Energy Aware Scheme for Underwater Wireless Sensor Networks

Heba M. Fadhil, Muna M. Hummady, Noor Q. Makhool, Zinah O. Dawood

Department of Information and Communication, Al-Khwarizmi College of Engineering, University of Baghdad, Iraq.

Emails: heba@kecbu.uobaghdad.edu.iq; muna@kecbu.uobaghdad.edu.iq; noor.q@kecbu.uobaghdad.edu.iq; zina_osama@kecbu.uobaghdad.edu.iq;

Abstract

The development of wireless sensor networks (WSNs) in the underwater environment leads to underwater WSN (UWSN). It has severe impact over the research field due to its extensive and real-time applications. However effective execution of underwater WSNs undergoes several problems. The main concern in the UWSN is sensor nodes' energy depletion issue. Energy saving and maintaining quality of service (QoS) becomes highly essential for UWASN because of necessity of QoS application and confined sensor nodes (SNs). To overcome this problem, numerous prevailing methods like adaptive data forwarding techniques, QoS-based congestion control approaches, and various methods have been devised with maximum throughput and minimum network lifespan. This study introduces a novel Seeker Optimization based Energy Aware Clustering Scheme for Underwater Wireless Sensor Networks (SOEACS-UWN). The presented SOEACS-UWN model follows the operation on a collection of solutions named search population (i.e., human team) and considered optimization procedure as a searching process of optimum solutions via human teams. The SOEACS-UWN model constructs a fitness function for effectual CH choices using diverse variables namely distance, residual energy, node degree, centrality, and link quality. The simulation analysis of the SOEACS-UWN model is tested and the outcomes were investigated under diverse aspects. The experimental outcomes demonstrated the supremacy of the SOEACS-UWN model over other approaches.

Keywords: Underwater wireless sensor networks; Energy efficiency; Clustering; Object function; Seeker optimization

1. Introduction

The ocean is an entrancing huge scope of water that has consistently drawn in individuals who needed to settle its secrets. For quite a long time the entrance of people to the ocean was restricted to the surface or the close by water, on the grounds that the scientists needed to utilize wire-line instruments and testing gear situated at the ocean surface [1]. This reality confined logical exploration tasks. These days there is a developing need for submerged checking (for example for investigation of regular undersea assets, social occasion of logical information, or recognition of marine occurrences [2], for example, compound contamination or oil slick) yet the current innovations don't compare the requesting prerequisites. Thus, another idea of minimal expense, all the more effectively deployable submerged networks with less confined conditions ought to be created: Underwater Wireless Sensor Networks (UWSNs) [3]. These sorts of organizations ought to be versatile, portable, and fit for self-association. They take out the requirement for links and don't obstruct delivering action [4]. UWSNs are another exploration worldview that postures invigorating difficulties contrasted with the ground-based existing organizations because of the inherent properties of the submerged conditions. Fig. 1 showcases the structure of UWSN.

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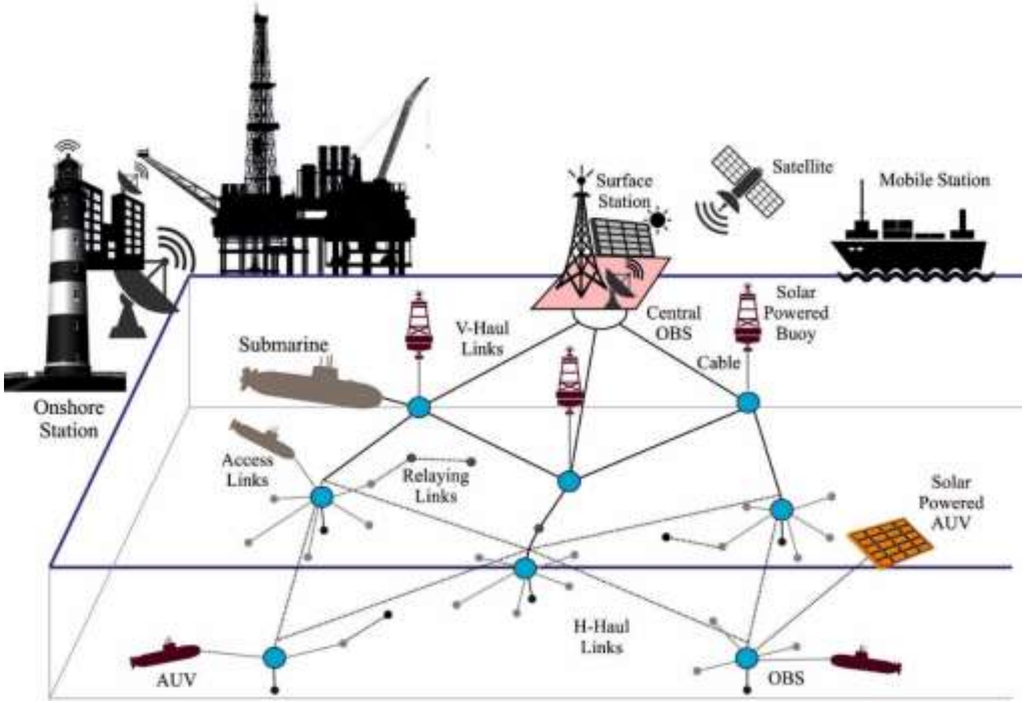

Figure 1: Structure of UWSN

Since radio correspondence isn't attainable for UWSN, it depends on acoustic correspondence. The sensor nodes in UWSN are inclined to the unforgiving climate of water, the saltiness of water, disturbance, constriction of signs, clamor, and so forth [5]. Aside from the issues expressed over, the essential worry in UWSN is the lifetime of the organization. Supplanting the battery or it is preposterous to expect to charge the battery [6]. The energy utilization ought to be enhanced to draw out the organization's lifetime. Energy utilization is mostly because of the transmission of information between nodes [7]. In writing, numerous strategies are proposed to manage energy protection: radio enhancement, information decrease, rest/wakeup plans, energy effectiveness steering, and battery exhaustion techniques. [8] Energy saving is a central issue in UWSNs in light of the fact that sensor nodes are fueled by batteries, which are hard to supplant or re-energize in sea-going conditions. The plan of powerful, versatile, and energy-productive directing conventions in this sort of organization is a crucial examination issue. Most existing information sending conventions proposed for ground-based sensor networks can't be straightforwardly applied in light of the fact that they have been intended for fixed networks. The current multi-bounce impromptu steering conventions are not satisfactory in light of the fact that they apply a nonstop trade of above messages (proactive impromptu directing) or utilize a course disclosure process in view of the flooding strategy (responsive specially appointed steering); these systems are wasteful devices in huge scope submerged systems administration since they consume extreme energy and data transmission assets.

Energy utilization is for the most part because of the transmission of information between nodes. In writing, numerous procedures are proposed to manage energy preservation: radio advancement, information decrease, rest/wakeup plans, energy productivity steering, and battery consumption techniques [9]. The various methodologies proposed in energy proficiency directing are clustering designs, involving energy as a steering metric, multi-way directing, hand-off node situation techniques, and sink portability components [10]. Solidly, in a clustered UWSN, sensors are isolated into various gatherings called clusters in which information assembling and moving happens. Each cluster has various cluster individuals, i.e., sensors and a cluster chief called Cluster Head (CH). It is liable for gathering assembled information from its individuals in an intra-cluster correspondence way and can collaborate with other CHs to report information to a BS by taking on a between cluster correspondence. Nonetheless, since the CHs have in most cases similar highlights to the other cluster individuals, choosing CHs suitably is expected to preserve the energy and in this manner draw out the organization's lifetime. For sure, lopsided energy utilization on CHs might cause a speedy demise of

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nodes and hence cut down the lifetime of the organization. This work targets tending to the existence time augmentation issue by handling the organization traffic and nodes' energy utilization issues.

Xiao et al. [11] introduce the GA related to a particular encoding method, a specific crossover operation, and an enriched mutation function. Moreover, the BPNN used for data fusion can be enhanced by adoption of an optimized momentum approach that diminishes energy consumption via the removal of data redundant and declines the amount of data which is transmitted. Also, presents an optimized cluster head node (CHN) choosing method assuming nodes positions and residual energy. Gomathi et al. [12] modelled a unique routing technique termed energy-efficient and mobilities-related dynamic CH selection routing protocol (EE-MDCHSRP) was proposed for UWSN for fruitful dynamic CH selections. The dynamic CH nodes were fixed by assuming the elements which include least mobility factor, node density, and remaining energy. Li et al. [13] formulated a clustered routing approach, such as location and energy-aware k-means clustered routing (LE-KCR) technique that implied K-means technology assuming the positioned place as well as the remaining energy of every node. In the presented LE-KCR technique, the positioned sites as well as the remaining energy of a candidate CH, along with the distance between them and their sink nodes, were regraded in CH selection.

Chaaf et al. [14] introduce a relay-related void hole prevention and repair (ReVOHPR) protocol through multiple autonomous underwater vehicle (AUV) for UWSN. It becomes a worldwide solution which applies various stages of functions which serve mutually to proficiently diminish and recognize void holes and snare relay nodes for ignoring it. ReVOHPR approves the subsequent functions as virtual graph-based routing, ocean depth (levels)-related equal cluster formations, relay-assisted void hole repair, and dynamic sleep scheduling. For energy-efficient cluster formation, entropy-related eligibility ranking (E2R) was offered, that chooses stable CHs. Afterward, dynamic sleep schedule can be applied by the dynamic kernel Kalman filter (DK2F) method where sleep and active modes were depends on the present state of nodes. Chenthil and Jayarin [15] introduce an Energy-aware QoS related cluster routing with an aggregation managing method (EQoS-CRAM) for offering effectual path discovery has low energy utility for UWSN. Data aggregation was executed utilizing sleep wake scheduling procedure from cluster region to ignore collision. EQoS-CRAM techniques render priority-related QoS data transmitting has lesser postponement.

This study introduces a novel Seeker Optimization based Energy Aware Clustering Scheme for Underwater Wireless Sensor Networks (SOEACS-UWN). The presented SOEACS-UWN model follows the operation on a collection of solutions named search population (i.e., human team) and considered optimization procedure as a searching process of optimum solutions via human teams. The SOEACS-UWN model constructs a fitness function for effectual CH choices using diverse variables namely distance, residual energy, node degree, centrality, and link quality. The simulation analysis of the SOEACS-UWN model is tested and the results are investigated under diverse aspects.

2. The Proposed Clustering Scheme

This study has developed an effective SOEACS-UWN model for proficient selection of CHs in the UWSN. The presented SOEACS-UWN model follows the operation on a collection of solutions named search population (i.e., human team) and considered optimization procedure as a searching process of optimum solutions via human teams.

2.1 System Model

Consider that there exist N sensors arbitrarily designed when periodically sensing the environment. The sensors design cluster through the suggested method. Each cluster has a Cluster Head (CH) that obtains the information from cluster member (CM). Fundamentally, the sensing device is constant through the comparable energy and capability of sensing the neighboring via information transmission and computation [16]. Radio connectivity recognized amongst the nodes are often symmetric. It mentions that the node supplies homogeneous energy to implement the information transferred in every direction. Similarly, Base Station (BS) can be positioned on the exterior side of a model. The sensors can able to alter the communication energy that is depends on the distance amongst receiver node. Moreover, the initial order radio method is functional to evaluate the energy desirable in the deployment model.

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Assume the packet size as m bits. The total energy employed in information transmission is m bits through l meter distance in the middle of a transmitter and receiver that is given below,

$$E_{TNE}(m,l) = \begin{cases} m * E_{elect} + m * \varepsilon_{fsp} * l^2 & if\, l < l_o \\ m * E_{elect} + m * \varepsilon_{mpf} * l^4 & if\, l \geq l_o \end{cases} \tag{1}$$

The energy applied to receive a packet of m bits from the transmitter node is predictable through,

$$E_{RCE}(m) = m * E_{elect} \tag{2}$$

In Eq. (2), $E_{elec\tau}$ indicates the information about electronic power diffusion. It is impacted through various factors such as modulation, digital coding, manageable bit-rate, etc. ε_{fsp} and ε_{mpf} represent energy exploiting factor in a multipath fading along with free space path. Once the source and receiver nodes are separated by a particular thresholding value $l_o(l_o = \sqrt{\mathcal{E}_{fsp}/\mathcal{E}_{mp}})$, then it uses free space model, otherwise, multipath fading was utilized for determining the power applications.

2.2 Algorithmic Design of SOA

In SOA, each seeker has a centralized location vector $\vec{c}$, that is, the initialized location to discover forthcoming solution, and it is assumed as projected value Ex. In addition, seeker has a searching direction $\vec{d}$, searching radius $\vec{r}$ assumed as En', and a trust level μ as membership degree [17]. Then, the seeker with certain level of trust follows a potential direction and arbitrarily moves to the next point (solution candidate) in searching radius from the present place. In t time step, the decision-making is performed to evaluate the four variables, and seekers move towards the novel position $\vec{x}(t+1)$. The updated place from the centralized place is described as y condition cloud generator:

$$\vec{x}_{ij}(t+1) = \vec{c}_{ij}(t) + \vec{d}_{ij}(t) \times \vec{r}_{ij}(t) \times \sqrt{-\ln(\mu_i)} \tag{3}$$

Now "i" indicates the subscript index of seeker, and "j" shows the subscript index of parameter. The pseudo code of presented method is shown in Algorithm 1.

Intuitively, centralized place vector $\vec{c}$ is fixed to the present place $\vec{x}(t)$. Like PSO approach, seeker encompasses a memory saved in the optimum place $\vec{\mathrm{p}}$ and a global optimum place g obtained by interacting with adjacent seekers. Each seeker is classified into k class in the subscript index, and the seeker in the same class belongs to virtual neighbor. Consequently, $\vec{g}$ is determined as the virtual neighbor.

$$\vec{c} = \vec{x}(t) + r_1\emptyset_1(\vec{\mathrm{p}}(t) - \vec{x}(t)) + r_2\emptyset_2(\vec{g}(t) - \vec{x}(t)) \tag{4}$$

Now, r_1, r_2 illustrates the cognitive and social learning rates. $\emptyset_1$ and $\emptyset_2$ represents the realistic number arbitrarily and uniformly chosen within zero and one. Each study performed in this work, $r_1 = 1$, $r_2 = 1$, and $k = 3$.

In general, seekers contain 4 considerable directions termed $\vec{d}_{lt}$ local temporal direction, $\vec{d}_{ls}$ local spacial direction, $\vec{d}_{gt}$ global temporal direction, and $\vec{d}_{gs}$ global spacial direction.

$$\vec{d}_{lt} = \begin{cases} sign\,(\vec{x}(t) - \vec{x}(t-1))\; if\; fit(\vec{x}(t)) \geq fit(\vec{x}(t-1)) \\ sign\,(\vec{x}(t-1) - \vec{x}(t))\; if\; fit(\vec{x}(t)) < fit(\vec{x}(t-1)) \end{cases} \tag{5}$$

$$\vec{d}_{ls} = sign\big(\vec{x}(t) - \vec{x}(t)\big) \tag{6}$$

$$\vec{d}_{gt} = sign\big(\vec{p}(t) - \vec{x}(t)\big) \tag{7}$$

$$\vec{d}_{gs} = sign\big(\vec{g}(t) - \vec{x}(t)\big) \tag{8}$$

Here, sign $(\cdot)$ denotes signum function, $\vec{x}'(t)$ indicates the seeker place with the maximal fitness in a neighboring area, fit $(\vec{x}(t))$ signifies the fitness function (FF) of $\vec{x}(t)$. Following, searching direction is allocated according to the four directions.

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$$\vec{d} = sign(\omega(sign(fit(\vec{x}(t)) - fit(\vec{x}(t-1))))(\vec{x}(t) - \vec{x}(t-1)) \\ + r_1\phi_1(\vec{p}(t) - \vec{x}(t)) + r_2\phi_2(\vec{g}(t) - \vec{x}(t))) \tag{9}$$

ω specifies the inertia weight viz. set as $\omega = (T_{max}\text{-}t)/T_{\max}$. Here, ϕ_1 and ϕ_2 shows real numbers uniformly and randomly chosen from zero and one.

Search Radius is indispensable, but complicated, to reasonably offer searching radius. For unimodal optimization problems, the efficiency is moderately oblivious to searching radius. But for multimodal problems, searching radius may results in different efficiencies of model predominantly when managing different challenges.

The μ parameter is taken into account by a quality valuation. It is corresponding to the fitness of $\vec{x}(t)$ or the index of ascensive sorting order of fitness of $\vec{x}(t)$. Particularly, the global optimum position has $\mu_{\max} = 1.0$, once other positions have a $\mu < 1.0$.

$$\mu = \mu_{\max} - \frac{S - Sn}{S - 1}(\mu_{\max} - \mu_{\min}) \tag{10}$$

Now, Sn shows the sequential value of $\vec{x}(t)$ after arranged the fitness of adjacent seekers in ascending order, $\mu_{\max}$ and $\mu_{\min}$ shows the maximal and the minimal μ. We adopted $\mu_{\max} = 1.0$, and $\mu_{\min} = 0.2$. Fig. 2 depicts the flowchart of SOA.

Algorithm 1: Pseudo code of SOA
$t \leftarrow 0$
Initialize generation of S location
$\{x_i(t) \mid x_i(t) = (x_{i1}, x_{i2}, \dots, x_{iD}), i = 1, \dots, S, t = 0\}$ Randomly and Uniformly in the parameter
Assess every seeker: evaluate the fitness.
Searching technique provides search variables including trust degree, centralized place vector, searching direction, and searching radius.
Upgrade novel position of each seeker is estimated.
$t \leftarrow t + 1$
If $t < T_{\max}$, then return to step3; or else, End.

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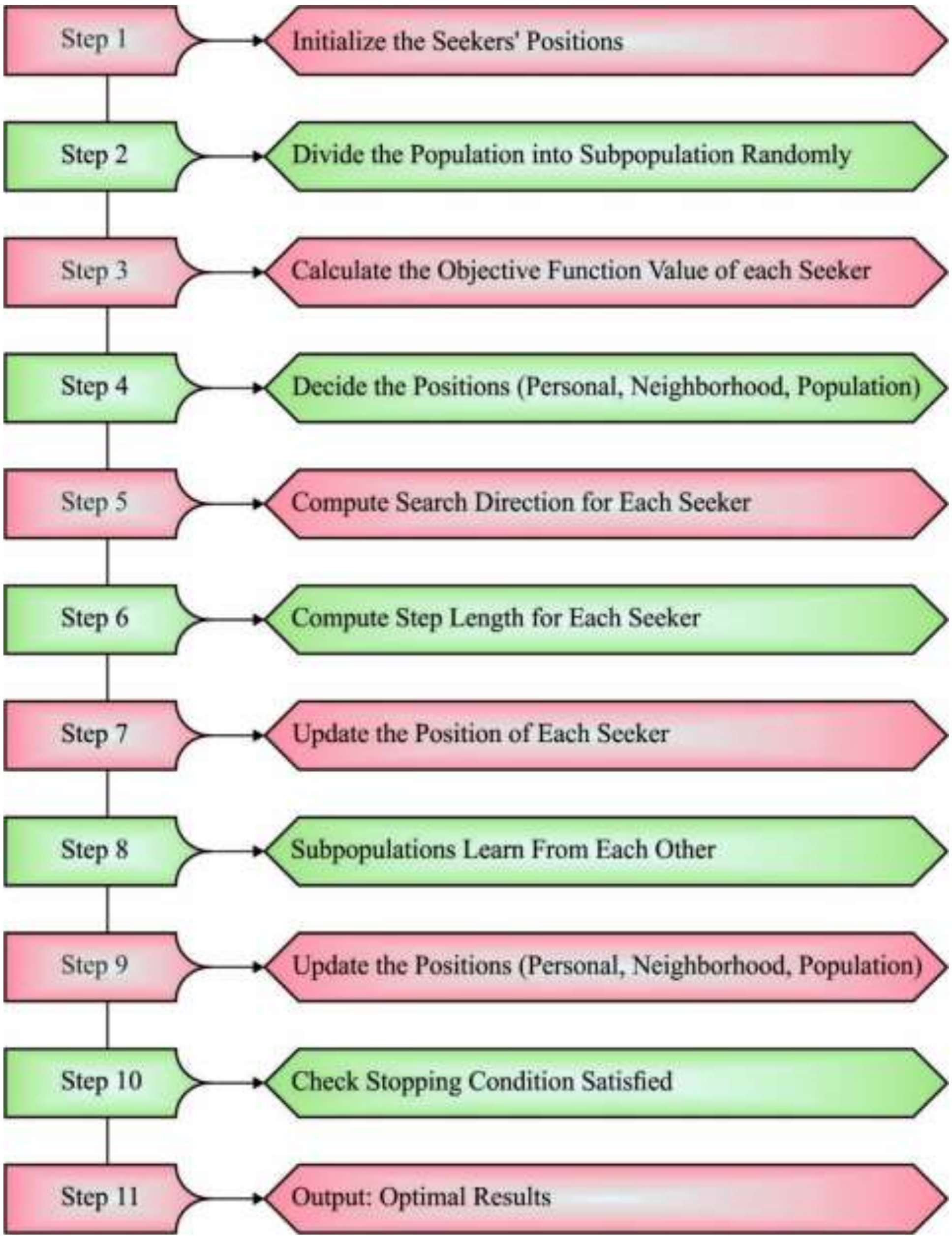

Figure 2: Flowchart of SOA

2.3 Steps involved in SOEACS-UWN Technique

The SOEACS-UWN model constructs a fitness function for effectual CH choices using diverse variables. The cluster construction procedure occurs then the chosen of CHs by SOA technique. The BS applies the subsequent steps for beginning the clustering procedure [18].

Step1. Transformation of problem domain as to SOA space whereas the hunter place contains 2D such as leader and successor places.

Step2. Define the fitness value (FV) with utilize of fitness function (FF). The FF of FCH selective technique proposes optimizing the 5 parameters such as Link Quality (LQ), Residual Energy (RE), Node Degree (ND), Distance to BS (D), and Node Centrality (NC). The FV was defined to all the hunters utilizing in Eq. (4):

$$FV = \alpha_1 \cdot \frac{\sum_{i=0}^{n} d\ (PN, member\ i)}{n} + \alpha_2 . \frac{\sum_{i=0}^{n} RE\ (memberi)}{RE(PN)}$$

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$$+\alpha_3.\frac{\sum_{i=0}^{n} ND\ (memberi)}{n} + \alpha_4.\frac{\sum_{i=0}^{n} NC\ (memberi)}{NC(PN)} + \alpha_5.\frac{\sum_{i=0}^{n} LQ\ (memberi)}{L(PN)}$$

$$+(1-\alpha_1-\alpha_2-\alpha_3-\alpha_4-\alpha_5).\frac{1}{No\ of\ members\ covered\ by\ PN} \quad (11)$$

whereas $\alpha_{1,}\alpha_2,\alpha_3,\alpha_4$, and α_5 signifies the weight parameters and n implies the amount of members covered by the cluster.

Step3. Create a novel place for hunters in the primary solution. The generation of novel place of the hunter in the preceding one is the formation of novel hunter.

Step3.1. Resolve of novel hunter place: the current place of hunters is considered as the rate at that the hunter place was changed. A novel hunter place was defined as provided under.

$$new\_position\ = \omega^*\ old\_position + w_1\ (local\_best\_position\text{-}\ current\_best\_position)$$

$$+w_2\ (global\_best\ position\text{-}\ current\_best\ position), \quad (12)$$

whereas ω signifies the inertia weighted and w_1 and w_2 represents the fundamental SOA tunable parameters.

Step3.2. Purpose of novel place of the hunter utilizing Eq. (11). Finally, the novel place obtains reached.

Step4. Estimate the FV of novel hunter place. The FV of novel hunter was defined in Step2 with novel hunter place.

Step5. Relate the FV of old and new hunter places and an optimum one was selected for the succeeding round:

If new FV $>$ *old* FV

select novel hunter place;

else

old one was propagated to succeeding round.

Step6. For all the rounds, an optimum solution is selected as the local optimum one.

Step7. The local optimum solution in all the iterations of hunter that is maximal on the prior solution was selective as the global optimum solution.

The BS manages the clusters with utilize of SOA technique and advertises a message to nodes. Every node stored the message and applies the CH selection process for choosing the FCHs.

3. Results and Discussion

In this section, the results analysis of the SOEACS-UWN model is tested under several dimensions. Table 1 and Fig. 3 study the NOAN results of the SOEACS-UWN model with recent models. The experimental values highlighted that the SOEACS-UWN model has shown improved values of NOAN under each round. For instance, with 600 rounds, the SOEACS-UWN model has attained higher NOAN of 300 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOAN of 243, 263, 290, 296, and 299 respectively. Also, with 700 rounds, the SOEACS-UWN model has reached higher NOAN of 287 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOAN of 80, 118, 209, 229, and 246 correspondingly. Then, with 800 rounds, the SOEACS-UWN model has acquired higher NOAN of 164 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOAN of 3, 3, 52, 66, and 119 correspondingly.

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Table 1: NOAN analysis of SOEACS-UWN approach with existing algorithms under distinct rounds

No. of Alive Nodes (NOAN)						
No. of Rounds	**EGRC Model**	**FBC-PSO Model**	**FCM-MFO Model**	**EECRP Model**	**IMCMR-UWSN Model**	**SOEACS-UWN model**
0	300	300	300	300	300	300
100	300	300	300	300	300	300
200	300	300	300	300	300	300
300	300	300	300	300	300	300
400	300	300	300	300	300	300
500	299	299	299	298	300	300
600	243	263	290	296	299	300
700	80	118	209	229	246	287
800	3	3	52	66	119	164
900	0	0	0	0	1	11
1000	0	0	0	0	0	0

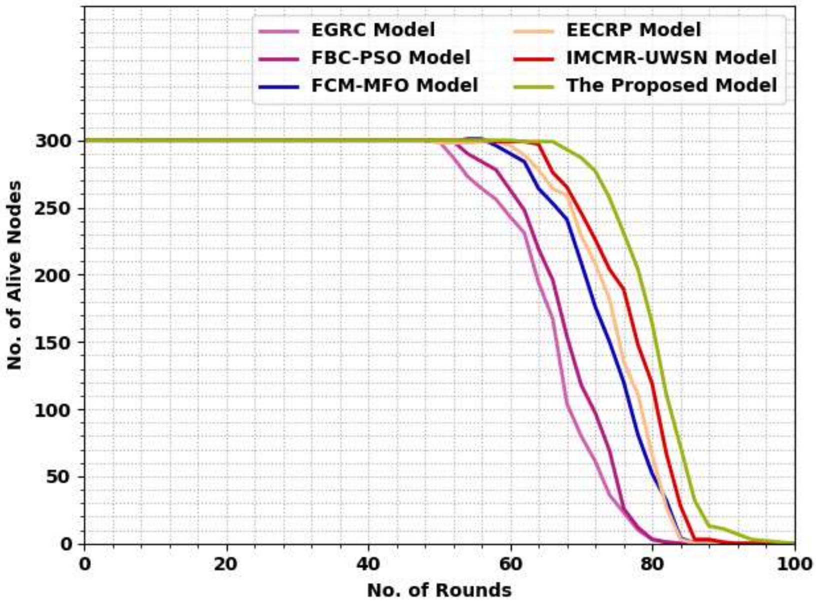

Figure 3: NOAN analysis of SOEACS-UWN approach under distinct rounds

A comparative NODN examination of the SOEACS-UWN model with other approaches is demonstrated in Table 2 and Fig. 4. The experimental values inferred that the SOEACS-UWN model has shown reduced values of NODN under each round. For instance, on 600 rounds, the SOEACS-UWN model has gained reduced NODN of 0 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased NODN of 57, 37, 10, 4, and 1 respectively. Together with that, on 700 rounds, the SOEACS-UWN model has acquired reduced NODN of 13 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased NODN of 220, 182, 91, 71, and 54 correspondingly. And then, on 800 rounds, the SOEACS-UWN model has attained reduced NODN of 136 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased NODN of 297, 297, 248, 234, and 181 correspondingly.

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Table 2: NODN analysis of SOEACS-UWN approach with existing algorithms under distinct rounds

No. of Dead Nodes (NODN)						
No. of Rounds	**EGRC Model**	**FBC-PSO Model**	**FCM-MFO Model**	**EECRP Model**	**IMCMR-UWSN Model**	**SOEACS-UWN model**
0	0	0	0	0	0	0
100	0	0	0	0	0	0
200	0	0	0	0	0	0
300	0	0	0	0	0	0
400	0	0	0	0	0	0
500	1	1	1	2	0	0
600	57	37	10	4	1	0
700	220	182	91	71	54	13
800	297	297	248	234	181	136
900	300	300	300	300	299	289
1000	300	300	300	300	300	300

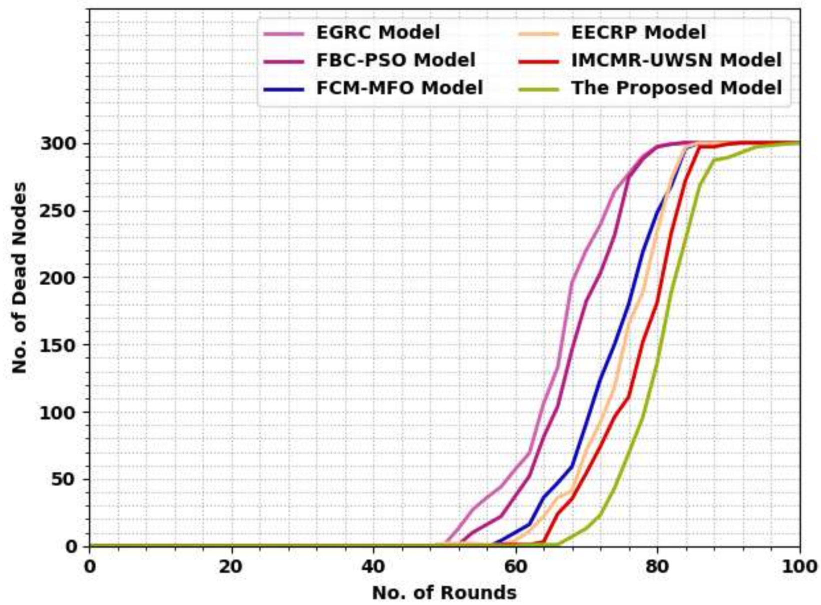

Figure 4: NODN analysis of SOEACS-UWN approach under distinct rounds

A comparative TEC inspection of the SOEACS-UWN model with other approaches is established in Table 3 and Fig. 5. The experimental values implicit the SOEACS-UWN model has displayed reduced values of TEC under each round. For example, on 600 rounds, the SOEACS-UWN model has attained reduced TEC of 27.63% whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased TEC of 96.77%, 55.35%, 42.49%, 38.20%, and 46.77% correspondingly. Also, on 700 rounds, the SOEACS-UWN model has gained reduced TEC of 39.06% whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased TEC of 100%, 73.35%, 56.77%, 49.35%, and 62.20% correspondingly. Finally, on 800 rounds, the SOEACS-UWN model has gained reduced TEC of 56.49% whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have reported increased TEC of 100%, 94.77%, 71.06%, 60.49%, and 77.63% respectively.

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Table 3: TEC analysis of SOEACS-UWN approach with existing algorithms under distinct rounds

Total Energy Consumption (%) (TEC)						
No. of Rounds	EGRC Model	FBC-PSO Model	FCM-MFO Model	EECRP Model	IMCMR-UWSN Model	SOEACS-UWN model
0	0.00	0.00	0.00	0.00	0.00	0.00
100	11.06	6.77	5.63	3.35	3.92	1.63
200	21.63	13.63	9.63	9.63	9.06	3.92
300	35.06	20.77	15.92	17.06	15.35	6.20
400	52.77	30.20	23.06	22.77	24.20	9.92
500	75.06	41.63	31.35	31.35	36.49	17.63
600	96.77	55.35	42.49	38.20	46.77	27.63
700	100.00	73.35	56.77	49.35	62.20	39.06
800	100.00	94.77	71.06	60.49	77.63	56.49
900	100.00	100.00	95.35	78.77	91.63	68.49
1000	100.00	100.00	100.00	100.00	100.00	82.35

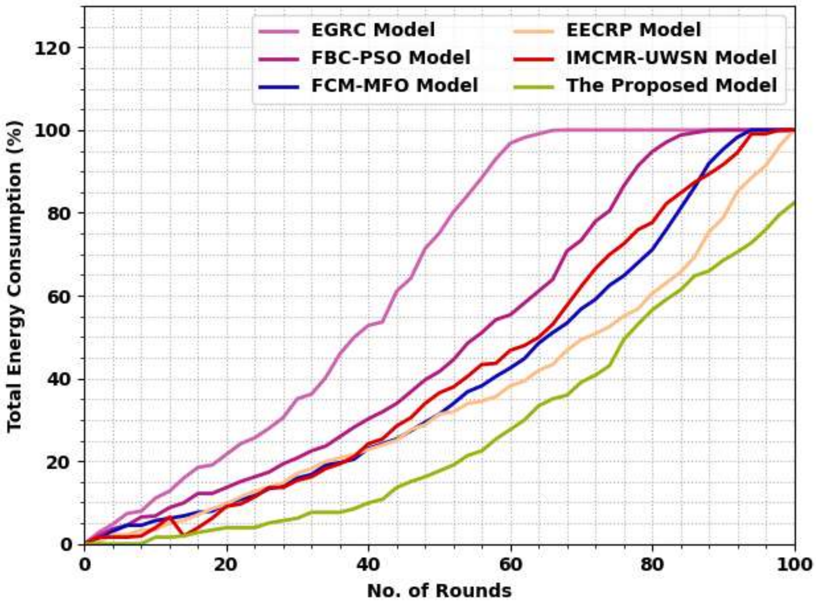

Figure 5: TEC analysis of SOEACS-UWN approach under distinct rounds

Table 4 and Fig. 6 study the NOPR results of the SOEACS-UWN model with recent models. The experimental values highlighted that the SOEACS-UWN model has exhibited improved values of NOPR under each round. For example, with 600 rounds, the SOEACS-UWN model has gained higher NOPR of 19630 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOPR of 12443, 16595, 17553, 19390, and 20348 correspondingly. In addition, with 700 rounds, the SOEACS-UWN model has reached higher NOPR of20828whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOPR of 13481, 17633, 18432, 20109, and 21706 respectively. Next, with 800 rounds, the SOEACS-UWN model has achieved higher NOAN of 22105 whereas the EGRC, FBC-PSO, FCM-MFO, EECRP, and IMCMR-UWSN techniques have resulted in reduced NOPR of 14439, 18192, 19470, 21227, and 22425 correspondingly.

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Table 4: NOPR analysis of SOEACS-UWN approach with existing algorithms under distinct rounds

No. of Packets Received (NOPR)						
No. of Rounds	**EGRC Model**	**FBC-PSO Model**	**FCM-MFO Model**	**EECRP Model**	**IMCMR-UWSN Model**	**SOEACS-UWN model**
0	65	145	65	544	1183	464
100	1343	4617	5575	6613	6693	6294
200	3499	8370	8210	10047	11325	9808
300	5974	11245	11245	13002	14519	12523
400	8210	13161	13880	15078	17074	15477
500	10287	14759	15477	16915	18991	17953
600	12443	16595	17553	19390	20348	19630
700	13481	17633	18432	20109	21706	20828
800	14439	18192	19470	21227	22425	22105
900	15397	18751	20348	21786	22505	22824
1000	16595	18751	20508	22025	23143	23702

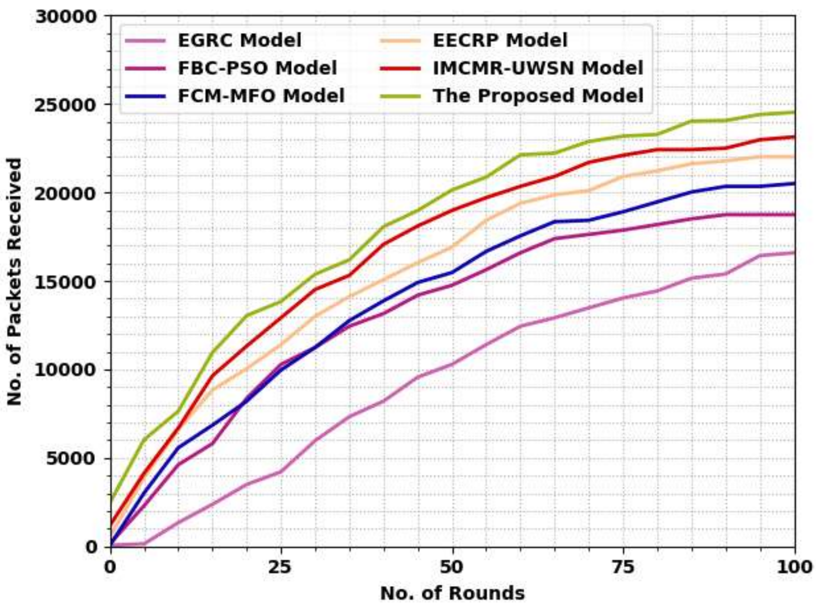

Figure 6: NOPR analysis of SOEACS-UWN approach under distinct rounds

Finally, a lifetime analysis of the SOEACS-UWN model is compared with recent models in Table 5.

Fig. 7 inspects the overall comparative FND inspection of the SOEACS-UWN model with other models. The figure implied that the EGRC and FBC-PSO models have shown ineffectual outcomes with lower FND of 500 and 510 rounds respectively. Next, the FCM-MFO and EECRP models have demonstrated slightly increased FND of 520 and 530 rounds respectively. In the meantime, the IMCMR-UWSN model has shown reasonable FND of 580 rounds. But the SOEACS-UWN model has demonstrated superior FND of 620 rounds.

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Table 5: Lifetime analysis of SOEACS-UWN approach with recent algorithms

Methods	FND	HND	LND
EGRC Model	500	670	822
FBC-PSO Model	510	690	825
FCM-MFO Model	520	740	858
EECRP Model	530	745	860
IMCMR-UWSN Model	580	775	920
SOEACS-UWN model	620	810	1030

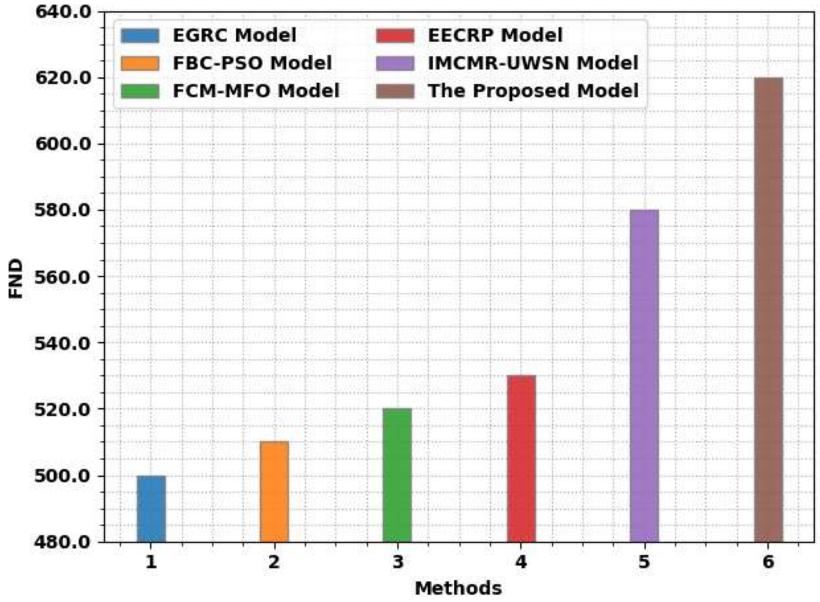

Figure 7: FND analysis of SOEACS-UWN approach with recent methodologies

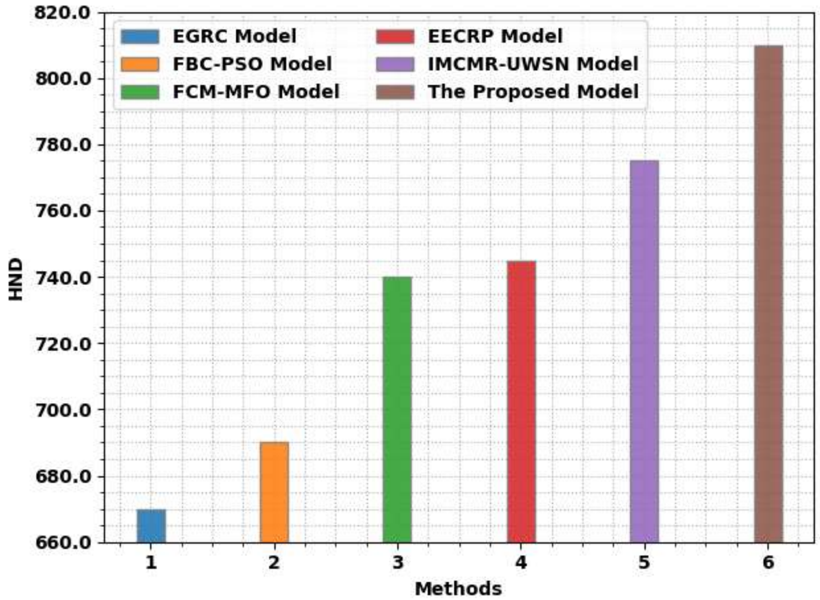

Figure 8: HND analysis of SOEACS-UWN approach with recent methodologies

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Fig. 8 examines the overall comparative HND analysis of the SOEACS-UWN model with other models. The figure implicit the EGRC and FBC-PSO models have shown ineffectual outcomes with lower HND of 670 and 690 rounds correspondingly. Next, the FCM-MFO and EECRP models have demonstrated slightly increased HND of 740 and 745 rounds correspondingly. Meanwhile, the IMCMR-UWSN model has shown reasonable HND of 775 rounds. But the SOEACS-UWN model has exhibited superior HND of 810 rounds.

Fig. 9 scrutinizes the overall comparative LND review of the SOEACS-UWN model with other models. The figure denoted the EGRC and FBC-PSO models have shown ineffectual outcomes with lower LND of 822and 825 rounds correspondingly. Followed by, the FCM-MFO and EECRP models have demonstrated slightly increased LND of 858 and 860 rounds correspondingly. Simultaneously, the IMCMR-UWSN model has exhibited reasonable LND of 920 rounds. But the SOEACS-UWN model has established superior LND of 1030 rounds.

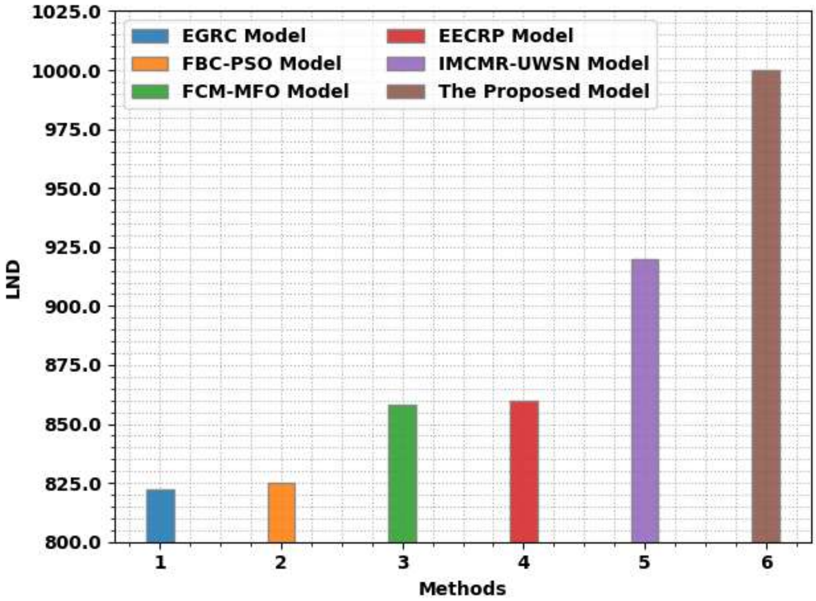

Figure 9: LND analysis of SOEACS-UWN approach with recent methodologies

4. Conclusion

This study has developed an effective SOEACS-UWN model for proficient selection of CHs in the UWSN. The presented SOEACS-UWN model follows the operation on a collection of solutions named search population (i.e., human team) and considered optimization procedure as a searching process of optimum solutions via human teams. The SOEACS-UWN model constructs a fitness function for effectual CH choices using diverse variables namely distance, residual energy, node degree, centrality, and link quality. The simulation analysis of the SOEACS-UWN model is tested and the results are investigated under diverse aspects. The experimental outcomes demonstrated the supremacy of the SOEACS-UWN model over other approaches.

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