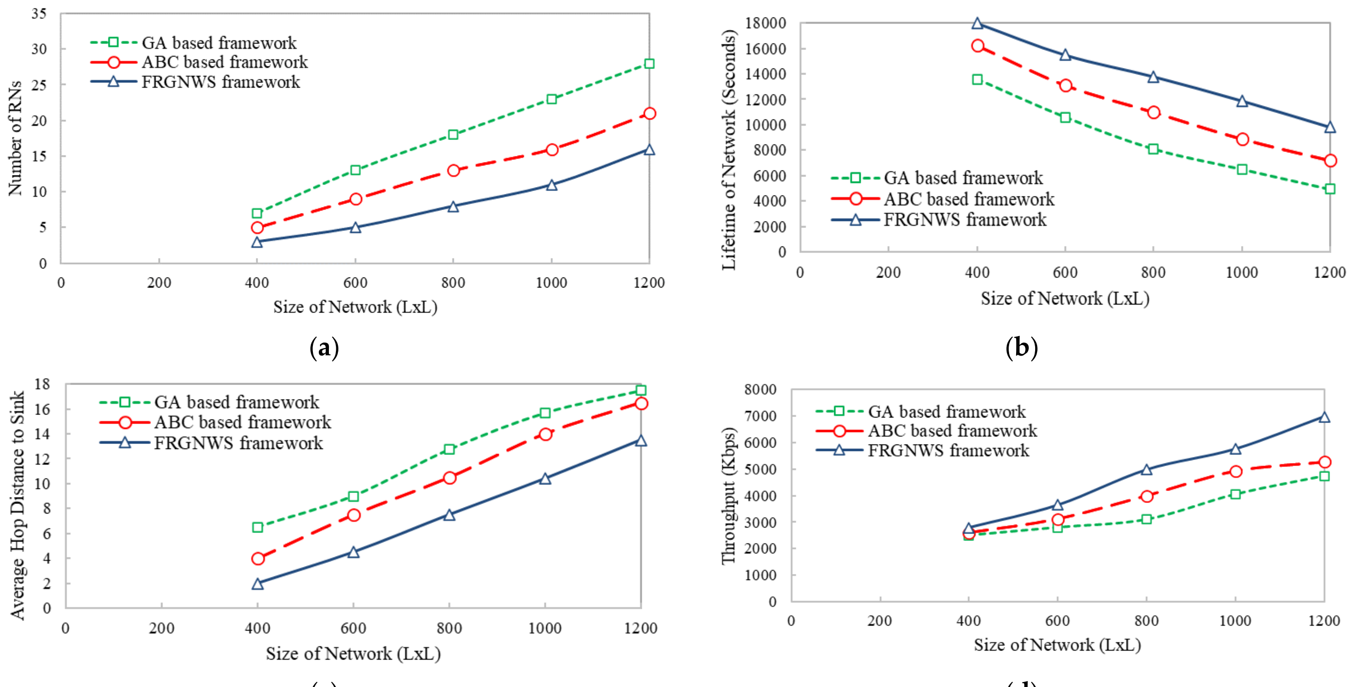


Figure 6. The outcomes of the set of simulation experiments conducted with variations in the network size: (**a**) number of RNs with variations in the network size; (**b**) lifetime of the network with variations in the network size; (**c**) average hop distance to the sink with variations in the network size; and (**d**) throughput with variations in the network size. Tables 7–10 are given below.

Table 7. The average % effectiveness of the proposed novel framework for the number of RNs metric with variations in the network size.

No. of RNs with Variations in the Size of the Network				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Size of Network ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
400 × 400	7	5	3	40.00	57.14
600 × 600	13	9	5	44.44	61.54
800 × 800	18	13	8	38.46	55.56
1000 × 1000	23	16	11	31.25	52.17
1200 × 1200	28	21	16	23.81	42.86
Avg. % Effectiveness→				35.59	53.85

Table 8. The average % effectiveness of the proposed novel framework for the lifetime of the network metric with variations in the network size.

Lifetime of Network (Seconds) with Variations in the Size of the Network				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Size of Network ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
400 × 400	13,590	16,250	18,000	9.72	24.50
600 × 600	10,600	13,120	15,500	15.35	31.61
800 × 800	8100	11,000	13,800	20.29	41.30
1000 × 1000	6500	8900	11,900	25.21	45.38
1200 × 1200	4930	7200	9825	26.72	49.82
Avg. % Effectiveness→				19.46	38.52

Table 9. The average % effectiveness of the proposed novel framework for the average hop distance to the sink metric with variations in the network size.

Avg. Hop Distance to the Sink with Variations in the Size of the Network				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Size of Network ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
400 × 400	6.5	4	2	50.00	69.23
600 × 600	9	7.5	4.5	40.00	50.00
800 × 800	12.75	10.5	7.5	28.57	41.18
1000 × 1000	15.7	14	10.4	25.71	33.76
1200 × 1200	17.5	16.5	13.5	18.18	22.86
Avg. % Effectiveness→				32.49	43.40

Considering Figure 6a, this figure clearly shows that our proposed novel framework again outperforms the existing frameworks for the number of RNs metric with variations in the network size. The network usually consists of nodes having a particular fixed range of communication; furthermore, if we are going to vary the network size, then, definitely, we require the deployment of extra RNs in order to effectively cover the entire network area. The proposed novel framework shows gradual increments in RN count and this reflects its efficient coverage capabilities. Table 7 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 35.59% and 53.85%, respectively.

Table 10. The average % effectiveness of the proposed novel framework for the throughput metric with variations in the network size.

Throughput (Kbps) with Variations in the Size of the Network				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Size of Network ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
400 × 400	2500	2600	2800	7.14	10.71
600 × 600	2800	3120	3650	14.52	23.29
800 × 800	3100	4000	4980	19.68	37.75
1000 × 1000	4050	4930	5760	14.41	29.69
1200 × 1200	4740	5270	6980	24.50	32.09
Avg. % Effectiveness→				16.05	26.71

The proposed novel framework is energy efficient. Minimum relay nodes are deployed for maintaining the effective coverage in the proposed framework. The remaining available energy of each node in the route along with the energy consumption of the edge between adjacent nodes in the route are the two main factors out of a total of six factors considered while selecting the best reliable node-disjoint route from each SN to BS. Therefore, the proposed novel framework show efficacy in effective utilization of energy in the network and results in lower energy consumption compared with existing frameworks, the latter lacking energy efficiency.

In the proposed novel framework, the maximum node-disjoint routes from all SNs to BS are explored using a minimum number of RNs. Next, from each SN to BS, *k*-node-disjoint routes use the minimum number of RNs. Further, the best reliable node-disjoint route is selected out of the *k*-node-disjoint routes from each SN to BS for routing. The existing frameworks lack in providing efficient coverage capabilities, since the ABC-based framework considers only two factors, namely, cost and connectivity; this framework thus lack consideration of the energy-depletion rate. On the other hand, the GA-based framework considers the connectivity factor, although this framework lacks considering the energy level along with coverage issue.

Furthermore, considering Figure 6b, this figure shows the excellent performance of the proposed novel framework for the network lifetime metric with existing frameworks. Table 8 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 19.46% and 38.52%, respectively.

Although the network lifetime gradually decreases with an increment in the network size, due to the higher consumption of energy, the proposed novel framework still shows excellency in these circumstances. Multiple objective functions are considered while designing an efficient, novel fitness function for selecting the most-reliable node-disjoint route from each SN to BS, namely, the remaining available energy of each node in the route, the distance of the edge between adjacent nodes in the route, the energy consumption of the edge between adjacent nodes in the route, delay in communication for the node in the route, relay hops for the packet in the route, and finally the reliability index (RI) of the particular route. Therefore, energy consumption is lower in the proposed novel framework when compared with the existing frameworks.

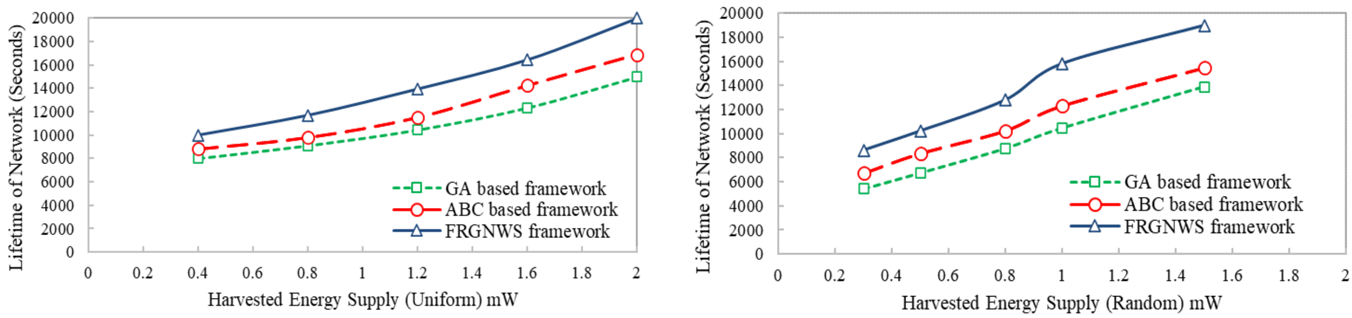
Considering Figure 6c, this figure elaborates the fact that the average hop distance to the sink increases with an increase in the network size, since the large network size requires more RNs to effectively cover the entire area. The proposed novel framework dominates the existing frameworks for the average hop distance metric. Table 9 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 32.49% and 43.40%, respectively.

The proposed novel framework is has excellent coverage capabilities. The minimum number of RNs is utilized for exploring the maximum number of node-disjoint routes from all SNs to BS. The existing frameworks do not have effective coverage capabilities and a higher number of RNs are required for covering large network areas. Therefore, existing frameworks result in a higher average hop distance to the sink.

Considering Figure 6d, this figure displays the fact that throughput increases with an increase in the network size, and our proposed novel framework outrightly performs well, considering the throughput metric compared to existing frameworks. Table 10 exhibits the average % effectiveness of proposed novel framework compared to the ABC-based framework and GA-based framework as 16.05% and 26.71%, respectively.

Throughput depends on various factors in the network, but the primary factor is the remaining energy level of the nodes in the network. This factor is effectively considered in the proposed novel framework while selecting the best reliable route from each SN to BS. The proposed novel framework shows energy efficiency, and therefore the throughput gradually increases with an increment in the network size, even though a large network area results in a higher consumption of energy. The existing frameworks lack energy efficiency, and therefore show poor results when comparing with the proposed novel framework.

Category 3: The third set of simulation experiments were carried out under this category. We vary the harvested energy supply uniformly and also randomly both ways. Further, we recorded the outcomes on the lifetime of the network metric. Figure 7a,b illustrate the efficacy of the proposed novel framework (FRGNWS) with the existing frameworks, namely, the ABC-based framework and GA-based framework. Tables 11 and 12 give more clarity on the effectiveness of the proposed novel framework by providing the average % effectiveness compared to the existing frameworks, considering the metric the lifetime of the network.



(**a**) (**b**)

Figure 7. The outcomes of the set of simulation experiments conducted with variations in the harvested energy supply uniformly as well as randomly: (**a**) lifetime of the network with variations in the harvested energy supply (uniformly); (**b**) lifetime of the network with variations in the harvested energy supply (randomly). Tables 11 and 12 are given below.

Considering Figure 7a, this figure tries to narrate the effectiveness of the proposed novel framework with existing frameworks, considering the network lifetime metric under variations in the harvested energy supply uniformly. Table 11 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 15.01% and 23.47%, respectively.

The network lifetime increases gradually when a uniform supply of harvested energy is considered. The reason for this outstanding performance of the proposed novel framework is the optimal energy efficiency of this framework. Although the energy-harvesting capability in the network maintains a continuous supply to nodes, optimization of energy use is needed for enhanced network lifetime, and the proposed novel framework shows this efficacy. The existing frameworks are unable to show strength towards energy efficiency and results in a lower network lifetime in this case.

Table 11. The average % effectiveness of the proposed novel framework for the lifetime of network metric with variations in the harvested energy supply (uniformly).

Lifetime of the Network (Seconds) with Variations in the Harvested Energy Supply (Uniform) (mW)				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Harvested Energy Supply (Uniform) (mW) ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
0.4	8000	8800	10,000	12.00	20.00
0.8	9100	9790	11,700	16.32	22.22
1.2	10,450	11,500	13,950	17.56	25.09
1.6	12,340	14,230	16,450	13.50	24.98
2	14,987	16,870	20,000	15.65	25.07
Avg. % Effectiveness→				15.01	23.47

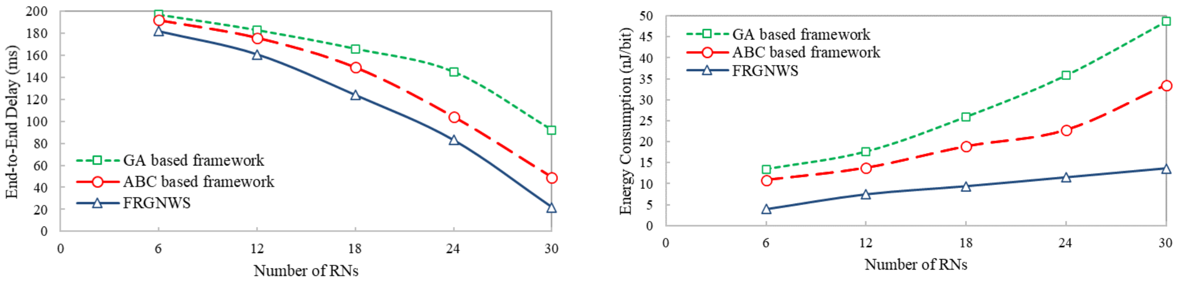
Table 12. The avg. % effectiveness of the proposed novel framework for the lifetime of the network metric with variations in the harvested energy supply (random).

Lifetime of the Network (Seconds) with Variations in the Harvested Energy Supply (Random) (mW)				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
Harvested Energy Supply (Random) (mW) ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
0.3	5400	6700	8600	22.09	37.21
0.5	6730	8340	10,200	18.24	34.02
0.8	8760	10,230	12,780	19.95	31.46
1	10,450	12,300	15,790	22.10	33.82
1.5	13,870	15,450	18,970	18.56	26.88
Avg. % Effectiveness→				20.19	32.68

Considering Figure 7b, although the network lifetime also increases under variations in the harvested energy supply (randomly), the results are somewhat lower when compared with the uniform supply of harvested energy. Table 12 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 20.19% and 32.68%, respectively.

The proposed novel framework unveils the efficacy for the network lifetime metric with existing frameworks due to energy efficiency capabilities that are lacking in the existing frameworks.

Category 4: The fourth set of simulation experiments were carried out under this category. We varied the number of RNs and recorded the outcomes on the end-to-end delay and energy consumption. Figure 8a,b illustrate the efficacy of the proposed novel framework (FRGNWS) compared to the existing frameworks, namely, the ABC-based framework and GA-based framework. Tables 13 and 14 give more clarity on the effectiveness of the proposed novel framework by providing the average % effectiveness compared to the existing frameworks, considering each metric one by one, namely, the end-to-end delay and energy consumption.



(**a**) (**b**)

Figure 8. The outcomes of the set of simulation experiments conducted with variations in the number of RNs: (**a**) end-to-end delay with variations in the number of RNs; (**b**) energy consumption with variations in the number of RNs. Tables 13 and 14 are given below.

Table 13. The average % effectiveness of the proposed novel framework for the end-to-end delay metric with variations in the number of RNs.

End to End Delay (ms) with Variations in the No. of RNs				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of RNs ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework with ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
6	197	192	182	5.21	7.61
12	183	176	161	8.52	12.02
18	166	149	124	16.78	25.30
24	145	104	83	20.19	42.76
30	92	49	22	55.10	76.09
	Avg. % Effectiveness→			21.16	32.76

Table 14. The average % effectiveness of the proposed novel framework for the energy consumption metric with variations in the number of RNs.

Energy Consumption(nJ/bit) with Variations in the No. of RNs				% Effectiveness of Proposed FRGNWS Framework with Existing Frameworks	
No. of RNs ↓	**GA-Based Framework**	**ABC-Based Framework**	**FRGNWS Framework**	**% Effectiveness of FRGNWS Framework With ABC-Based Framework**	**% Effectiveness of FRGNWS Framework with GA-Based Framework**
6	13.4	10.9	4	63.30	70.15
12	17.6	13.8	7.5	45.65	57.39
18	25.9	18.9	9.4	50.26	63.71
24	35.8	22.8	11.5	49.56	67.88
30	48.7	33.5	13.6	59.40	72.07
	Avg. % Effectiveness→			53.64	66.24

Considering Figure 8a, the proposed novel framework once again outperforms the existing frameworks for the delay metric. Further, the role of RNs in reducing the delay is crucial in the network. As the number of RNs are increasing in the network, the data packets can quickly reach the BS. Table 13 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 21.16 and 32.76%, respectively.

The proposed novel framework explores the maximum number of node-disjoint routes from all SNs to BS using the minimum number of RNs. The proposed framework provides reliability in routing by selecting the best reliable node-disjoint route from each SN to BS out of the available k-node-disjoint routes from each SN to BS. Therefore, the proposed novel framework represents efficient coverage along with effective connectivity in the network and consequently results in a lower delay when compared with existing frameworks.

Furthermore, considering Figure 8b, though the energy consumption increases with an increase in the number of RNs, our proposed novel framework demonstrates efficacy compared to the existing frameworks for the energy consumption metric. More RNs in the network result in an increment in the energy utilization in the network, since the traffic increases in the network and this further results in various different activities inducing higher energy utilization. Table 14 exhibits the average % effectiveness of the proposed novel framework compared to the ABC-based framework and GA-based framework as 53.64 and 66.24%, respectively.

The proposed novel framework is energy efficient. Minimum relay nodes are deployed for maintaining the effective coverage in the proposed framework. The remaining available energy of each node in the route along with the energy consumption of the edge between adjacent nodes in the route are the two main factors out of a total of six factors considered while selecting the most-reliable node-disjoint route from each SN to BS. Therefore, the proposed novel framework shows efficacy in effective utilization of energy in the network and results in lower energy consumption compared to existing frameworks, the latter lacking energy efficiency. Some recent studies [15,16] critically investigated the theoretical analysis aspects and found that the proposed framework still outperforms the related research works. The effective performance of the proposed framework is due to its ability to handle NP-hard and NP-complete optimization problems simultaneously using metaheuristic optimization algorithms, which was not considered in the recent literature.

5. Conclusions

In this research article, a novel framework is proposed considering single-tiered EH-WSN with constrained RN deployment. Next, the problem of relay node optimization is considered an NP-hard optimization problem. Further, the designing of effective fault-tolerant routing in EH-WSN constitutes the NP-complete problem. In the proposed novel framework, we have used metaheuristic optimization algorithms, namely, adaptive grey wolf optimizer, adaptive sine cosine optimizer, and adaptive whale optimizer, to provide solutions to the NP-hard and NP-complete problems. The proposed novel framework consists of two phases. In the first phase of the proposed novel framework, maximum node-disjoint routes from all SNs to BS using minimum RNs are explored based on the hybrid adapted grey wolf sine cosine optimizer (HA-GWSCO) framework, utilizing a properly designed fitness function; this HA-GWSCO framework also discovers the k-node-disjoint routes from each SN to BS, with $k \geq 2$, which enhances the fault-tolerance capability in EH-WSN. In the second phase of the proposed novel framework, out of k-node-disjoint routes from each SN to BS, with $k \geq 2$, the most-appropriate reliable route is selected from each SN to BS for routing, which enhances the reliability in routing for EH-WSN based on the hybrid adapted grey wolf whale optimizer (HA-GWWO), utilizing a novel and efficient fitness function covering multiple objective functions. The effectiveness of our proposed novel framework was assessed by considering five metrics, namely, energy consumption, the lifetime of the network, throughput, delay, and the delivery ratio, and the simulation results clearly validate the efficacy of our proposed novel framework. In this way, we finally got the fully connected EH-WSN, ensuring the maximum network life, low latency, efficient distribution of the load for relieving the overloaded sensor nodes, and with minimum energy consumption due to the high connectivity. The proposed novel research effectively handles both the NP-hard (relay node optimization) as well as NP-complete (fault-tolerant reliable routing) optimization problems simultaneously in EH-WSN. This salient feature of the proposed novel research distinguishes it from others existing in the literature. As a future research direction, we would like to implement this novel framework on a real-time EH-WSN, for real-time analysis of the outcomes, by utilizing the optimal number of heterogeneous RNs for maintaining k-connectivity.

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