IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 15 February 2024, accepted 3 March 2024, date of publication 12 March 2024, date of current version 18 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3374781

RESEARCH ARTICLE

A Chaotic Reptile Search Algorithm for Energy Consumption Optimization in Wireless Sensor Networks

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ABSTRACT A wireless sensor network (WSN) uses sensor nodes, which have an integrated processor for managing and monitoring the environment in a certain area. They are connected to the base station (BS), which functions as the central processing unit (CPU) of the WSN system. WSN has several difficulties, such as low processing power and a brief network lifespan. To solve the problem of network lifetime, we present a hybrid meta-heuristic (MH) optimization algorithm called the chaotic reptile search algorithm (CRSA) for energy conservation in WSNs. The proposed algorithm is an improvement on the original Reptile Search Algorithm (RSA) by combining the RSA algorithm and a chaotic map. RSA, like other meta-heuristic algorithms, suffers from trapping in local minima. Invoking the chaotic maps in the proposed algorithm can boost diversity and prevent becoming stuck in local minima. In the WSN, selecting the optimal cluster heads (CHs) helps save energy consumption. The proposed CRSA is used for selecting an optimum set of cluster heads amongst the other sensing nodes via the sensing field in a WSN. The experiments have evaluated the proposed algorithm under different conditions against five meta-heuristic algorithms and three versions of the low-energy adaptive clustering hierarchy (LEACH) algorithm. The proposed CRSA has verified the effectiveness of the mentioned algorithms in terms of the total consumed energy, the number of operating nodes, the packet reception by the base station, and the network lifetime. The findings of the experiment indicate that the suggested CRSA is a promising algorithm, and it achieves improvements against all these previously mentioned algorithms.

INDEX TERMS Cluster head selection, energy consumption optimization, meta-heuristic (MH) algorithms, network lifetime, reptile search algorithm (RSA), wireless sensor network (WSN).

I. INTRODUCTION

In the domain associated with intelligent networks, WSN appears as a smart motivated technology for improving people's lives. Hence, It can be used in a wide range of fields such as smart cities, bio-medical, civil, industry, transport, science, agriculture, military, and the Internet of Things (IoT) [1], [2]. It is formed by embedding physical sensor nodes (SNs) randomly in a deployment area to sense scalar information from this area. SNs are tiny and low-cost, but at the same time, they usually suffer from limited memory and limited energy supply and aren't rechargeable. Hence, the energy utilization of SNs is still a critical requirement in the design of WSNs. To solve this issue and increase the network duration, the energy resource of each node needs to be efficiently managed [3], [4]. The clustering process guarantees logical organization and energy management for the sensor network and thus decreases energy consumption and prolongs the sensor network's lifespan. The clue to the clustering method is to divide the deployment region

The associate editor coordinating the review of this manuscript and approving it for publication was Hosam El-Ocla.

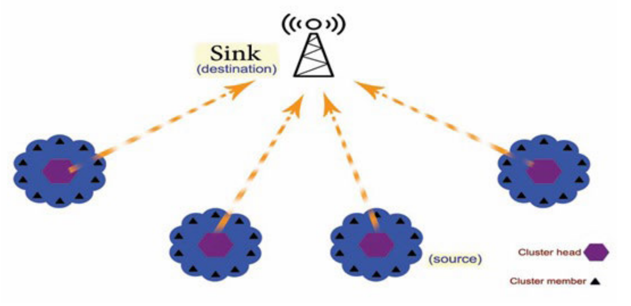

FIGURE 1. Data transformation from the CHs to the BS.

into several sub-regions (clusters). Each cluster consists of multiple regular SNs and a primary node known as the cluster head (CH). CHs collect sensor node data and transfer it to the intended location, which is called the base station (BS). Figure 1 shows The WSN's architecture. In Figure 1, three clusters contain some sensors each sensor sends its data to the cluster head, and each cluster head sends its data to the base station (BS). Selecting an optimum set of cluster heads among the SNs in the WSN is an non-deterministic polynomial (NP)-hard optimization issue [5], [6].

Indeed, naturally inspired algorithms such as swarm intelligence (SI) algorithms have been presented as appropriate solutions for complicated optimization problems [2]. Most SI algorithms suffer from slow convergence and trapping in local minima. To solve these issues, we propose a new hybrid algorithm called the chaotic reptile search algorithm (CRSA) by combining the chaotic maps and the standard reptile search algorithm. To make the RSA less prone to local minima and more diverse, it can make use of its chaotic maps.

A. THE MAIN CONTRIBUTION OF THIS PAPER

The following is how we highlight the primary contribution of this work in this subsection:

- As far as we know, this presented work is the first that employs the RSA for energy consumption in WSNs and develops a new hybrid meta-heuristic algorithm based on the original RSA. Our proposed algorithm is called the chaotic reptile search (CRSA).
- Invoking the chaotic map in the suggested algorithm improves its diversity and prevents it from trapping in local minima.
- The proposed CRSA compares its outcomes to those of the other five meta-heuristics methods and three versions of the LEACH algorithm using four different standard performance metrics.
- Based on experimental results, the suggested CRSA achieves higher performance when considering network lifetime while ensuring low energy consumption.
- The proposed algorithm has a greater number of operation nodes and more packets were received at the BS than with the other comparison techniques.

B. THE LIMITATION OF THE PROPOSED ALGORITHM

Though the proposed CRSA achieves comprehensive improvement in the simulation scenarios, many challenges have to be considered, as follows:

- Experiments were performed using homogeneous SNs. Nevertheless, WSNs with heterogeneous topologies can make use of the suggested CRSA.
- It does not depend on mobile base stations. So, it is necessary to initialize a mobile wireless sensor network as a solution, especially in large-scale networks, instead of a single stationary base station, to greatly improve the network lifespan.
- The proposed algorithm cannot handle multiple node failures in its current design.

The remainder of this paper is structured as follows: Section II presents some of the related works, and Section III illustrates the problem formulation. Section IV presents the standard RSA and the proposed CRSA algorithm. Section V depicts the experiment results and discussion. Finally, the derived conclusions from this research article and the future directions are provided in Section VI.

II. RELATED WORK

This review sheds light on some of the existing clustering algorithms and reports their merits and demerits. The literature emphasizes that the starting point for the clustering concept is the LEACH [7] protocol. LEACH considers the presumed clustering protocol for the topology control features. It is a distributive approach to selecting CHs randomly. LEACH achieves improvements in terms of energy savings and boosting the sensor network lifetime compared to pre-existing protocols. On the other hand, CH selection with low energy may cause premature death and accordingly reduce network performance. Since then, LEACH has received numerous enhancements from researchers to produce variants of LEACH.

The power-efficient gathering in sensor information systems (PEGASIS) protocol is proposed by Lindsey et al. [8] PEGASIS is a greedy-based chain protocol called Power-Efficient Gathering in Sensor Information Systems (PEGASIS) to solve data-gathering problems in sensor networks. PEGASIS outperforms LEACH in several alive nodes. On the other hand, PEGASIS becomes unstable in large networks. In [9], Fan et al. have proposed an improved version of LEACH called energy-LEACH (E-LAECH). It improves the method of choosing CHs as it avoids selecting low-energy nodes. E-LAECH outperforms LEACH in energy savings and network lifetime. On the other hand, the effectiveness of E-LAECH is evaluated against only the LEACH protocol. With the involvement of simulated annealing (SA), centralized LEACH (LEACH-C) was developed by Heinzelman et al. in [10] to improve the LEACH protocol. LEACH-C enhances the network lifetime and energy efficiency. On the other hand, this protocol completely condones the arrangement of clusters; accordingly, this leads to energy inefficiency in the network. Another algorithm introduced in [11] is called particle swarm optimization-clustering (PSO-C) for CHs selection. PSO-C considers the intra-cluster distance and ratio of all nodes' total initial energy to all CHs' total current remaining energy as factors in CHs selection. Furthermore, PSO-C outperforms its competitors in terms of data delivery at the BS and network lifetime. On the other hand, PSO-C ignores inter-cluster distance, which is significant for inter-communication among cluster heads and BS. In [12], they have proposed a hybrid method that combines the firefly algorithm and particle swarm optimization (HFAPSO) to choose an ideal set of CHs. In terms of network lifetime, energy utilization, and number of alive nodes, this method provides considerable improvements over the other algorithms. On the other hand, the performance evolution of HFAPSO has been compared with only two algorithms. A hybrid routing algorithm that capitalized on ant colony optimization (ACO), PSO, and the difference operator of the differential algorithm to reach the BS-optimized track is presented in [13]. It significantly improves packet reception rate and network lifetime compared to other comparative optimization algorithms. On the other hand, the proposed algorithm is not able to discover the possible solutions if the area is large.

A PSO algorithm-based clustering energy schema and sink mobility (PSO-ECSM) is presented in [14]. PSO to address both proper CHs selection and sink mobility problems. PSO-ECSM offers comprehensive improvement regarding five different evolution metrics. On the other hand, PSO-ECSM cannot be implemented in real-time applications.

Another routing protocol called the reposition particle swarm optimization (RPSO) algorithm has been introduced for energy savings in WSNs by the authors in [15]. RPSO achieves improvements regarding the number of delivered packets at the sink, energy consumption, network lifetime, and number of dead sensors. On the other hand, they have located the BS in one position only. In [16], the authors have presented an efficient clustering method that depends on particle swarm optimization called PSO-EECS to better select cluster heads. PSO-EECS overtakes the other comparative works concerning operation time and network stability. On the other hand, the performance of the proposed method is compared with only three existing works. A hybrid clustering approach based on chicken swarm optimization and a genetic algorithm called (CSOCA-GA) has been proposed in [17]. This approach considers crossover and mutation operators for the best cluster head selection in each round of WSNs. Energy consumption is reduced, and the sensor network's lifespan is increased compared to other methods. On the other hand, they have to evaluate this work using further performance metrics.

In [18], a distributed routing model is proposed capitalized on glow-worm swarm optimization (GSO) to select cluster heads and reduce the expected energy consumption, especially for applications with high traffic. The proposed model reduces the consumed energy, throughput, and latency. Moreover, it enhances load balancing in the network. On the other hand, the location of the BS has been assumed to be in only one position.

Gorgich and Tabatabaei [19] have presented a clustering protocol based on an artificial fish swarm optimization algorithm called AFSAP. This protocol aims to address the challenges of energy utilization in WSNs. AFSAP is more efficient in energy consumption, throughput rate, media access delay, throughput rate, media access delay, and noise ratio than the ERA protocol. On the other hand, this protocol has been evaluated against only the ERA protocol.

The work in [20] solves the energy consumption challenge in WSNs by integrating the simulated annealing algorithm and the cuckoo search algorithm. This hybrid natural algorithm is called (HRP-CSSA). HRP-CSSA algorithm achieves progress in energy usage, received data items at the BS, and network span against the other protocols. On the other hand, the performance of HRP-CSSA has been compared with only two protocols. Cat swarm optimization (CSO) based clustering protocols for real-time applications have been developed by Chandirasekaran and Jayabarathi [21]. It mainly considers residual battery voltage, intra-cluster distance, and received signal strength in CH selection. The proposed protocol enhances significantly energy consumption, overhead, throughput, and network lifetime compared with LEACH and PSO. On the other hand, the performance of the proposed protocol is compared with only two other protocols.

Bandi et al. [22] have proposed a scheme that combines the boosted ant bee colony (ABC) algorithm and self-adapting differential activity for cluster head election strategy with high quality of service. In terms of residual energy and alive nodes, the proposed scheme confirms better performance than the compared schemes. On the other hand, this scheme has precipitated convergence in the impending search process. Gul et al. [23], the authors have explored a data acquisition problem via an unmanned aerial vehicle (UAV) with limited battery capacity in the robot networks. This approach significantly overtakes the comparative approach regarding the total energy consumption and the network lifetime. On the other hand, the accuracy and amount of all data from whole CH robots were considered equally.

Capitalized on the firefly algorithm (FA), an optimized cluster head selection method for WSNs is presented by Sarkar et al. in [24]. This method is called firefly cyclic randomization (FCR). FCR prolongs the network lifetime and the energy efficiency of other previous methods compared with it. On the other hand, they assumed that the sink location was only in the center of the network.

The author of the work [25] has proposed a hybrid clustering technique that integrates dragonfly algorithm (DF) and firefly (FF) optimization called (FPU-DFA) to perform an optimal CHs selection. FPU-DFA improves network energy, risk probability, delay, and number of alive nodes compared to other conventional models. On the other hand, the selection of cluster heads could be further enhanced by considering extra factors.

Krishnan et al. [26] have explained a routing and clustering approach for sink mobility purposes and avoiding travelling salesman problems with the help of ant colony optimization (ACO). It mainly focuses on enhancing the network lifetime by achieving dynamic data load balancing in the network. It achieves more progress in terms of network lifetime and number of dead nodes than other comparative algorithms. On the other hand, sink mobility is not optimized with efficient parameters. The BS location has been assumed to be in the center of the network field; however, they overlooked the possibility that the BS was out of the field.

John and Rodrigues [27], the authors, have suggested a hybrid optimized clustering method. It combines the Crow search algorithm (CSA) and the Taylor series called Multi-Objective Taylor Crow Optimization (MOTCO). This method effectively provides an improvement in terms of energy consumption and throughput compared to other existing methods. On the other hand, MOTCO is computationally complex.

We can summarize the studies that conducted literature reviews, as shown in Tables 1, 2.

III. PROBLEM FORMULATION

Our study seeks to accomplish better management of energy utilization because it is one of the most important resources in the WSN, which will result in an increase in the the WSN expected lifetime. This can be done by employing the clustering method, which will save energy by selecting the best CH for the WSN. As a result, the network will remain operational for longer. Clustering occurs in two steps in our CRSA: first, the CHs are chosen, and then the clusters are created. The following subsections will have an explanation of these two steps.

Firstly, the used terminologies will be explained for a better understanding of the suggested algorithm for choosing cluster heads, as shown in Table 3

A. SELECTING CLUSTER HEADS PHASE

The proposed CRSA selects the CHs by using a distinct fitness function that is based on a variety of factors as follows.

- **The mean distance CHs and SNs.** The distances between all SNs s_i and each CH_j (CH_j) are added up in this step. The mean is then determined as given in Equation 1.

$$\frac{1}{M}\sum_{i=1}^{N} dist(CH_j, s_i) \tag{1}$$

where the total number of SNs is N, M denotes the number of CHs and *dist* is the distance between all SNs and every CH.

- **The mean distance between CHs and BS.** The mean distance between the CHs and every BS is calculate as shown in Equation 2

$$\frac{1}{M}\, dist(BS, CH_j) \tag{2}$$

Each CH begins to transfer the data it has gathered from its SNs to the BS. Therefore, it is preferable to choose CHs that are near the BS. Since we aim to minimize the separations between CHs and nodes, as well as the separations between the BS and each CH, we may combine Equations 1 and 2 into Equation 3 as follows.

$$Min\ f_{dist} = \sum_{j=1}^{M}\frac{1}{M}\left(\sum_{i=1}^{N} dist(CH_j, s_i) + dist(BS, CH_j)\right) \tag{3}$$

- **CHs' overall energy.** The total current energy for each of the chosen CHs is what this parameter denotes. To choose the best CHs, we want to maximize this total. In other words, we want to reduce the value of the f_{ENG} term that represents the opposite of this sum as stated in Equation 4. Because data transmission uses some energy on each node. Selecting CHs from nodes with higher energy levels than other nodes is crucial.

$$Min\ f_{ENG} = \frac{1}{\sum_{j=1}^{M}(E_{CH_j})} \tag{4}$$

$E(CH_j)$ is the cluster head j's current energy value, where ($1 \leq j \leq M$). We may create the fitness function from the two prior functions, f_{dist} and f_{ENG} by combining them into a single function, f_{fit} as illustrated in Equation 5

$$\begin{aligned} Min \quad & F_{fit} = \gamma \times f_{dist} + (1-\gamma) \times f_{ENG} \\ \text{s.t.} \quad & dist(CH_j, s_i) \leq RNG \ \ \forall s_i \in SNs, \quad CH_j \in C \\ & dist(BS, CH_j) \leq RNG_{max} \ \ \forall CH_j \in C \\ & E_{CH_j} > E_{th}, \quad 1 \leq j \leq M \\ & 0 < \gamma < 1 \\ & 0 < f_{dist}, f_{ENG} < 1 \end{aligned} \tag{5}$$

where *RNG* is each SN's maximum communication range. The maximum communication range for each CH is determined by the variables s_i, RNG_{max}, C, $C = CH_1, CH_2, \ldots, CH_M$, E_{th}, It is a CH and stands for "threshold energy", and γ, which is a control factor. SNs is the grouping of all sensor nodes. We attempt to lower the fitness function's value in Equation 5 when choosing the best CHs. The top CH situation is when the fitness value is lower.

B. CLUSTER CONSTRUCTION PHASE

The cluster construction phase can play a crucial role in prolonging the network lifetime and decreasing energy consumption in WSNs. This phase has three parameters which are remnant energy, the separation between CHs and BS, the separation between SNs and CHs, and the number

TABLE 1. Some of the studies that conducted literature reviews - part 1.

Study	Algorithm Description	Benefits	Limitation
Pitchaimanickam et al. [12]	They have proposed a hybrid method that combines the firefly algorithm and particle swarm optimization (HFAPSO) to choose an ideal set of CHs.	In terms of network lifetime, energy utilization and number of alive nodes, this method provides considerable improvements against the other algorithms.	The performance evolution of HFAPSO has been compared with only two algorithms.
Osamy et al. [17]	A hybrid clustering approach based on chicken swarm optimization and genetic algorithm called (CSOCA-GA) have been proposed.	This approach considers crossover and mutation operators for the best cluster head selection in each round in WSNs. This approach enhances the energy consumption and the network lifespan compared to the other comparative r approaches.	They have to evaluate this work using further performance metrics
Sahoo et al. [14]	The authors have developed PSO algorithm-based clustering energy schema and sink mobility (PSO-ECSM) to address both proper CHs selection and sink mobility problems.	PSO-ECSM offers comprehensive improvement regarding five different evolution metrics.	PSO-ECSM cannot be implemented in real time applications.
Gorgich and Tabatabaei [19]	They have presented a clustering protocol based on an artificial fish swarm optimization algorithm called AFSAP. This protocol aims to address energy utilization challenge in WSNs.	AFSAP is more efficient in energy consumption, throughput rate, media access delay and noise ratio than ERA protocol.	AFSAP protocol has been evaluated against only ERA protocol.
Demri et al. [20]	This work solves the energy consumption challenge in WSNs by integrating between simulated annealing algorithm and cuckoo search algorithm. This hybrid natural algorithm is called (HRP-CSSA).	HRP-CSSA algorithm achieves progress in energy usage, received data items at the BS, and network span against the other protocols.	The performance of HRP-CSSA has been compared with only two protocols.
Elshrkawey et al. [15]	Another routing protocol called reposition particle swarm optimization (RPSO) algorithm has been introduced for energy saving in WSNs.	RPSO algorithm achieves improvements regarding number of the delivered packets at the sink, energy consumption, the network lifetime, and number of dead sensors.	They have located the BS at one position only.
Heinzelman et al. [7]	The authors have presented a distributive approach called Low Energy Adaptive Clustering Hierarchy (LEACH) to select CHs randomly.	LEACH achieves improvement in terms energy saving and boosting the sensor network lifetime of against pre-existing protocols	CH selection with low energy may cause premature death and accordingly reduces the network performance.
Lindsey et al. [8]	They have proposed a greedy-based chain protocol called Power-Efficient Gathering in Sensor Information Systems (PEGASIS)to solve data -gathering problem in sensor networks.	PEGASIS outperforms LEACH in number of alive nodes.	In large size networks, PEGASIS becomes unstable.
Fan et al. [9]	They have proposed an improved version of LEACH called energy-LEACH(E-LAECH). It improves the method of choosing CHs as it avoids selecting low energy nodes.	E-LAECH outperforms LEACH in energy saving and network lifetime.	The effectiveness of E-LAECH is evaluated against only the LEACH protocol.
Heinzelman et al. [10]	They have developed to improve LEACH protocol called LEACH-C or centralized LEACH. It was applied using simulated annealing (SA).	LEACH-C extends the lifetime of the network and enhances the energy efficiency.	This protocol completely condones the arrangement of clusters. Accordingly, this leads to energy inefficiency of the network.
Latiff et al. [11]	They have developed an energy aware CH selection algorithm that depending on particle swarm optimization. This improved PSO version is called PSO-C. It aims to minimize intra-cluster distance and optimize the energy consumption.	PSO-C algorithm outperforms over its comparatives in terms of data delivery at the BS and the network lifetime.	PSO-C algorithm ignores inter-cluster distance which is significant for inter communication among cluster heads and BS.
Wang et al. [13]	They have presented a hybrid routing algorithm that capitalized on ant colony optimization (ACO), PSO and difference operator of differential algorithm to reach to the BS optimized track.	It significantly improves packet reception rate and network lifetime than other comparative optimization algorithms.	The proposed algorithm is not able to discover the possible solutions if the area is large.
Prakash et al. [16]	The authors have presented an efficient clustering method depends on particle swarm optimization called PSO-EECS to better selection for the cluster heads.	PSO-EECS overtakes the other comparative works with respect to operation time and network stability.	The performance of the proposed method is compared with only three existing works.
Ramesh et al. [18]	A distributed routing model is proposed that capitalized on glow-worm swarm optimization (GSO) to select cluster heads and reduce expected energy consumption especially for applications of high-traffic.	Proposed model reduces the consumed energy, throughput and latency. Moreover, it enhances the load balancing in the network.	The location of the BS has been assumed only at one position.

TABLE 2. Some of the studies that conducted literature reviews - part 2.

Study	Algorithm Description	Benefits	Limitation
Chandirasekaran and Jayabarathi [21]	They have presented a clustering protocol for real time applications that based on cat swarm optimization (CSO). It mainly considers residual battery voltage, intra cluster distance and received signal strength in CH selection.	Proposed protocol enhances significantly battery energy level and network lifetime compared with other techniques.	The performance of the proposed protocol is compared with only two techniques.
Bandi et al. [22]	They have proposed a scheme that combines between boosted ant bee colony (ABC) algorithm and self -adapting differential activity for cluster head election strategy with high quality of service.	In terms of residual energy, alive nodes, the proposed scheme confirms better performance against the compared schemes.	This scheme has precipitate convergence in the impending search process.
Gul et al. [28]	The authors have explored a data acquisition problem via an unmanned aerial vehicle (UAV) with limited battery capacity in the robot networks.	This approach significantly overtakes the comparative approach regarding the total energy consumption and the network lifetime.	The effectiveness of this approach has been examined against only UAV-oriented approach. The accuracy and amount of all data from whole CH robots were considered equally.
Sarkar et al. [24]	Capitalized on firefly algorithm (FA), an optimized cluster head selection method for WSNs is presented by the authors. This method is called firefly cyclic randomization (FCR).	FCR protracts the network lifetime and the energy efficiency than other previous methods compared with it.	They assumed that the sink location is only in the center of the network.
Alghamdi [25]	The author of has proposed a hybrid clustering technique integrates between dragon fly algorithm (DF) and firefly (FF) optimization called (FPU-DFA) to perform an optimal CHs selection.	FPU-DFA improves network energy, risk probability, delay and number of alive nodes with respect to other conventional models.	The selection of cluster head could be further enhanced by consideration of extra factors.
Krishnan et al. [26]	Another routing and clustering approach is suggested for sink mobility purpose and avoid traveling salesman problem with the help of ant colony optimization (ACO). It mainly focuses on enhancing the network lifetime via achieving dynamic data load balancing in the network.	It achieves progress in terms of network lifetime and number of dead nodes than other comparative algorithms.	The sink mobility is not optimized with efficient parameters.
John and Rodrigues [27]	The authors have suggested a hybrid optimized clustering method. It combines between crow search algorithm (CSA) and Taylor Series called Multi-Objective Taylor Crow Optimization (MOTCO).	This method effectively provides improvement in terms of consumed energy and throughput than other existing methods.	MOTCO is computationally complex.

TABLE 3. The symbols in the CHs selection phase.

Symbol	Description
s_i	Set of the sensor nodes.
CH	Cluster head.
BS	Base station.
N	Total number of SNs.
M	Number of CHs.
C	Set of the cluster heads.
RNG	Maximum communication range for a SN.
RNG_{max}	Maximum communication range for each CH.
E_{th}	Threshold energy for being a CH.
γ	Control factor.

of neighboring nodes. These parameters are calculated as follows.

- **The CH remnant energy.** In order for an SN s_i to communicate with other SNs in its communication range, it must to merge with a CH_j (CH_j) that has greater remanent energy than other CHs as follows.

$$WF(CH_j, s_i) \propto E_{rem}(CH_j) \tag{6}$$

WF is a weight function, and $E_{rem}(CH_j)$ refers to the residual power for a CH_j.

- **The distance between CH and SN.** In order to combine with the nearest CH_j within the range of communication, a sensor node s_i should be used. Whereas doing so will aid in using less energy as follows.

$$WF(CH_j, s_i) \propto \frac{1}{dist(CH_j, s_i)} \tag{7}$$

- **The distance between BS and CH.** Getting the information from the SNs and sending it to the BS is the responsibility of the CHs. Because the other CHs are within its communication range and they are farther away from the BS, an SN s_i should unite with a CH that is nearer the BS.

$$WF(CH_j, s_i) \propto \frac{1}{dist(CH_j, BS)} \tag{8}$$

- **The level of the CH node.** A SN s_i must merge to a (CH_j) that has the lowest degree of nodes $node\_deg$ within its communication range as follows.

$$WF(CH_j, s_i) \propto \frac{1}{node\_deg(CH_j)} \tag{9}$$

The previous Equations 7, 8, and 9 can be combined to form Equation 10.

$$WF(CH_j, s_i) \propto \frac{E_{rem}(CH_j)}{dist(CH_j, s_i)} \times \frac{1}{dist(CH_j, BS)} \times \frac{1}{node\_deg(CH_j)} \tag{10}$$

A cluster's final weight function can be shown in Equation 11.

$$WF(CH_j, s_i) = \beta \times \frac{E_{rem}(CH_j)}{dist(CH_j, s_i)} \times \frac{1}{dist(CH_j, BS)} \times \frac{1}{node\_deg(CH_j)} \tag{11}$$

where β is a constant and its value is 1. Each SN determines its weight function using Equation 11, and it must then come together to a CH that has the highest weight value in order to form the clusters.

IV. THE PROPOSED CRSA

The reptile search algorithm (RSA) and the proposed CRSA are highlighted in the subsection as follows.

A. REPTILE SEARCH ALGORITHM (RSA)

The following sections detail the social interactions and daily activities of crocodiles as well as the design of the reptile search algorithm (RSA).

1) CROCODILES' DAILY LIVES IN THE WILD

A type of reptile that lives in the tropics is the crocodile. Crocodiles are predators with a variety of traits that make it easier for them to catch prey. These traits can be summed up as follows.

- **The body's structure and shape.** Crocodiles have a unique body form that makes it easier for them to travel quickly through water and in the air. Crocodiles also have webbed feet, which can aid in their rapid swimming.
- **The vision at night.** Because of their keen eyesight, crocodiles can take advantage of their prey's poor vision, especially at night.
- **Food kinds and foraging.** As predators, crocodiles can consume a variety of species, including fishs, deers, zebras, and even fruits. Due to their slow metabolism, they can go for extended periods of time without eating.
- **The mental faculties.** Crocodiles possess a unique cognitive ability that enables them to anticipate the behaviour of their prey as they approach water (a river) to drink.
- **The belly-high walking.** When crocodiles encircle their prey, they use various strategies. By keeping their legs straight beneath them, they can move quickly. The term "high walk" refers to this style of stroll. They can also move slowly when looking for prey. A belly stroll is the name for this kind of walking. Crocodiles can alternate between the two methods as they scavenge for prey in their surroundings.
- **Cooperative hunting and collaboration.** Crocodiles hunt in packs, and their hunting strategy is based on two processes known as coordination and collaboration. The larger crocodiles swim deeply to lure the fish from the river's bottom to the shallows, where they are pursued and caught by the smaller crocodiles. The same methods are used to hunt the animal: they startle it as it approaches the river to drink, and when it falls into the water, smaller crocodiles catch it.

2) THE NATURAL BEHAVIOUR OF THE RSA

RSA is a population-based algorithm that mimics natural behaviour by taking instructions from the environment of crocodiles throughout their normal hunting season. Abualigah et al. proposed the RSA algorithm in 2022 [29]. Following is a description of the RSA's main steps and pseudo-code.

3) THE INITIALIZATION STEP

The initial individuals are produced at random in the area of the specified problem as shown below.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Nd} \end{bmatrix}$$

where x is a variable, d is the problem size and N is the population size.

4) THE EXPLORATION TECHNIQUE (ENCIRCLING)

Crocodiles encircle their victim before beginning to hunt. The high walk and the belly walk are two walking techniques that are used in the encircling habit. Depending on how many iterations there are, t, the two walk techniques are used. The high walk method can be stated as follows and begins at $t \leq \frac{T}{4}$.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times -HO_{ij}^{(t)} \times \lambda - RF_{ij}^{(t)} \times r \tag{12}$$

where $x_j^{*(t)}$ is the j^{th} position (variable) in the ideal solution, HO is hunting operator, λ is a parameter control an it equal to 0.1, RF is a reduced function and r is a number selected at random from [0 , 1]. The operator for hunting can be expressed as follows.

$$HO = x_j^{*(t)} \times PD_{ij} \tag{13}$$

where PD_{ij} is the percentage difference and it can be computed as shown in Equation 14.

$$PD_{ij} = \mu + \frac{x_{ij} - M(x_i)}{x_j^{*(t)} \times (U_j - L_j) + \varepsilon} \tag{14}$$

where $M(x_i)$ is the average position of the solution i, U, L are the position's upper and lower bounds of j, and ε is a small number, μ, a sensitive parameter, is equal to 0.1. As seen below, the reduction function RF can be computed.

$$RF_{ij} = \frac{x_j^{*(t)} - x_{r_2 j}}{x_j^{*(t)} + \varepsilon} \tag{15}$$

where r_2 is a random value between [1, N]. The belly walk process starts at $\frac{T}{2} \leq t < \frac{T}{4}$ and it can be formulated as shown in Equation 16.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times x_{r_1 j}^{(t)} \times EVS^{(t)} \times r \tag{16}$$

where $x_{r_1 j}^{(t)}$ is the j^{th} position of the random solution, r_1 is a random number between [1, N], EVS is the evolutionary sense. The evolutionary sense EVS can be formulated as follows.

$$EVS^{(t)} = 2 \times r_3 \times (1 - \frac{1}{T}) \tag{17}$$

where T is the highest number of iterations.

5) THE EXPLOITATION TECHNIQUE (HUNTING)

The hunting process in nature is represented by the exploitation process. When pursuing their prey, crocodiles employ two techniques known as coordination and cooperation. The coordination method, which operates at $\frac{T}{2} < t \leq 3\frac{T}{4}$, can be stated as follows.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times PD_{ij}^{(t)} \times r \tag{18}$$

where $PD_{ij}^{(t)}$ represents the percentage difference between position j and i and is calculated as indicated in Equation 14. The collaboration method can be used as follows and is applied at $3\frac{T}{4} < t \leq T$.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times -HO_{ij}^{(t)} \times \varepsilon - RF_{ij}^{(t)} \times r \tag{19}$$

where ε is a small value. The exploration and exploitation processes, as well as when they are used, are depicted in Figure 2.

6) THE RSA'S MAIN COMPONENTS

The main components of the RSA is described as shown in Algorithm 1.

B. THE CHAOTIC MAPS

Table 4 displays the ten chaotic maps in mathematical form. The ten chaotic maps exhibit random action, as seen in Figure 3, despite the absence of random factors. To boost the algorithm's random behavior and prevent it from getting stuck in the local optima, we investigate how the ten chaotic maps behave when they are invoked in the suggested algorithm. For all 10 chaotic maps, the starting point is a random value in the range [0, 1]. The starting point $x^0 = 0.7$ selected in [30] is what we employ.

Algorithm 1 The Pseudo-Code RSA

Set the parameters λ, μ, T, and ε to their initial values.
Set the iteration counters to $t := 0$.
Set the population X_i's initialization to a random value, with $i = \{1, \ldots, N\}$ for $X_i^{(t)}$.
Determine each individual's fitness function, $X_i^{(t)}$.
Give the overall best individual X^*.
Determine the evolutionary sense EVS in accordance with Equation 17.
repeat
    for i=1 to N **do**
        for j=1 to d **do**
            According to Equation 13, update the hunting operator HO.
            Update a percentage difference PD according to Equation 14.
            As per Equation 15, update the reduced function RF.
            if ($t \leq \frac{T}{4}$) **then**
                Update the individual according to Equation 12. {**High Walking (Exploration process)**}
            else if ($\frac{T}{4} < t \leq \frac{T}{2}$) **then**
                Update the individual according to Equation 16. {**Belly walking (Exploration process)**}
            else if ($\frac{T}{2} < t \leq 3\frac{T}{4}$) **then**
                Update the individual according to Equation 18. {**Hunting coordination (Exploitation process)**}
            else
                Update the individual according to Equation 19. {**Hunting cooperation (Exploitation process)**}
            end if
        end for
    end for
    Set $t = t + 1$.
until $t > T$.
submit the overall individual.

C. THE ARCHITECTURE OF THE CRSA

In the suggested algorithm, we invoked a chaotic map (C4) (Iterative map) [34], [40] in the standard RSA. Such a combination can improve the diversity ability of the CRSA and prevent it to stuck in local minima. The Equations 12, 16, 18 and 19 in the standard RSA are replaced in the proposed CRSA as follows. The random variable r in the high walk method in Equation 12 is replaced with a chaotic map (Iterative map) CM as shown in Equation 20.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times -HO_{ij}^{(t)} \times \lambda - RF_{ij}^{(t)} \times CM. \tag{20}$$

The random variable r in the belly walk method in Equation 16 is replaced with a chaotic map (Iterative map)

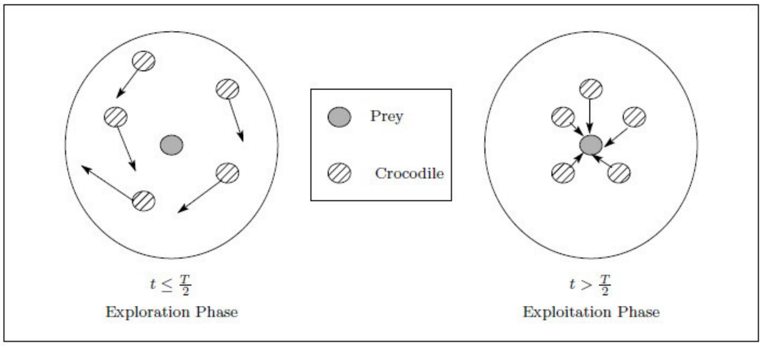

FIGURE 2. An example of the exploration and exploitation processes.

TABLE 4. Chaotic maps.

No	Name	Chaotic map	Range
C1	Chebyshev [31]	$x_{i+1} = \cos(i\cos^{-1}(x_i))$	(-1,1).
C2	Circle [32]	$x_{i+1} = \mod(x_i + b - (\frac{a}{2\pi})\sin(2\pi x_k), 1), a = 0.5$ and $b = 0.2$	(0,1).
C3	Gauss/mouse [33]	$x_{i+1} = \begin{cases} 1 & x_i = 0 \\ \frac{1}{\mod(x_i, 1)} & \text{otherwise} \end{cases}$	(0,1).
C4	Iterative [34]	$x_{i+1} = \sin(\frac{a\pi}{x_i}, a = 0.7$	(-1,1).
C5	Logistic [34]	$x_{i+1} = ax_i(1 - x_i), a = 4$	(0,1).
C6	Piecewise [35]	$x_{i+1} = \begin{cases} \frac{x_i}{P} & 0 \leq x_i < P \\ \frac{x_i - P}{0.5 - P} & P \leq x_i < 0.5 \\ \frac{1 - P - x_i}{0.5 - P} & 0.5 \leq x_i < 1 - P \\ \frac{1 - x_i}{P} & 1 - P \leq x_i < 1, \quad P = 0.4 \end{cases}$	(0,1).
C7	Sine [36]	$x_{i+1} = \frac{a}{4}\sin(\pi x_i), a = 4$	(0,1).
C8	Singer [37]	$x_{i+1} = \mu(7.86x_i - 23.31x_i^2 + 28.75x_i^3 - 13.302875x_i^4), \mu = 1.07$	(0,1).
C9	Sinusoidal [38]	$x_{i+1} = ax_i^2\sin(\pi x_i), a = 2.3$ (0,1).	
C10	Tent [39]	$x_{i+1} = \begin{cases} \frac{x_i}{0.7} & x_i < 0 \\ \frac{10}{3}(1 - x_i) & xi \geq 0.7 \end{cases}$	(0,1).

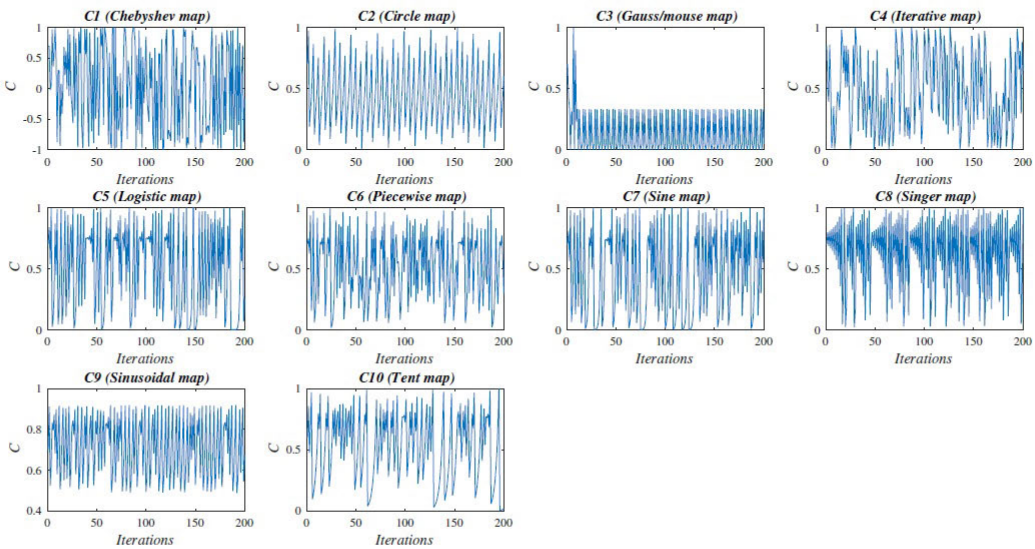

FIGURE 3. Chaotic map visualisation.

CM in Equation 21.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times x_{r_1j}^{(t)} \times EVS^{(t)} \times CM. \tag{21}$$

The random variable r in the coordination method in Equation 18 is replaced with a chaotic map (Iterative map) CM in Equation 22.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times PD_{ij}^{(t)} \times CM. \tag{22}$$

Finally, The random variable r in the collaboration method in Equation 19 is replaced with a chaotic map (Iterative map)

CM in Equation 23.

$$x_{ij}^{(t+1)} = x_j^{*(t)} \times -HO_{ij}^{(t)} \times \varepsilon - RF_{ij}^{(t)} \times CM. \tag{23}$$

The overall procedure for the suggested CRSA is described in the flowchart as shown in Figure 4

V. EXPERIMENTAL RESULTS

This section displays the simulation environment and illustrates the obtained results by the proposed CRSA. To carry out the implementation and plotting of the results of the source code for the CRSA and other MH algorithms, we utilized MATLAB software (version R2020a). During the evolution of the CRSA, its execution is compared with three versions of the LEACH algorithm and other five comparative meta-heuristic optimization algorithms. The proposed CRSA algorithm was simulated on a PC of an Intel core i7-6820 HQ processor with 2.70 GHz, and 8 GB RAM that running Microsoft Windows 10. The execution of the experiment is done for 15 evaluation runs for the proposed CRSA and each of the other existing solutions. To plot the results, the average of these instances is taken. Moreover, the total number of iterations was 5000 iterations.

A. EXPERIMENT PARAMETERS

The supposed network configuration in the experiment is represented in the Table 5 Furthermore, the value of the parameters that have been introduced by Heintzelman et al. in [7] are represented in Table 5. In the simulations, the network is formed from 300 SNs randomly distributed and the ratio that specified for CHs is set to 10%. i.e., 30 CHs, over the deployment area ($200m \times 200m$). Initially, each SN is set for an energy amount of 2 joules. There is a single BS and it is located at (100,100), (200,200), and (300,300) respectively as shown in Figures 5, 6, 7 . The terms E_{TX} and E_{RX} denote the energy required for transmission and reception of data. The term ε_{fs} refers to the amplification energy of the free space model. While the term ε_{mp} refers to the amplification energy of the model with multiple paths. The energy of data aggregation is equal to 5 nJ/ bit. The transmission distance threshold is equal to 30 m. And the data package size = 4000 bits.

Table 6 clarifies the used parameters of the proposed CRSA algorithm. Where N indicates the number of agents (crocodile population). D refers to the problem demission, LB and UB donate the lower value and upper value of the search space. T indicates the maximum number of iterations, α is a parameter to control energy and distance parameters. As α_1 and β_1 are sensitive parameters that control the exploration accuracy.

B. THE EFFICIENCY INVESTIGATION OF THE CRSA

We examine the effectiveness of the CRSA algorithm in the subsequent experiments by comparing it against the standard RSA in terms of the total consumed energy, the number of operating nodes, the network lifetime, and the packet reception by the base station. These terms are described as follows.

TABLE 5. Network Parameters used during the simulation.

Parameter	description	value
E_{RX}	Energy loss when receiving	50nJ/bit.
E_{TX}	Energy loss when transmitting	50nJ/bit.
ε_{mp}	Lose of energy for transmit amplifier	0.003nJ/bit.
ε_{fs}	Lose of energy for transmit amplifier	10PJ/bit/m2.

TABLE 6. The Parameters of the proposed CRSA.

Parameter	description	value
N	population size	300
D	Dimension of the problem	30
UB	Upper limit	200
LB	Lower limit	1
T	No. of iterations allowed maximum	5000
α	Control Parameter	0.3
α_1	Control Parameter	0.1
β_1	Control Parameter	0.005

- **Total energy consumption:** It is an overall estimated energy at the whole network lifetime and it is measured by joule(J) unit. Total energy consumption gives an estimation of the efficiency of the algorithm.
- **Number of the operating nodes (ON):** It is the number of nodes alive or operating nodes after the completion of a whole network lifetime.
- **Network lifetime:** It can be evaluated in different ways. Here we used half-node death (HND) measurement, which determines the iteration number at which the death of the half-nodes takes place. Network longevity is influenced by overall energy usage. If the energy of an SN reduces below the threshold value, then it is presumed to be dead. Also, last node death (LND) can be used as another measurement for the network lifespan.
- **Received packets at the BS/throughput:** This measurement indicates the total number of received packets at the BS successfully in the whole network lifetime. For a routing protocol, it is an important factor to measure its efficiency.

1) THE COMPARISON BETWEEN THE PROPOSED CRSA AND THE STANDARD RSA IN TERMS OF TOTAL ENERGY CONSUMPTION

It is the total energy spent by sensor nodes to perform the tasks of aggregating, transmission, and reception of data in a specific number of iterations. In our experiments, the maximum iteration number is 5000. Figure 8, 9, and 10 show the overall consumed energy of the proposed CRSA and original RSA when the base station is at (100,100), (200,200), and (300,300) respectively. The proposed CRSA achieves lower energy consumption than RSA 14.8%.

2) THE COMPARISON BETWEEN THE CRSA AND THE STANDARD RSA CONCERNING THE NUMBER OF OPERATING NODES

When there are more iterations, the operating nodes count gets reduced. In Figures 11, 12 and 13, the solid line

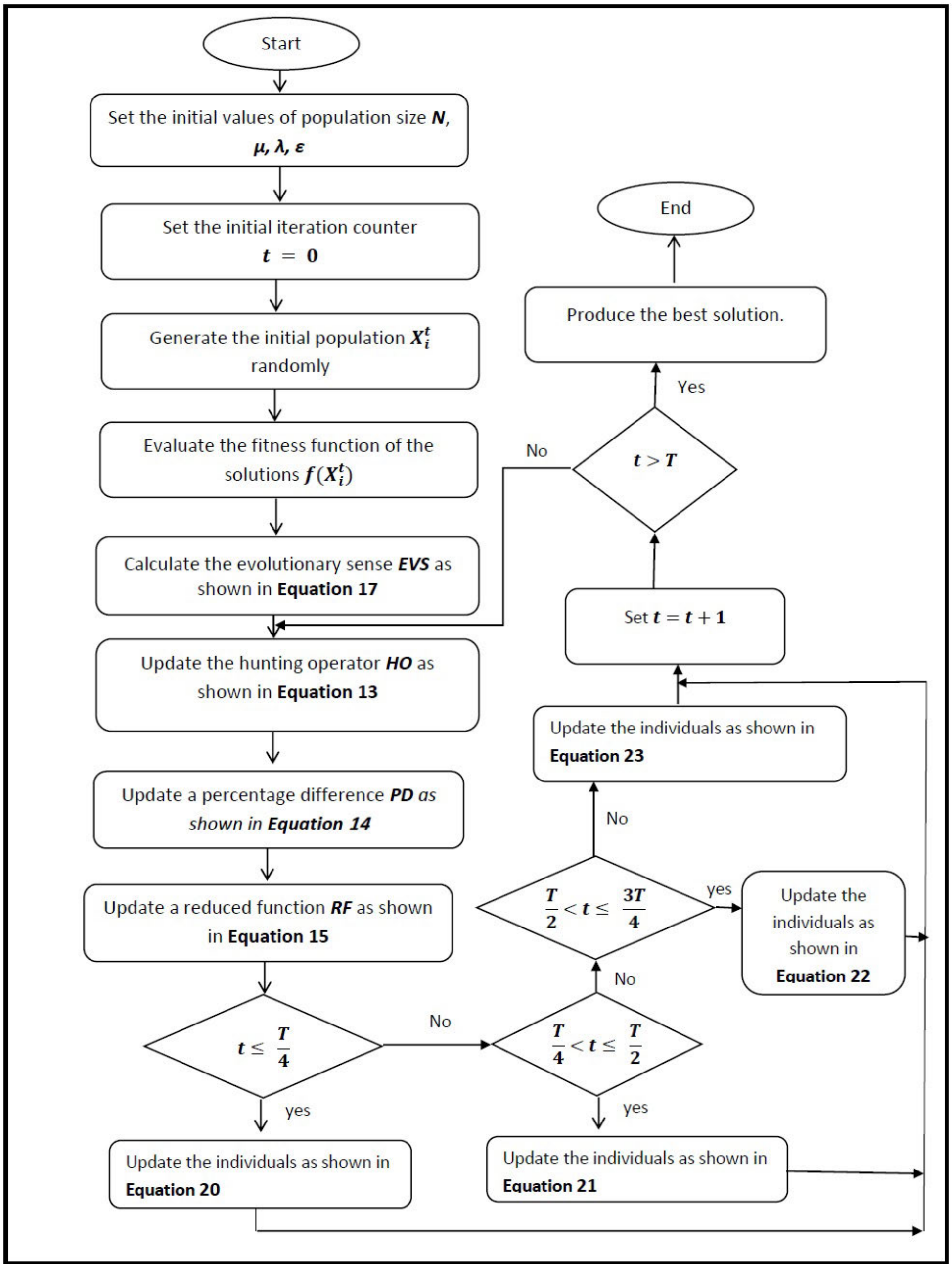

FIGURE 4. The flowchart of the main structure of the CRSA.

represents the proposed CRSA, while the dashed line stands for the standard RSA. The convergence curves in Figures 11, 12 and 13 indicate that the proposed CRSA keeps with more operating nodes than the other competing algorithms at three different locations of BS, which are (100,100), (200,200) and (300,300).

3) THE COMPARISON BETWEEN THE CRSA AND THE STANDARD RSA CONCERNING THE PACKET RECEPTION BY THE BASE STATION

The CRSA and the RSA are compared in terms of the packet reception by the base station at different locations (100, 100), (200, 200), and (300, 300), as shown in Figure 14. The results in Figure 14, show that the CRSA exceeds the RSA and can transfer more packets to the base station than the standard RSA.

4) THE COMPARISON BETWEEN THE CRSA AND THE STANDARD RSA CONCERNING THE NETWORK LIFETIME

The proposed CRSA and the RSA are compared in terms of the network lifetime at different locations of the BS (100, 100), (200, 200), and (300, 300), as shown in Figure 15. The results in Figure 15, show that the network lifetime of the CRSA is larger than that of RSA.

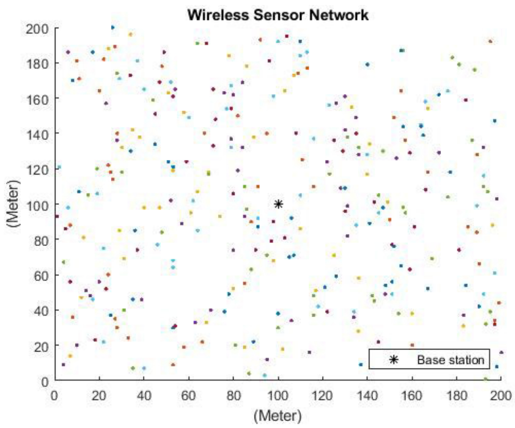

FIGURE 5. The random distribution for 300 nodes where the BS is in the field center (100,100).

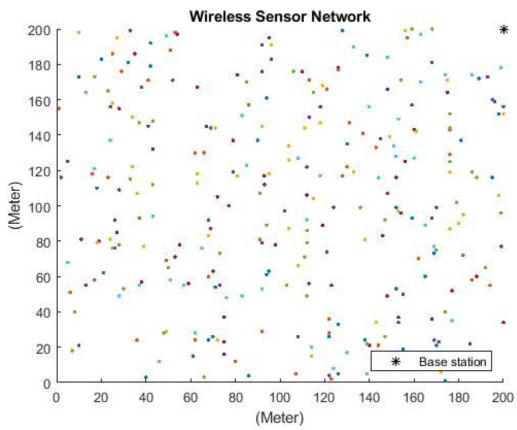

FIGURE 6. The random distribution for 300 nodes where the BS is at the top right corner (200,200).

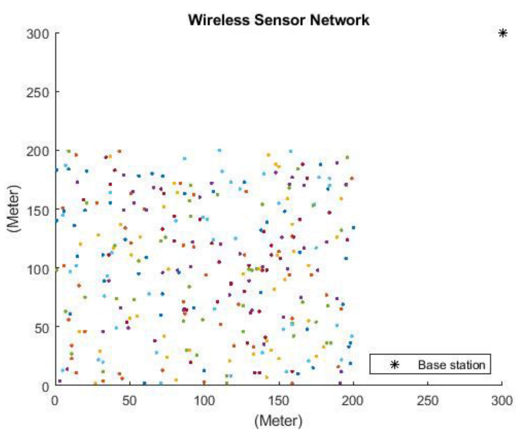

FIGURE 7. The random distribution for 300 nodes where 300 nodes where the BS is outside the field (300,300).

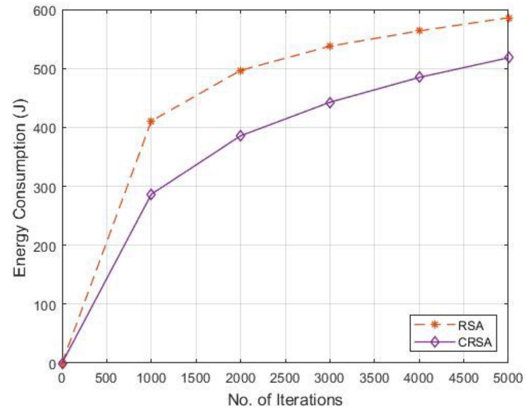

FIGURE 8. The overall consumed energy of proposed CRSA and RSA where the BS is located at (100,100).

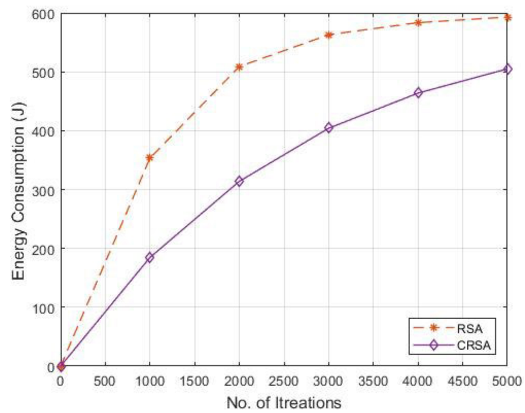

FIGURE 9. The overall consumed energy of proposed CRSA and RSA where the BS is located at (200,200).

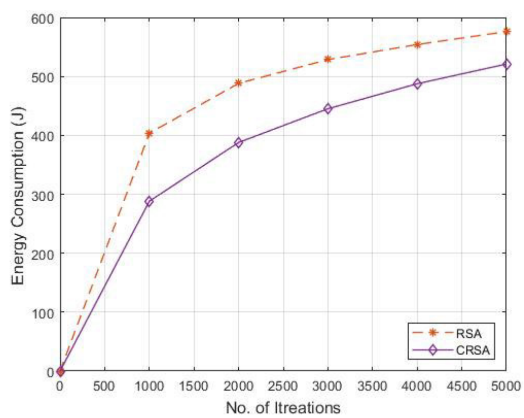

FIGURE 10. The total consumed energy of proposed CRSA and RSA where the BS is located at (300,300).

C. THE COMPARISON BETWEEN THE PROPOSED CRSA AND OTHER META-HEURISTICS ALGORITHMS

The proposed CRSA is evaluated based on the total consumed energy, the number of operating nodes, the packet reception by the base station, and the network lifetime. The proposed CRSA is compared with five MH algorithms namely: Particle Swarm Optimization (PSO) [41], Grey Wolf Optimizer (GWO) [42], Harris Hawks Optimization (HHO) [43], Wheal Optimization Algorithm (WOA) [44] and Reptile Search Algorithm (RSA) [29]. For a fair comparison, the average results of the total consumed energy in CRSA and other MH

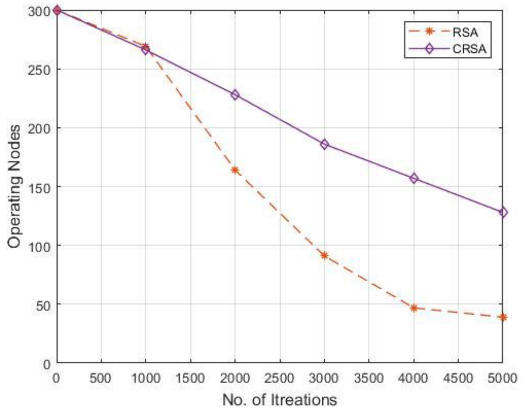

FIGURE 11. The operating nodes of the proposed CRSA and RSA where BS is located at (100,100).

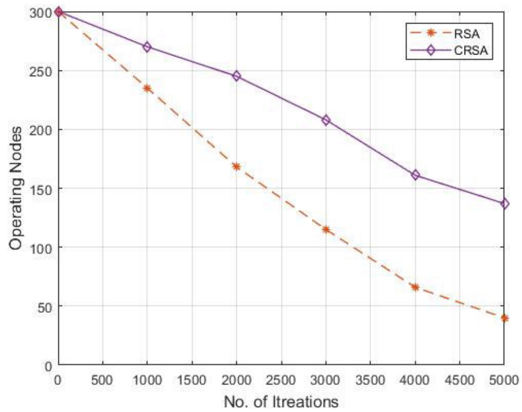

FIGURE 12. The operating nodes of the proposed CRSA and RSA where BS is located at (200,200).

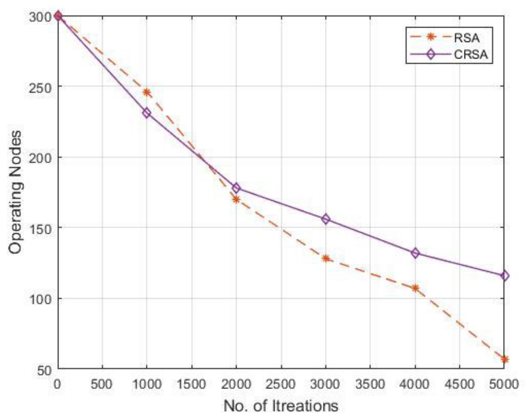

FIGURE 13. The operating nodes of the proposed CRSA and RSA where BS is located at (300,300).

algorithms after 15 evolution runs, are used to compare CRSA with other mentioned MH algorithms.

1) THE RESULTS OF THE PROPOSED CRSA AND THE OTHER ALGORITHMS IN TERMS OF TOTAL ENERGY CONSUMPTION

The proposed CRSA is compared against the other algorithms in terms of total energy consumption. The average results are

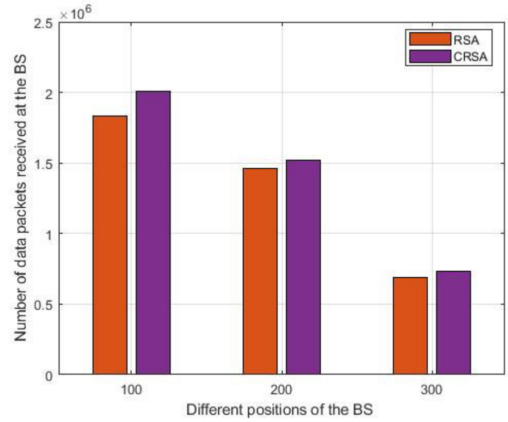

FIGURE 14. The packet reception by the base station of the proposed CRSA and RSA where BS is located at (100,100), (200,200), and (300,300).

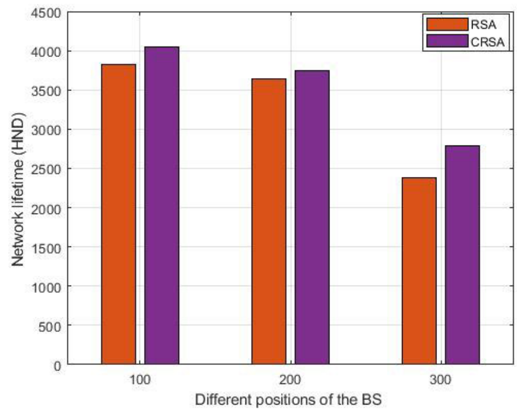

FIGURE 15. The half nodes death (HND) of the proposed CRSA and RSA where BS is located at (100,100), (200,200), and (300,300).

TABLE 7. The overall energy consumption for all algorithms where BS at (100,100), (200,200), and (300,300).

Algorithm	(100, 100)	(200, 200)	(300, 300)
PSO	576.26	577.26	601.40
GWO	574.63	575.86	599.10
HHO	565.60	570.60	590.42
WOA	551.43	557.90	586.11
RSA	533.90	542.09	545.49
CRSA	**522.94**	**532.86**	**537.30**

reported in Tables 7 after 5000 iterations and over 15 runs. The overall best results are reported in **bold** text. Also, the performance of the CRSA, the five MH algorithms, and the LEACH algorithm are shown in Figures 16, 17, and 18. The results in Tables 7 and Figures 16, 17, and 18 show that the CRSA performs better than the other algorithms.

2) THE RESULTS OF THE CRSA AND THE OTHER ALGORITHMS CONCERNING THE NUMBER OF OPERATING NODES (ON)

The CRSA is compared against the other algorithms concerning the number of operating nodes (ON). The average

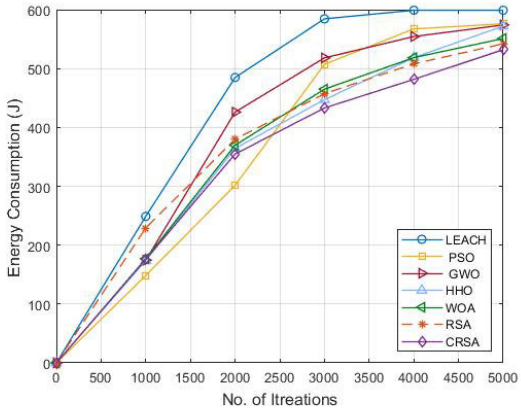

FIGURE 16. The total energy consumption where BS at (100,100).

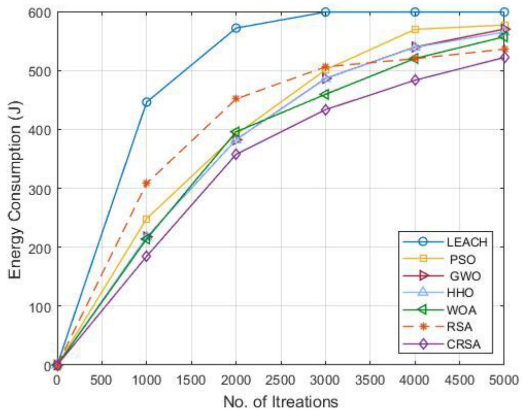

FIGURE 17. The total energy consumption where BS at (200,200).

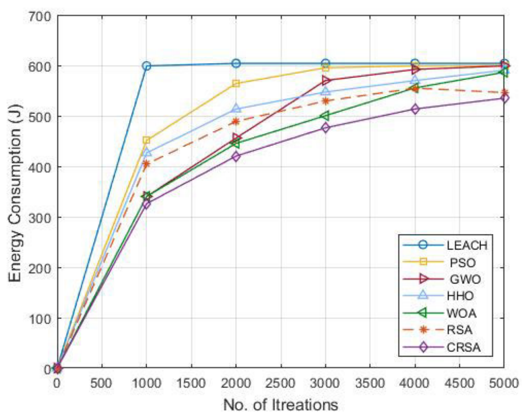

FIGURE 18. The total energy consumption where BS at (300,300).

results are reported in Tables 8 after 5000 iterations and over 15 runs. The overall best outcomes are documented in **bold** text. As the number of iterations increases, the operating nodes count gets reduced. The convergence curves in Figures 19, 20, 21 indicates that the proposed CRSA keeps with more operating nodes than the other competing algorithms at three different locations of BS, which are (100,100), (200,200), and (300,300). Similarly, it is clear that the proposed CRSA has fewer sensor nodes count as shown in Table 8.

TABLE 8. The operating and dead nodes numbers for all algorithms where BS at (100,100), (200,200), (300,300).

Algorithm	(100, 100)	(200, 200)	(300, 300)
PSO	68	46	9
GWO	76	48	15
HHO	75	72	29
WOA	93	92	43
RSA	114	100	74
CRSA	**127**	**112**	**87**

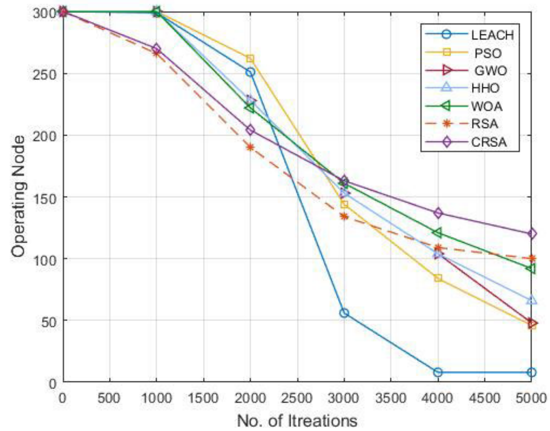

FIGURE 19. The convergence curves of the operating nodes for all algorithms where BS at (100,100).

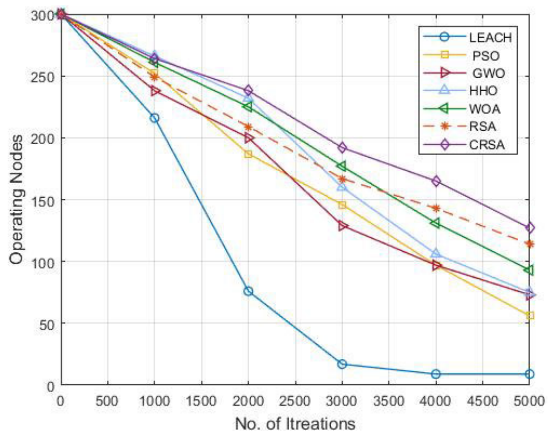

FIGURE 20. The convergence curves of the operating nodes for all algorithms where BS at (200,200).

3) THE RESULTS OF THE CRSA AND THE OTHER ALGORITHMS CONCERNING THE PACKET RECEPTION BY THE BASE STATION

The CRSA is compared against the other MH algorithms concerning the packet reception by the base station. The average (Avg) results are reported in Table 9 after 5000 iterations and over 15 runs. The best outcomes are documented in **bold** text. The results in the Table 9 show that the proposed CRSA outperforms the other MH algorithms.

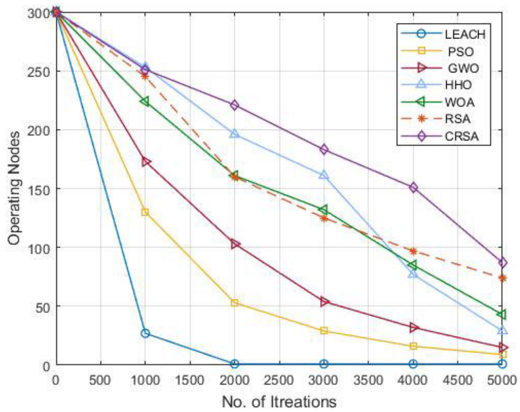

FIGURE 21. The convergence curves of the operating nodes for all algorithms where BS at (300,300).

TABLE 9. The packet reception by the base station for all algorithms where BS at (100,100), (220,220), and (300,300).

Algorithm	(100, 100)	(200,200)	(300,300)
PSO	1.42E+06	1.14E+06	4.12E+05
GWO	1.20E+06	9.18E+05	3.96E+05
HHO	1.61E+06	1.35E+06	4.6E+05
WOA	1.63E+06	1.33E+06	4.83E+05
RSA	1.83E+6	1.46E+06	6.92E+05
CRSA	**2.01E+06**	**1.49E+06**	**7.19E+05**

TABLE 10. The half node death for all algorithms where BS at (100,100), (220,220), and (300,300).

Algorithm	(100, 100)	(200,200)	(300,300)
PSO	2841	2449	795
GWO	2916	2805	1136
HHO	3415	2990	1788
WOA	3789	3107	1825
RSA	3830	3636	2375
CRSA	**4048**	**3741**	**2791**

4) THE RESULTS OF THE CRSA AND THE OTHER ALGORITHMS CONCERNING THE NETWORK LIFETIME

The CRSA is compared against the other MH algorithms concerning of the network lifetime. The average (Avg) results are reported in Table 10 after 5000 iterations and over 15 runs. The best outcomes are documented in **bold** text. The results in the Table 10 show that the CRSA outperforms the other MH algorithms.

D. THE COMPARISON BETWEEN THE CRSA AND THREE VERSIONS OF THE LEACH ALGORITHM

The CRSA is evaluated based on the total consumed energy, the number of operating nodes, the packet reception by the BS, and the network lifetime. The CRSA is compared with three LEACH algorithms namely. LEACH [7], energy LEACH (E-LEACH) [9], centralized LEACH (LEACH-C) [10].

1) THE RESULTS OF THE CRSA AND THE OTHER LEACH ALGORITHMS CONCERNING TOTAL ENERGY CONSUMPTION

The CRSA is compared against the other LEACH algorithms concerning total energy consumption. The average (Avg) results are reported in Table 11 after 5000 iterations and over 15 runs. The overall best results are reported in **bold** text. The results in the Table 11 show that the proposed CRSA outperforms the other LEACH algorithms.

TABLE 11. The overall energy consumption for LEACH algorithms where BS at (100,100), (200,200), and (300,300).

Algorithm	(100, 100)	(200, 200)	(300,300)
LEACH	600.23	6001.21	604.50
E-LEACH	600	600	600
LEACH-C	599.45	599.77	599.95
CRSA	**522.94**	**532.86**	**537.30**

TABLE 12. The operating nodes numbers for LEACH algorithms where BS at (100,100), (200,200), (300,300).

Algorithm	(100, 100)	(200, 200)	(300, 300)
LEACH	2	1	0
E-LEACH	3	2	0
LEACH-C	6	4	0
CRSA	**127**	**112**	**87**

TABLE 13. The packet reception by the base station for LEACH algorithms where BS at (100,100), (200,200), and (300,300).

Algorithm	(100, 100)	(200, 200)	(300, 300)
LEACH	7.12E+05	6.09E+05	2.81E+05
E-LEACH	1.14E+06	9.08E+05	3.71E+05
LEACH-C	1.32E+06	1.05E+06	4.00E+05
CRSA	**2.01E+06**	**1.49E+06**	**7.19E+05**

2) THE RESULTS OF THE PROPOSED CRSA AND THE OTHER LEACH ALGORITHMS CONCERNING THE NUMBER OF OPERATING NODES (ON)

The CRSA is compared against the other LEACH algorithms concerning the number of operating nodes (ON). The average (Avg) results are reported in Table 12 after 5000 iterations and over 15 runs. The best outcomes are documented in **bold** text. The results in the Table 12 show that the CRSA outperforms the other LEACH algorithms.

3) THE RESULTS OF THE CRSA AND THE OTHER LEACH ALGORITHMS CONCERNING THE PACKET RECEPTION BY THE BASE STATION

The CRSA is compared against the other LEACH algorithms in terms of the packet reception by the base station. The average (Avg) results are reported in Table 13 after 5000 iterations and over 15 runs. The best outcomes are documented in **bold** text. The results in the Table 13 show that the CRSA outperforms the other LEACH algorithms.

4) THE RESULTS OF THE CRSA AND THE OTHER LEACH ALGORITHMS CONCERNING THE NETWORK LIFETIME

The CRSA is compared against the other LEACH algorithms concerning the packet reception by the base station. The average (Avg) results are reported in Table 14 after 5000 iterations and over 15 runs. The best outcomes are documented in **bold** text. The results in the Table 14 show that the proposed CRSA outperforms the other LEACH algorithms.

TABLE 14. The last nodes death (LND) for LEACH algorithms where BS at (100,100), (200,200), and (300,300).

Algorithm	(100, 100)	(200, 200)	(300, 300)
LEACH	5398	3537	1271
E-LEACH	3951	3349	1297
LEACH-C	5000	3446	1863
CRSA	**8827**	**7790**	**6831**

VI. CONCLUSION AND FUTURE WORK

In this article, a new hybrid algorithm called CRSA is introduced. The proposed CRSA hybridizes between the original RSA and the chaotic map. This combination is used to select an optimum set of CHs in WSNs, avoid trapping in local optima, and achieve diversity in the search process. The performance of the proposed CRSA was compared with other existing meta-heuristics algorithms, such as PSO, GWO, HHO, WOA, and RSA, and with three versions of the LEACH algorithm. The CRSA has verified the effectiveness of the mentioned algorithms in terms of the total consumed energy, the number of operating nodes, the packet reception by the base station, and the network lifetime. Outcomes of the simulation have indicated that the CRSA outperforms the three LEACH algorithms and the other five competitor meta-heuristic optimization algorithms. In future directions, we will improve the proposed algorithm to handle multiple node failures and develop a real-time data routing protocol for WSNs. Also, in large-scale networks, we can use two mobile base stations to decrease the overhead on the single stationary base station and thus the network's longevity.

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