Computer Systems Science & Engineering
DOI: 10.32604/csse.2023.029133
Article

Metaheuristic Secure Clustering Scheme for Energy Harvesting Wireless Sensor Networks

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Received: 25 February 2022; Accepted: 12 April 2022

Abstract: Recently, energy harvesting wireless sensor networks (EHWSN) have increased significant attention among research communities. By harvesting energy from the neighboring environment, the sensors in EHWSN resolve the energy constraint problem and offers lengthened network lifetime. Clustering is one of the proficient ways for accomplishing even improved lifetime in EHWSN. The clustering process intends to appropriately elect the cluster heads (CHs) and construct clusters. Though several models are available in the literature, it is still needed to accomplish energy efficiency and security in EHWSN. In this view, this study develops a novel Chaotic Rider Optimization Based Clustering Protocol for Secure Energy Harvesting Wireless Sensor Networks (CROC-SEHWSN) model. The presented CROC-SEHWSN model aims to accomplish energy efficiency by clustering the node in EHWSN. The CROC-SEHWSN model is based on the integration of chaotic concepts with traditional rider optimization (RO) algorithm. Besides, the CROC-SEHWSN model derives a fitness function (FF) involving seven distinct parameters connected to WSN. To accomplish security, trust factor and link quality metrics are considered in the FF. The design of RO algorithm for secure clustering process shows the novelty of the work. In order to demonstrate the enhanced performance of the CROC-SEHWSN approach, a wide range of simulations are carried out and the outcomes are inspected in distinct aspects. The experimental outcome demonstrated the superior performance of the CROC-SEHWSN technique on the recent approaches with maximum network lifetime of 387.40 and 393.30 s under two scenarios.

Keywords: Clustering; wireless sensor networks; network lifetime; energy efficiency; metaheuristics; energy harvesting; rider optimization

1 Introduction

Wireless Sensor Network (WSN) contains autonomous, wireless, networked sensing, spatially distributed devices that are utilized for monitoring a physical space [1]. WSN utilized for environment monitoring, includes disaster monitoring, animal or plant tracking, air quality monitoring, and water quality monitoring. This environment monitoring WSN, otherwise known as "field system," frequently comprise multiple sensors shared in the environment as well as a local gateway node that collects the information for storage or to transfer the information to a remote server. Newly, several researchers are working on different aspects of energy harvesting WSNs (EHWSNs) [2]. It plays a vital role in several applications, besides, in EHWSNs, sensor nodes (SNs) are harvest energy in the environments [3]. In this system, the sensors are battery-operated, lower-cost devices with the capacity to sense the certain environment parameter needed by the application and transmit the gathered information to the local gateway for storage and processing. Therefore, sensors consist of a wireless transceiver, the sensor(s), memory, a battery to power the node, and a micro-controller. Fig. 1 illustrates the process of energy harvesting in WSN.

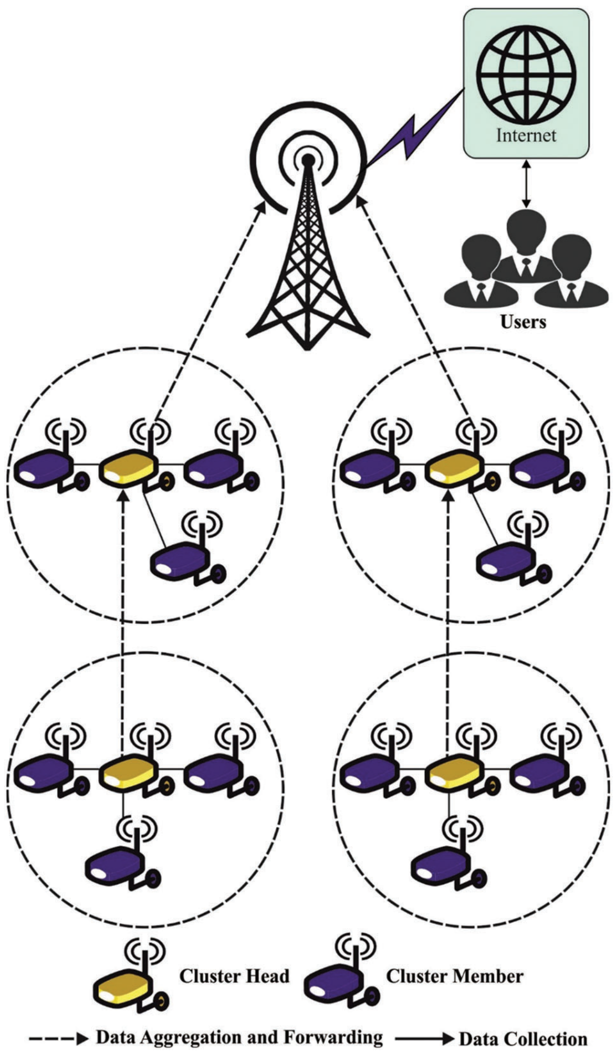


Figure 1: Energy harvesting in WSN

While running on batteries, the short lifetime of the sensors is major problem in executing WSN for environment monitoring applications [4]. In most of these applications, it can be hard to change the battery of node frequently, and when sensors deplete its battery, that node could be considered dead. In the past few decades, authors have focused on developing energy saving techniques to minimalize the power utilization of the sensors at the medium access (MAC), routing, and physical (PHY) layers. To resolve the problem of the constraint power supply to sensors driven by battery, new WSN platform that assists the energy harvesting from the immediate surrounding has been proposed [5]. Furthermore, the renewable energy system is the most promising way to resolve the EE problem of EHWSN situated in remote and rural regions. In the terrain profile, it can be hard to replace batteries because of geographical limitations (difficult terrain), that make access to this site [6].

The harvested energy is transformed into electrical signal that is either stored or consumed directly for future use. For instance, using solar panels to charge a rechargeable battery in the daytime [7]. Renewable energy technique is related to energy estimation systems for astute energy management. Therefore, it is necessary for undertaking inept power-saving mechanisms along with renewable energy techniques for attaining a higher reliability condition [8]. The sensor might integrate dynamic behaviour tendency in the face of the evaluated energy not being capable of sustaining them in the following recharge cycle. Therefore, it can be optimized decisive parameters including duty cycling, sampling rate, and transmit power to adopt the power utilization based on the magnitude and periodicity of the harvestable resource [9]. At the same time, it is justified to assign sensors with high residual energy with shorter RF range and bigger sleep duration, where, those with higher residual energy are carefully chosen as the preferred routing path [10]. But effort has not been made to propose protocol considering battery degradation over time (storage loss, leakage) that impacts the performance of EHWSN.

This study develops a novel Chaotic Rider Optimization Based Clustering Protocol for Secure Energy Harvesting Wireless Sensor Networks (CROC-SEHWSN) model. The presented CROC-SEHWSN model aims to accomplish energy efficiency by clustering the nodes in EHWSN. The CROC-SEHWSN technique was based on the integration of chaotic concepts with traditional rider optimization (RO) algorithm. Besides, the CROC-SEHWSN model derives a fitness function (FF) involving 7 distinct parameters related to WSN. For demonstrating the enhanced performance of the CROC-SEHWSN technique, a wide range of simulations were carried out and the outcomes are inspected under distinct aspects.

The rest of the paper is organized as follows. Section 2 offers a detailed review of existing clustering techniques for EHWSN. Next, Section 3 discusses the proposed model and Section 4 offers performance validation. Lastly, Section 5 concludes the paper.

2 Literature Review

Several clustering techniques for EHWSN is available in the literature [7–10]. Bao et al. [11] proposed a structure of software-defined EHWSN (SD-EHWSN) for collaborative beamforming (CB) communication. In detail, it can be initial design the process of CB communication dependent upon the software-defined network (SDN) infrastructure for reducing the communications and computational overhead of SN. Afterward, it can be assumed that solar energy-harvesting model for achieving long-term function of WSN and employ a stationary Markov (SM) chain for modeling the arriving procedure of solar energy. Garg [12] presented an optimized technique dependent upon metaheuristic, for enhancing the energy efficiency of increase and forward relay IoT network. The energy constraint relay exploits power-splitting based relay protocol for acquiring energy in source and transmission data to target. It is developed expression to energy efficiency of scheme utilizing the throughput at target and outage probability to performance estimate.

Al-Otaibi et al. [13] progressed a hybridization of meta-heuristic cluster based routing (HMBCR) approach for WSN. The HMBCR approach primarily contains a brainstorm optimization with levy distribution (BSO-LD) based clustering method utilizing a FF integrating 4 parameters like distance to neighbors, network load, energy, and distance to base station (DBS). In addition, the water wave optimization with hill climbing (WWO-HC) based routing procedure was executed to an optimum route selection. Rathore et al. [14] presented the hybrid whale and grey wolf optimization (WGWO) based cluster process to EHWSNs. During this study, it can be utilized 2 metaheuristic techniques such as whale and grey wolf for increasing the efficacy of clustering process. The exploitation as well as exploration abilities of the presented hybrid WGWO technique are significantly greater than the typical several present meta-heuristic techniques in the estimation of the technique.

Lin et al. [15] examine a New Harmony search algorithm with multiple populations and local search (HSAML) to this issue with heterogeneity, dynamics, and EH sensor. With simulating, the stability, network lifespan, and implementing time of presented technique are examined. In the experimental outcomes, the presented HSAML executes superior to the conventional technique. Han et al. [16] presented a clustering process for EHWSN (CPEH) which considers the variety of EH capability amongst sensors from both cluster development and inter-cluster transmission. It proceeds the node data namely local density, local energy state, and remote degree as to account for and utilize fuzzy logic (FL) for conducting the CH selective and cluster size allocating. In the meantime, the ACO as a reinforcement learning (RL) approach was employed by CPEH for discovering an extremely effectual inter-cluster routing. Nair et al. [17] utilize 4 varieties of bio-inspired techniques for attaining the maximal EH assuming parameter of PS ratio, amplitude, and phase imbalance from the Rayleigh fading environments.

3 The Proposed Model

This study has developed a novel CROC-SEHWSN model for accomplishing maximum energy efficiency in the EHWSN. The proposed CROC-SEHWSN model is based on the integration of chaotic concepts with conventional RO algorithm. In addition, the CROC-SEHWSN model has derived a FF comprising seven different parameters related to WSN. For accomplishing secrecy, trust factor and link quality metrics are considered in the FF. Fig. 2 illustrates the overall block diagram of CROC-SEHWSN technique.

3.1 System Model

For energy harvesting, we assumed that sensor could endlessly harvest energy from the nearby environment at a constant rate. But because of the hardware diversity and location, the energy harvesting rate differs between sensors. Usually, sensor harvests the energy from vibration or heat of the machine, we believed that this assumption is practical for the EHWSN utilized in Industry 4.0. Then utilize harvest-use mechanism to define the energy obtainability of sensor. The harvested energy is immediately utilized minimizes the difficulty of energy management and easier to implement. Then, apply the traditional radio energy dissipation [18]. The sender consumes energy for running the power amplifier and the radio electronics, where the receiver dissipates energy for running the radio electronics. Representing the packet size as l bits and the transmission distance as d; the energy cost of transmitter (E_{tx}) and receiver (E_{rx}) a packet is given in the following:

$$E_{tx}(l,\ d) = \begin{cases} E_{elec} \cdot l + E_{fs} \cdot d^2 \cdot l, & d \leq\ d_0, \\ E_{elec} \cdot l + E_{mp} \cdot d^4 \cdot l, & d > d_0, \end{cases} \tag{1}$$

$$E_{rx}(l,\ d) = E_{elec} \cdot l, \tag{2}$$

whereas E_{elec} denotes the energy cost for each bit by the radio electronics of transmitting and receiver and $E_{fs} \cdot d^2$ and $E_{mp} \cdot d^4$ represents the energy required for each bit for the power amplifier in the free space channel (d^2) and the multipath channel (d^4). d_0 denotes the threshold distance as follows

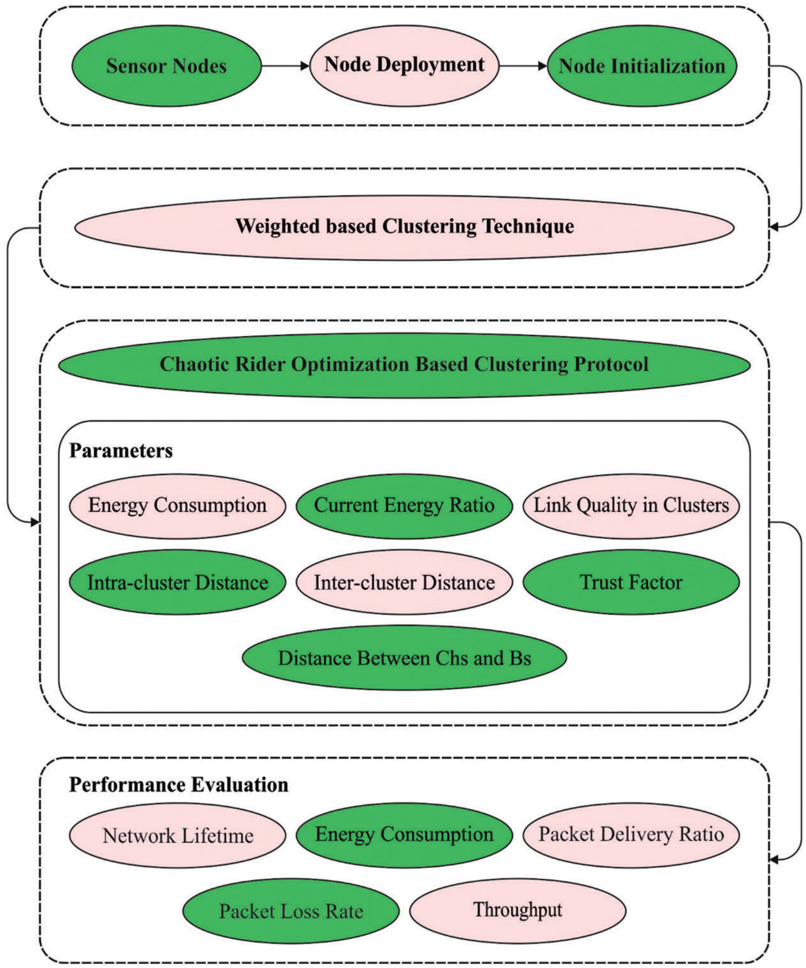


Figure 2: Overall block diagram of CROC-SEHWSN technique

$$d_{0=}\sqrt{\frac{E_{fs}}{E_{mp}}}. \quad (3)$$

Noted that E_{elec}, E_{fs}, and E_{mp} depends on the transceiver character and the acceptable bit-error rate. IT must be carefully set. For aggregating data, assume the CH consumes E_{da} energy to manage one-bit data and the cluster has W sensors (CH), the energy dissipation for CH in the aggregation process as follows

$$E_{agg} = l \cdot W \cdot E_{da}. \quad (4)$$

3.2 Overview of CRO Algorithm

RO algorithm is a popular optimization that includes four-rider groups namely follower, bypass rider, attacker, and over-taker.

- Bypass riders bypass the leading path to attain the destination.
- Follower follows the leading rider to attain the target.
- The over-taker takes its own location to attain the destination.
- The attacker attempts to attain the destination with the highest speed.

It is started by 4 rider groups *Gr*, which can be accurately shown in Eq. (5), in which U represent the rider count i.e., analogous to *Gr*, the dimension or count of coordinates is represented as J, $D_t(i, j)$ i^{th} rider's position at the time.

$$D_t = \{D_t(i\,j)\};\ 1 \le i \le U;\ 1 \le j \le J. \tag{5}$$

The rider count is determined in Eq. (6), where, the count of bypass rider is represented as *By*, Follower count is represented as *Fl*, the count of over-taker is represented as *Ot* and the attacked count is represented by *Ak*. The relationship amongst the variables is shown in the following.

$$H = By + Fl + Ot + Ak. \tag{6}$$

$$By = Fl = Ot = Ak = H\,/\,4. \tag{7}$$

The steering angle at the time t is provided below, where $Si^t(i, j)$ denotes the steering angle of i rider vehicle. Eq. (9) determines the first steering angle, where the location angle of i^{th} rider vehicle is represented by θ_j, and the co-ordinate angle is given as ϕ. The coordinate angle defines the steering angle as follows [19].

$$Si_t = \{Si_i^t\};\ 1 \le i \le U;\ 1 \le j \le J. \tag{8}$$

$$Si_{i,j} = \begin{cases} \theta_i & if\ j = 1 \\ Si_{ij} + \varphi & if\ j \ne 1\ \&\ Si_{i,i} + \varphi \le 360 \\ Si_{ij} + \varphi - 360 & otherwise \end{cases} \tag{9}$$

$$\varphi = \frac{360}{J}. \tag{10}$$

Therefore, the initialization of brake, gear, and accelerator is modelled in the following. The gear of i rider vehicle is represented as A_i. The accelerator of i rider vehicle was represented as B_i and the brake of i rider vehicle is C_i.

$$A = \{A_i\}1 \le i \le U. \tag{11}$$

$$B = \{B_i\}1 \le i \le U. \tag{12}$$

$$C = \{C_i\}1 \le i \le U. \tag{13}$$

The success rate of rider was calculated afterward initializing the rider group and parameter. For estimating the success rate, distance is the main parameter calculated between the rider destination and the position. Now, the location of i rider is represented as D_i and K_{Si} indicates the target location.

$$r_i = \frac{1}{\|D_i - K_{Si}\|}. \tag{14}$$

Determine leading rider: the success rate performs a significant role. However, it isn't a constant factor. Since the location of the rider changes at each time step.

The location of rider group is upgraded: The bypass rider doesn't go after other riders. Hence, the location upgraded arbitrarily. Where, β, δ denotes the random integer and it ranges from 0 and 1, η and ξ signify the other arbitrary numbers in the range of 1to U, and β has a size of $1 \times J$.

$$D_{t+1}^{By}(i, j) = (\beta * (D_t(\eta, j)) * \delta) + D_t((\xi, j) * [1 - \beta(j)]). \tag{15}$$

The update procedure of the follower location is performed based on the location of the leading rider. The location update of the follower is modelled. The co-ordinate selector has been represented as k the leading rider location is represented by D^K, leading rider index is denoted as K, i^{th} rider steering angle in the k coordinate is indicated as $Si^t_{i,k}$ and the i^{th} rider traveling distance is characterized as $h^t_i.k$ chosen according to the on-time probability P^t_{ON} as follows.

$$D^{Fl}_{t+1}(i,\ k = D^K(K,\ k + [\cos\ (Si^t_{i,k}) * D^K(K,\ k + h^t_i)] \tag{16}$$

$$P^t_{ON} = \left(\frac{t}{T_{0ff}}\right) * J. \tag{17}$$

The over-taker update is continuously depending on three components namely relative success rate, coordinate selector, and direction indicator. The over-taker location update is determined. The i^{th} rider location in k^{th} coordinate is given by $D_{t(i,k)}$ and the direction indicator of i^{th} rider in time t is given by $Id_t(i)$.

$$D^{Ot}_{t+1}(i,\ k = D_t(i,\ k + [Id_t(i) * D^K(K,\ k)] \tag{18}$$

It is similar to the follower position update. But the attacker upgrades the coordinate value rather than selecting one. Eq. (19) depicts the attacker update procedure and the leading rider location is represented as $D^K(K, j)$.

$$D^{Ak}_{t+1}(i,\ j) = D^K(K,\ j) + [\cos\ (Si^t_{ij}) * D^K(K,\ j)] + h^t_i. \tag{19}$$

The achievement of the optimum solution is essential. Thus, the upgrading of the rider parameter is vital. To improve the performance of the RO algorithm, the CRO algorithm has been developed with the inclusion of chaotic concepts. The chaotic map creates random sequence that is employed during the process of encryption. Several concepts in chaos theory, e.g., sensitivity and mixing to primary condition and parameter, match with cryptography. The two essential properties of C-function are sensitivity to primary condition and mixing property. The C-function stream was made by distinct chaotic maps.

$$a_{n+1} = \alpha * a_n(1 - a_n)a_n \in (0,\ 1)\ and\ n = 0,\ 1,\ \ldots,\ \alpha \in (0,\ 4). \tag{20}$$

During the logistic map, a semi-group was made by the process of composition of function, as $\alpha \in (0, 4)$ denotes a period-doubling bifurcation method.

3.3 Process Involved in CROC-SEHWSN Model

There are seven objective functions in the CROC-SEHWSN model [14]. Those functions are covering each significant aspect required for energy-effective clustering namely finding the current energy ratio, saving the energy by reducing the amount of CHs, minimizing the distance among CHs and BS, improving the link quality from cluster, maximizing the inter-cluster distance among CHs, trust level, and decreasing the intra-cluster distance. The presented approach offers the optimal solution by reducing each objective function. The FF is the sum of each 7 main functions with 7 weight constants. It can be expressed in the following

$$FF = minimum(m_1y_1 + m_2y_2 + m_3y_3 + m_4y_4 + m_5y_5 + m_6y_6 + m_7y_7). \tag{21}$$

Whereas m_1, m_2, m_3, m_4, m_5, m_6, and m_7 denotes weight constant determined by user, and FF indicates the FF. As well, $y_1, y_2, y_3, y_4, y_5, y_6$, and y_7 represent the objective functions. The presented method is utilized for finding the optimal solution based on the FF. During the presented method, the solution has been provided by all the agents. The optimal solution for the abovementioned FF comprises of minimal amount of clusters with higher link quality and dynamically chosen CH with higher residual energy.

The initial function has been dedicated to saving energy, and it could reduce the optimum amount of CHs, energy utilization would be minimized.

$$y_1 = \frac{optimal\ number\ of\ clusters\ (c)}{size\ of\ set\ of\ CH\ contestants\ (s)}. \tag{22}$$

The 2nd function offers data regarding the present energy ratio; when there are overall M nodes, R cluster the 2nd function is the ratio of first energy of nodes and the present CH energy.

$$y_2 = \frac{\sum_{p=1}^{M} \text{Energy}\ (node_p)}{\sum_{q=1}^{R} \text{Energy}\ (cluster\_head_q)}. \tag{23}$$

The 3rd function's aim is to enhance the link quality in cluster. This function creates the cluster that distances among SNs are minimal. Euclidean distance is estimated among the SN and CH.

$$y_3 = \sum_{q=1}^{R} \frac{\sum_{\forall node_j \varepsilon cluster_q} euclidean\_distance(node_j,\ cluster\_head_q)}{minimum_{\forall node_j \in cluster_q} euclidean\_distance(node_j,\ cluster\_head_q)}. \tag{24}$$

The 4th function reduces the distance among CHs and BS. Now, the area is considered as $A \times A$; overall clusters are R.

$$y_4 = \frac{\frac{1}{R}\sum_{q=1}^{R} \text{euclidean} - \text{distance}\ (cluster - head_q,\ base - \text{station})}{\frac{A}{2}}. \tag{25}$$

The 5th function aim is for minimizing the tra-cluster distance of SN and the respective CH. The binary variable is taking value 1 when a certain node is allocated to a CH; or else, their value is 0.

$$y_5 = \frac{\frac{1}{M}\sum_{p=1}^{M}\sum_{q=1}^{R} \text{euclidean\_distance}\ (node_p,\ \ \text{cluster}\ \_head_q) \times binary - parameter_{pq}}{\frac{Average\_distance\_two\_neighbors\_cluster\_heads}{2}}. \tag{26}$$

The 6th function is dedicated to maximizing the inter-cluster distance among CHs. $|CN_q|$ denotes the amount of nodes in cluster q.

$$y_6 = \frac{Average\_distance\_two\_neighbors\_cluster\_heads}{\frac{1}{|CN_q|}\sum_{q=1}^{|CN_q|} \text{euclidean} - \text{distance}\ (cluster\_head_q,\ cluster - head_r)}. \tag{27}$$

The 7th function is utilized for handling the trust level of nodes. Eq. (28) reduces the maximal load among CHs. $|CN_q|$ denotes the amount of trust level in cluster q. Now, the area is considered as $A \times A$; overall= clusters are R.

$$y_7 = \frac{MAXIMUM(|TL_q|)}{\frac{1}{R}\sum_{q=1}^{R}(|TL_q|)} \tag{28}$$

4 Results Analysis

This section examines the experimental validation of the CROC-SEHWSN model with existing approaches such as low energy adaptive clustering hierarchy (LEACH), Multi-objective fuzzy clustering algorithm (MOFCA), energy aware fuzzy unequal clustering (EAUCF), and CPEH. Tab. 1 and Fig. 3 examine the packet delivery ratio (PDR) investigation of the CROC-SEHWSN model with recent methods under two scenarios. The experimental values indicated that the CPEH model has resulted in worse outcomes with the minimal values of PDR. Followed by, the EAUCF, MOFCA, and LEACH models have accomplished slightly improved values of PDR. However, the CROC-SEHWSN model has gained maximum outcomes with higher values of PDR. For instance, with scenarios 1 and 50 nodes, the CROC-SEHWSN model has offered increased PDR of 97.14% whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained decreased PDR of 95.31%, 89.81%, 88.50%, and 65.72% respectively. Similarly, with scenarios 2 and 50 nodes, the CROC-SEHWSN model has provided maximum PDR of 98.82% whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have reached minimum PDR of 97.36%, 93.29%, 81.95%, and 50.26% respectively.

Table 1: PDR and PLR analysis of CROC-SEHWSN technique with recent methods under two scenarios

No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Packet Delivery Ratio (%)					
Scenario-1					
50	97.14	95.31	89.81	88.50	65.72
100	96.09	93.74	84.05	79.07	58.39
150	91.12	86.41	77.24	70.44	53.42
200	85.10	76.98	67.82	62.06	47.92
250	76.98	70.17	61.53	56.04	43.47
300	70.44	64.68	54.99	51.06	40.85
350	63.37	54.73	50.80	47.40	39.02
400	57.61	51.32	46.87	43.99	34.83
Scenario-2					
50	98.82	97.36	93.29	81.95	50.26
100	97.94	95.04	85.44	74.39	46.19
150	97.07	91.84	77.01	67.13	41.25
200	96.78	89.22	69.74	61.31	39.51
250	92.71	82.83	62.18	56.37	36.31
300	85.44	78.46	57.24	52.01	34.27
350	80.50	70.91	52.59	48.52	33.11
400	73.81	57.53	46.48	43.87	29.62
Packet Loss Rate (%)					
Scenario-1					
50	2.86	4.69	10.19	11.50	34.28
100	3.91	6.26	15.95	20.93	41.61
150	8.88	13.59	22.76	29.56	46.58
200	14.90	23.02	32.18	37.94	52.08
250	23.02	29.83	38.47	43.96	56.53
300	29.56	35.32	45.01	48.94	59.15
350	36.63	45.27	49.20	52.60	60.98
400	42.39	48.68	53.13	56.01	65.17

(Continued)

Table 1 (continued)

No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Packet Loss Rate (%)					
Scenario-2					
50	1.18	2.64	6.71	18.05	49.74
100	2.06	4.96	14.56	25.61	53.81
150	2.93	8.16	22.99	32.87	58.75
200	3.22	10.78	30.26	38.69	60.49
250	7.29	17.17	37.82	43.63	63.69
300	14.56	21.54	42.76	47.99	65.73
350	19.50	29.09	47.41	51.48	66.89
400	26.19	42.47	53.52	56.13	70.38

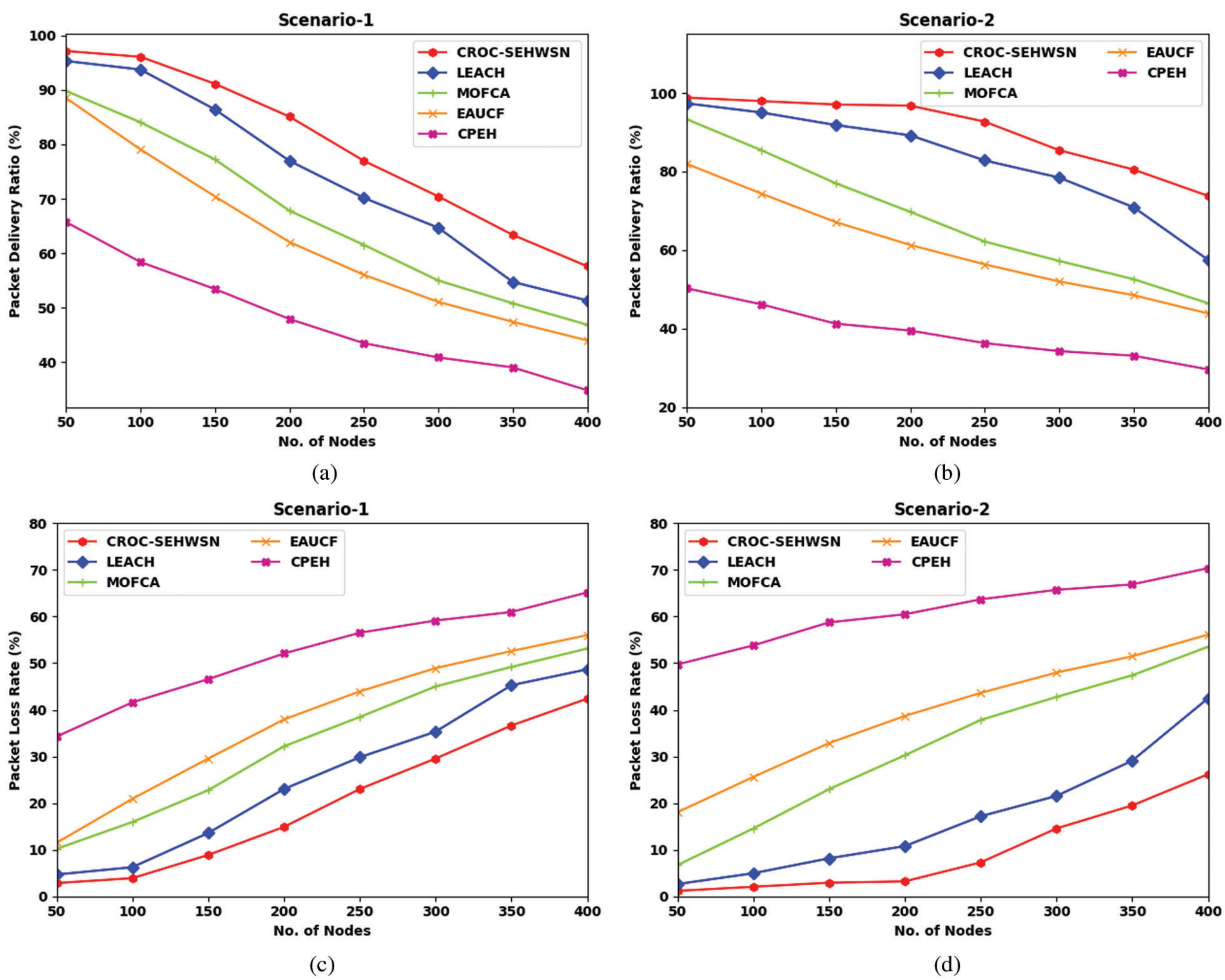


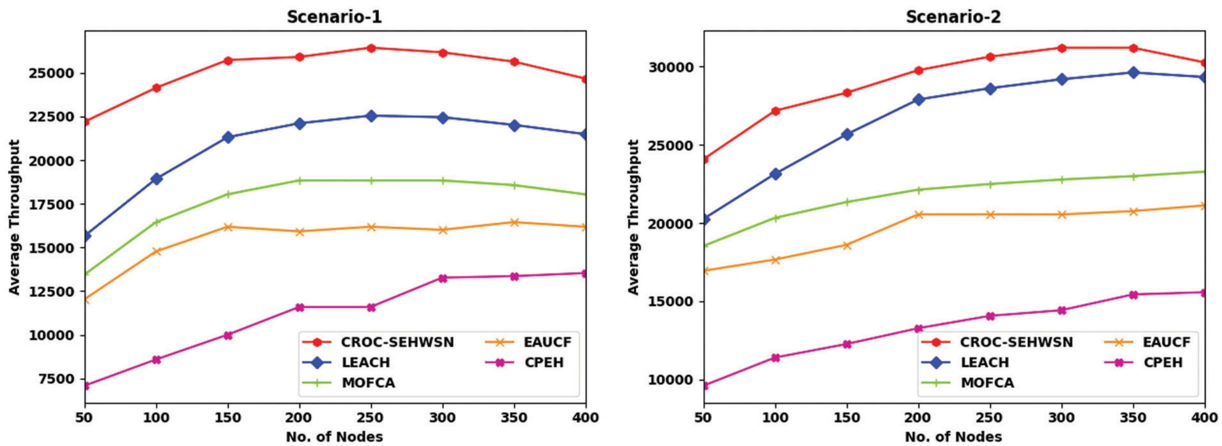
Figure 3: PDR and PLR analysis of CROC-SEHWSN technique under two scenarios

The figures illustrate a detailed packet loss rate (PLR) inspection of the CROC-SEHWSN model with existing techniques under two scenarios. The figure reported that the CROC-SEHWSN model has outperformed the other methods under all nodes. For instance, with scenarios 1 and 50 nodes, the CROC-SEHWSN model has resulted in lower PLR of 2.86% whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained higher PLR of 4.69%, 10.19%, 11.50%, and 34.28% respectively. Meanwhile, with scenarios 1 and 400 nodes, the CROC-SEHWSN method has resulted in lower PLR of 42.39% whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained higher PLR of 48.68%, 53.13%, 56.01%, and 65.17% correspondingly. Eventually, with scenario 2 and 50 nodes, the CROC-SEHWSN algorithm has resulted to lower PLR of 1.18% whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained maximum PLR of 2.64%, 6.71%, 18.05%, and 49.74% correspondingly.

Tab. 2 and Fig. 4 inspect the average throughput (ATP) investigation of the CROC-SEHWSN model with recent methods under 2 scenarios. The experimental values indicated that the CPEH model has resulted in worse outcome with the minimal values of ATP. Followed by, the EAUCF, MOFCA, and LEACH models have accomplished somewhat improved values of ATP. But, the CROC-SEHWSN model has gained maximum outcome with higher values of ATP. For instance, with scenarios 1 and 50 nodes, the CROC-SEHWSN system has obtainable increased ATP of 22195 whereas the LEACH, MOFCA, EAUCF, and CPEH approaches have obtained decreased ATP of 15654, 13444, 12030, and 7079 correspondingly. In addition, with scenarios 2 and 50 nodes, the CROC-SEHWSN methodology has offered maximal ATP of 24082 whereas the LEACH, MOFCA, EAUCF, and CPEH systems have reached lower ATP of 20262, 18533, 16947, and 9596 correspondingly.

Table 2: Average throughput analysis of CROC-SEHWSN technique with recent methods under two scenarios

	Average Throughput				
No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Scenario-1					
50	22195	15654	13444	12030	7079
100	24140	18925	16449	14770	8582
150	25731	21311	18041	16184	9997
200	25908	22107	18836	15919	11588
250	26438	22549	18836	16184	11588
300	26173	22460	18836	16007	13267
350	25643	22018	18571	16449	13356
400	24670	21488	18041	16184	13532
Scenario-2					
50	24082	20262	18533	16947	9596
100	27181	23145	20334	17668	11397
150	28334	25668	21343	18605	12262
200	29776	27902	22136	20551	13271
250	30641	28623	22497	20551	14064
300	31217	29199	22785	20551	14424
350	31217	29632	23001	20767	15433
400	30280	29343	23289	21127	15578



(a) (b)

Figure 4: ATP analysis of CROC-SEHWSN technique under two scenarios

Tab. 3 and Fig. 5 demonstrate a detailed average energy consumption (AECM) inspection of the CROC-SEHWSN model with existing techniques under two scenarios. The figure reported that the CROC-SEHWSN model has outperformed the other methods under all nodes. For instance, with scenarios 1 and 50 nodes, the CROC-SEHWSN approach has resulted in lower AECM of 0.00066 J whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained higher AECM of 0.00073, 0.00082, 0.00093, and 0.00119 J respectively. In the meantime, with scenarios 1 and 400 nodes, the CROC-SEHWSN approach has resulted to lower AECM of 0.00077 J whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained supeiror AECM of 0.00084, 0.00092, 0.00097, and 0.00100 J correspondingly. Finally, with scenarios 2 and 50 nodes, the CROC-SEHWSN system has resulted in lower AECM of 0.00064 J whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained higher AECM of 0.00068, 0.00072, 0.00085, and 0.00108 J correspondingly.

Table 3: Average energy consumption analysis of CROC-SEHWSN technique with recent methods under two scenarios

	Average Energy Consumption (J)				
No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Scenario-1					
50	0.00066	0.00073	0.00082	0.00093	0.00119
100	0.00068	0.00074	0.00082	0.00095	0.00113
150	0.00068	0.00073	0.00084	0.00095	0.00111
200	0.00069	0.00074	0.00087	0.00097	0.00110
250	0.00069	0.00077	0.00089	0.00097	0.00110
300	0.00072	0.00080	0.00091	0.00097	0.00108
350	0.00074	0.00082	0.00092	0.00097	0.00104
400	0.00077	0.00084	0.00092	0.00097	0.00100

(Continued)

Table 3 (continued)

	Average Energy Consumption (J)				
No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Scenario-2					
50	0.00064	0.00068	0.00072	0.00085	0.00108
100	0.00064	0.00069	0.00078	0.00087	0.00105
150	0.00064	0.00069	0.00080	0.00088	0.00104
200	0.00065	0.00070	0.00082	0.00088	0.00102
250	0.00065	0.00071	0.00084	0.00089	0.00101
300	0.00068	0.00071	0.00084	0.00089	0.00099
350	0.00070	0.00074	0.00084	0.00090	0.00098
400	0.00073	0.00078	0.00084	0.00090	0.00098

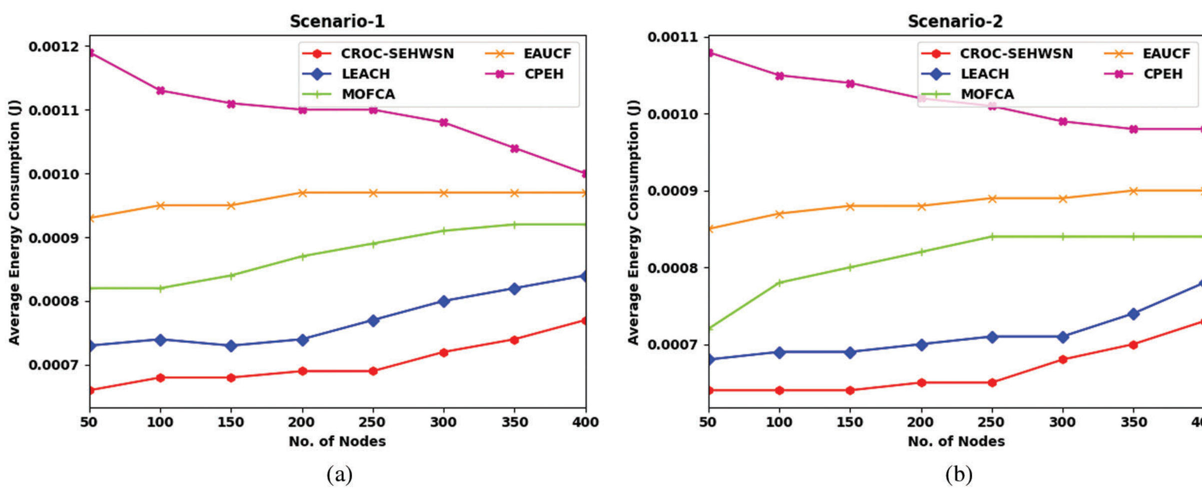
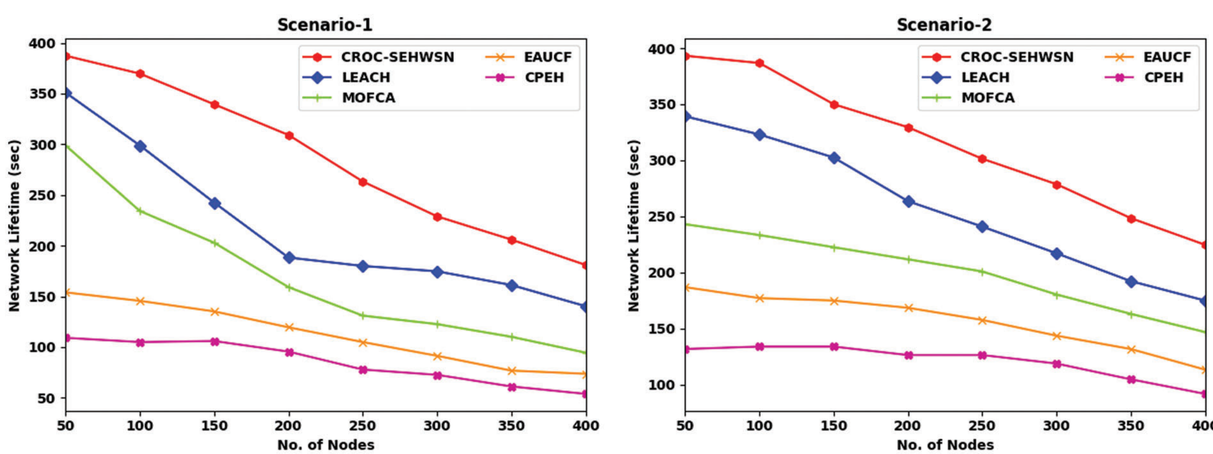


Figure 5: AECM analysis of CROC-SEHWSN technique under two scenarios

Tab. 4 and Fig. 6 inspect the network lifetime (NLT) investigation of the CROC-SEHWSN technique with recent methods under two scenarios. The experimental values indicated that the CPEH methodology has resulted in worse outcomes with the minimal values of NLT. Along with that, the EAUCF, MOFCA, and LEACH models have accomplished somewhat enhanced values of NLT. Then, the CROC-SEHWSN model has gained maximum outcome with higher values of NLT. For instance, with scenarios 1 and 50 nodes, the CROC-SEHWSN approach has offered increased NLT of 387.40 s whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have obtained decreased NLT of 350.92, 298.82, 153.96, and 109.15 s correspondingly. At the same time, with scenarios 2 and 50 nodes, the CROC-SEHWSN methodology has provided maximal NLT of 393.30 s whereas the LEACH, MOFCA, EAUCF, and CPEH techniques have reached minimal NLT of 339.27, 243.08, 186.89, and 131.77 s correspondingly.

Table 4: Network lifetime analysis of CROC-SEHWSN approach with recent methods under two scenarios

	Network Lifetime (s)				
No. of Nodes	CROC-SEHWSN	LEACH	MOFCA	EAUCF	CPEH
Scenario-1					
50	387.40	350.92	298.82	153.96	109.15
100	369.68	298.82	234.21	145.63	104.98
150	339.46	242.54	202.94	135.20	106.02
200	309.24	188.35	159.17	119.57	95.60
250	263.38	180.02	131.04	104.98	77.89
300	228.99	174.80	122.70	91.44	72.68
350	206.07	161.26	110.19	76.85	61.21
400	181.06	140.41	94.56	73.72	53.92
Scenario-2					
50	393.30	339.27	243.08	186.89	131.77
100	386.82	323.06	233.36	177.16	133.93
150	350.07	302.52	222.55	175.00	133.93
200	329.54	263.62	211.74	168.51	126.36
250	301.44	240.92	200.93	157.71	126.36
300	278.75	217.15	180.40	143.66	118.80
350	248.49	192.29	163.11	131.77	104.75
400	224.71	175.00	146.90	113.40	91.78



(a) (b)

Figure 6: NLT analysis of CROC-SEHWSN technique under two scenarios

5 Conclusion

This study has developed a novel CROC-SEHWSN model for accomplishing maximum energy efficiency in the EHWSN. The proposed CROC-SEHWSN model is based on the integration of chaotic concepts with conventional RO algorithm. In addition, the CROC-SEHWSN model has derived a FF comprising seven different parameters related to WSN. For accomplishing secrecy, trust factor and link quality metrics are considered in the FF. For demonstrating the enhanced performance of the CROC-SEHWSN technique, a wide range of simulations were carried out and the outcomes are inspected under distinct aspects. The experimental outcome demonstrated the maximum performance of the CROC-SEHWSN technique on existing approaches with maximum lifetime of 387.40 and 393.30 s respectively. In future, multihop routing protocols with lightweight cryptographic solutions can be designed for EHWSN.

Acknowledgement: The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University, Kingdom of Saudi Arabia for funding this work through General Research Project under the grant number: RGP. 2/162/43.

Funding Statement: This research was supported by the Deanship of Scientific Research Project (RGP. 2/162/43) King Khalid University, Kingdom of Saudi Arabia.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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