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Energy efficient multi-objective evolutionary routing scheme for reliable data gathering in Internet of underwater acoustic sensor networks

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ABSTRACT

Earth's surface is covered with two-thirds of water. The marine world covers the lakes, rivers and sea and is rich in natural resources largely unexplored by human beings. Recently, underwater wireless sensor network (UWSN) with the advancement in the Internet of underwater smart things has emerged as promising networking techniques to explore the mysteries of vastly unexplored ocean environments for several underwater applications. These applications include offshore exploration, pollution monitoring, disaster prevention, oceanographic data collection, offshore oil fields monitoring, tactical surveillance applications and several others. However, the underwater channel impairments caused by multipath effects, fading, bit errors, variable and high latency and low bandwidth severely limits the data transmission reliability for UWSNs-based applications. This results in poor quality-aware data gathering in UWSNs. Therefore, designing a quality of service (QoS)-aware data gathering protocol to monitor and explore oceans is challenging in the underwater environments. In this paper, we propose a bio-inspired multi-objective evolutionary routing protocol (called MERP) for UWSNs-based applications. The designed routing protocol exploits the features of the natural evolution of the multi-objective genetic algorithm in order to provide reliable and energy-aware information gathering in UWSNs. The extensive simulation results show that the developed protocol attains its defined goals compared to existing UWSNs-based routing protocols during monitoring and exploring underwater environments.

1. Introduction

In human's survivability, water plays a vital role. Therefore, the oceanic world has been fascinating humans due to means of transportation and natural resources, such as oil, natural gases, mines, etc. [1]. In the last several years, humans with the advancement in science and technology seriously started to explore the underwater world. However, only about 10% of the 71% water world has been explored and the rest 61% is yet to be scrutinized. In recent years, the use of automated sensor and communication technologies has attracted attention for unmanned exploration of the terrestrial environment [2]. The key aim of sensor technology is to perform collaborative monitoring tasks in a given area and convey observed data to the user by employing advanced wireless or wired communication technologies [3]. However, the terrestrial sensors based on radio waves due to the presence of absorption of high-frequency components and high attenuation cannot propagate well in the underwater environment. The terrestrial sensor network can only achieve high-speed transmission in short with the expense of high-power consumption and long antennas. They cannot fulfill the requirements of long-distance underwater communication and thus not suitable for UWSNs [4]. Therefore, the terrestrial network protocols behave differently and show degradation in performance when tested in the underwater environment. Consequently, the underwater application requirements hinder the use of terrestrial sensor network algorithms or protocols directly in underwater environments. This gives rise to use acoustic waves for unmanned exploration of the underwater environment [5].

On the other hand, the key aim of the Internet of underwater things is to connect all devices located in the underwater to monitor and control the events in a real-time from any remote location worldwide [6]. The Internet of underwater things in the UWSNs has several numerous applications, such as maritime rescue, tactical surveillance, disaster prevention, oil and gas reservoir discovery and study of aquatic life. However, exploration of the oceans with the UWSNs is challenging due to corrosion, fouling, low

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bandwidth, high bit error rate, multi-path fading, latency, high water pressure, and other uncertain events. Therefore, the routing protocols designed with self-configuring and communicating capabilities for the acoustic sensor networks perform poorly due to time-varying link quality characteristics during unmanned exploration in the underwater environment. This results in poor quality-aware data gathering in UWSNs [7]. The low energy consumption (E_c) is another fundamental requirement for the acoustic sensor nodes (ASNs) in UWSNs. They carry limited batteries that cannot be replaced easily to recharge the energy of nodes at any time due to the unpredictable and complex environment of the ocean. Therefore, consideration of the energy efficiency and quality-aware data are vital in UWSNs [8]. Recently, the clustering mechanism has been proven as a prominent networking mechanism for balancing the network energy consumption and providing quality-aware data delivery to the end user. The key aim of the clustering mechanism is to divide the entire network into subgroups of two-level hierarchy. In a higher level hierarchy, cluster heads (CHs) are grouped together while sensors are organized autonomously to each CH as member nodes in the lower level for achieving basic network performance in UWSNs [9].

In each subgroup, a cluster leader acts as an overseer and tightly holds its member nodes for data gathering in the UWSNs. The cluster leader is responsible to provide intra-cluster transmission schedules, compute links quality and periodically monitors its member nodes. Moreover, it fuses the received data and transmits the aggregated data via direct or multi-hop manner with the help of intermediate CHs toward the sink. In addition, it is also responsible to perform tasks like relaying data, route maintenance and other routine activities [10]. Therefore, it consumes available resources at higher rates compared to other sensors in the network. This heavy data traffic distribution load most of the times leading to the early death of the cluster leaders, which may result in partitioning a region or the entire network. Hence, the cluster leaders must have higher energy than other nodes in the groups. However, appointing a clustering leader without considering its residual energy ($\mathcal{R}_e$), Euclidean distance and network load also degrade the overall network performance in UWSNs [11]. In addition, a cluster leader must be rotated in each cluster in a round ribbon manner to equalize the network power depletion burden of the UWSNs. Moreover, unequal size clustering architecture and a cluster leader with high residual energy and average lower distance to the neighboring sensors can significantly increase the overall data gathering efficiency and balances the network lifetime in UWSNs. Moreover, the data gathering in a multi-hop manner over highly stable links between cluster leaders can also significantly increase the data gathering efficiency with reduced energy consumption in UWSNs [12]. However, designing a highly stable clustering-based routing mechanism for efficient data gathering with low energy consumption is challenging due to unique underwater characteristics.

In this paper to handle aforesaid challenges, we propose a bio-inspired, multi-objective evolutionary routing scheme for UWSNs. The designed routing scheme exploits the features of the natural evolution of the multi-objective genetic algorithm in order to provide quality-aware and energy efficient information gathering for UWSN-based events monitoring applications. In this study, we have three contributions to the literature: First, we propose a multi-objective clustering mechanism for UWSNs-based applications. The proposed dynamic clustering mechanism generates a set of different size clusters with rotating cluster leaders, which organize sensors into a connected hierarchy over highly reliable links for distributing the data traffic load evenly in UWSNs. In addition, the small size clusters formation nearer to the sink further avoids the hotspot and memory-overrun issues in the network. Second, we propose a multi-objective cluster-based routing mechanism for UWSNs-based underwater applications. The proposed multi-objective routing method by considering the genetic alteration in the mating procedure of an evolutionary algorithm finds the best shortest routing paths from the source toward the destination in UWSNs. Due to its self-learning mechanism, the proposed scheme intelligently selects highly stable links among CHs during relaying events information from the source toward the destination in UWSNs. This results in high network throughput, packet delivery ratio and energy consumption in UWSNs. Moreover, the proposed scheme minimizes the data path loops and hotspot issues due to conveying information over predefined routing paths in a greedy manner in UWSNs. In addition, the proposed scheme minimizes route failure issues and significantly repairs a broken link in a bounded time interval by employing self-learning based intelligent mechanism in UWSNs. Third, based on the realistic underwater channel model, the detailed performance evaluations have been conducted. The extensive simulation results reveal that the proposed scheme attains its defined goals in terms of data packets delivery, packet error rates, congestion, latency, throughput, and energy consumption compared to existing UWSNs-based routing schemes during monitoring and exploring aquatic environments.

The rest of this study is organized as follows. Previous work, routing protocol design challenges, and motivations are summarized in Section 2. The proposed scheme is presented in Section 3. Section 4 presents the underwater channel model and the energy consumption model in detail. In addition, Section 4 also illustrates the simulation metrics, settings and simulation results of the proposed scheme against the existing schemes. Lastly, Section 5 concludes the paper with potential research guidelines.

2. Literature review

In the last couple of years, numerous routing protocols for events driven applications have been proposed to convey quality-aware data from the source toward the sink in UWSNs. For example, the authors in [13] propose a pressure sensor-based information collection protocol for UWSNs. The designed protocol considers the residual energy and distance information to estimate the link quality between acoustic sensors in UWSNs. The designed protocol performs superior in terms of E_c, latency and data delivery in UWSNs. However, it faces the problems of data redundancy and excessive control message overheads ($\mathcal{C}_{m\sigma}$) with consuming a significant amount of network energy in UWSNs. In [14] an energy-aware cluster-based data gathering protocol has been proposed for UWSNs. The proposed scheme employs an idea of cubic architecture to generate small size clusters for reducing information collection delay and high E_c in UWSNs. The experimental facts show that the developed protocol works better in low latency, E_c and high reliability with the expense of poor load balancing and corrupted data packets generated in UWSNs. In [15] direct data packets transmitted over a long distance is avoided by employing a novel balanced transmission mechanism in UWSNs. In the proposed method, the residual energy of the sensors is divided into low and high energy levels. In the proposed scheme, a next hop relay ASN is selected based on its energy level and optimal distance threshold information to the neighboring nodes in UWSNs. The proposed scheme increases the network throughput and balances the network energy consumption with the expense of data latency in UWSNs. A greedy cluster-based routing strategy to achieve the location free data packets forwarding is employed in [16]. The proposed scheme appoints a next hop data forwarding acoustic node based on its residual energy and network topology. The experimental facts show that the proposed scheme minimizes the communication cost and latency. However, it faces the issues of data path loops and corrupted data packets due to poor link quality among acoustic nodes in UWSNs.

The authors discuss a based vector data collection scheme for UWSNs in [17]. In the proposed mechanism, the idea of received signal strength information is used to describe the length of different vectors. Consequently, it appoints a next hop forwarding ASN, which is nearer to the vector with high residual energy in UWSNs. The proposed scheme minimizes energy consumption and data delivery latency with the expense of high interference, network stability and unnecessary multi-hop data transmission. The authors in [18] propose a multipath environment-friendly routing scheme to achieve reliable data delivery in UWSNs. The proposed scheme during establishing routing paths between relay nodes greedily uses the idea of value color space, hue and saturation mode. The suggested scheme improves the packet delivery ratio by reducing latency and energy consumption in UWSNs. However, the chance of data path loops and average energy consumption at each relay node increases due to increasing path lengths in UWSNs. The authors in [19] propose an energy-aware data collection for UWSNs. The main idea is to select reliable data paths from the source node toward the sink for reliable information transfer in UWSNs. The proposed protocol minimizes the packets collision and route length, and thus minimizes the network energy consumption. However, low network throughput and reliable data transmission at hop are challenging due to high interference in UWSNs. In [20] authors try to solve the data transmission energy consumption problem by introducing a novel fuzzy logic-based cooperative opportunistic routing protocol in UWSNs. The suggested scheme avoids data packets collision by employing a new concept of holding time at each hop during conveying data packets between the source and sink in UWSNs. The performance of the proposed scheme is remarkable in terms of packet delivery ratio, energy consumption and network lifetime with the robustness and scalability in UWSNs.

A multi-path geographical routing protocol for UWSNs is proposed in [21]. The proposed scheme consists of three different phases, namely gateway election, neighbor updating and relaying data packets. The proposed scheme employs grid-by-grid disjoint paths routing mechanism where a next hop gateway is selected based on its location and residual energy. The experimental results show that the proposed scheme performs better in terms of latency and packet delivery ratio. However, it faces issues such as poor network throughput and synchronization in UWSNs. In [22] a cluster and chain-based energy efficient data collection scheme has been proposed for UWSNs. The proposed scheme in order to guarantee link reliability uses the key idea of distance-based communication for monitoring underwater events. To improve the data reliability, the confidence level of forwarding nodes is computed toward the sink. The proposed scheme reduces the average communication cost in UWSNs. However, the early death of the relay nodes, poor loading balancing and congestion are the main issues for the sensor close to the sink. A novel on fuzzy logic vector-based data gathering scheme for monitoring underwater events is proposed in [23]. The proposed scheme during conveying information selects a next hop relay node based on its distance, projection and battery level toward the sink. The proposed scheme performs better in terms of latency, energy consumption and reliability. However, the corrupted data packets due to poor link quality between ASNs degrade the data quality in UWSNs.

The researchers in [24] attempt to fix the issue of high E_c by introducing a multi-level clustering routing protocol for UWSNs. The proposed scheme employs a multi-level data gathering architecture between CHs and sink-based on the distance, $\mathcal{R}_e$ and competition radius. The proposed scheme avoids the early death of the CHs and selects low energy consumption data paths from the source to the sink. However, the proposed scheme does not appropriately address the issues like link quality, corrupted data packets, varying number of sensors with long distance in a cluster and periodic rotating architecture of the CHs in UWSNs. In [25] an anycast geographical opportunistic data collection scheme is proposed for UWSNs. The proposed scheme uses the range-based equation and time of arrival technique to overcome horizontal transmission, latency, voids and energy consumption issues in UWSNs. However, data reliability is challenging due to lack of employing appropriate acknowledgment mechanism. In addition, the suggested scheme in underwater dynamic environments faces the problem of high network instability. Tuna in [26] discusses a novel cluster-based information collection protocol for UWSNs. In the suggested protocol, various size clusters are constructed based on nodes radius, residual energy and distance information in UWSNs. The developed protocol achieves better performance in E_c and balances the over data traffic load for reliable data delivery in UWSNs. However, it faces the issues of high interference when tested in various underwater environments. A novel radius based multi-path routing protocol for underwater events driven applications is proposed in [27]. The proposed scheme employs a radius-based architecture, including residual energy, track identification and cost function to appoint a next hop forwarding node for efficient data delivery in UWSNs. The suggested protocol achieves better performance in low latency, E_c and packet delivery ratio. However, it faces the issues such as corrupted data packets and congestions particularly for ASNs closer to the sink.

The key aims of the above-mentioned routing schemes are to provide energy and quality-aware data delivery for UWSNs-based events monitoring applications. Although these routing schemes help in designing protocol architecture for various types of underwater applications, they are facing several challenges when tested in UWSNs. In most of the existing works, shortest hop or shortest path data transformation architecture has been employed for guaranteeing link quality among ASNs in UWSNs. However, due to the complex underwater environment, the distance-based routing protocols often choose capricious links, which result in inefficient energy and data delivery performance in a variety of ocean monitoring applications. Consequently, the data reliability cannot be provided without estimating the appropriate quality of the link between ASNs in these schemes. The shortest hop-based techniques might balance the overall *Re* of the acoustic sensor network but depletes individual ASN energy rapidly because of many hops with the lower distance between the source and the sink. This not only increases the chance of data path loops but also numerous issues like high interference, corrupted data packets, packets collision, latency and network security. As a result, the overall network throughput performance is degraded in UWSNs. Although some clustering-based routing solutions recently have been proposed, they are also facing the issues of unbalanced energy consumption of clusters as well as CHs due to poor link quality in UWSNs. On the other hand, recently proposed single-to-noise ratio based schemes handle some of the above-mentioned issues, however facing the problems of high data redundancy, latency and energy consumption in UWSNs. In addition, these routing schemes due to lack of considering some hard and soft rules defined by bio-inspired techniques fail to provide a set of feasible routing solutions from the source toward the sink. Moreover, these traditional routing schemes can only achieve two or three objects with the loss of others due to lack of incorporating the multi-objective characteristics in UWSNs. Furthermore, these schemes due to lack of considering the underwater of things characteristics cannot provide real-time events occurrence information to the user/s located in a remote area. Hence, the design of an energy and quality-aware data scheme that provides events occurrence information in a real-time is essential for UWSNs in order to facilitate the discovery of the vast unexplored ocean.

All above-mentioned factors motivate the researchers for designing a multi-objective bio-inspired clustering-based data

Table 1
Comparison of routing schemes in UWSNs.

Sr. no.	Routing scheme	Architecture	Corrupted data packets	Packet delivery ratio	Delay	Energy efficient	Network relilability	Throughput
1	PSBR [13]	Flat		√	√	√		
2	EGRC [14]	Clustering		√	√	√	√	
3	EEBET [15]	Flat		√	√			
4	E-CARP [16]	Flat		√		√		
5	MER [4]	Flat		√	√	√		
6	RRSS [17]	Flat		√	√	√		
7	ENMR [18]	Flat		√	√	√		
8	DRP [19]	Flat			√	√		√
9	EECOR [20]	Flat		√	√	√		
10	EMGGR [21]	Flat		√		√	√	
11	E-CBCCP [22]	Clustering		√		√		
12	FVBF [23]	Flat		√	√	√		√
13	ACUN [24]	Clustering		√		√		
14	TORA [25]	Flat		√	√	√		
15	CBEER [26]	Clustering		√		√		
16	RMCN [27]	Flat		√	√	√		
17	MERP	Clustering	√		√	√	√	√

collection mechanism incorporated with the ideas of the Internet of underwater things for UWSNs-based event-driven applications. In our previous study, this gap is partially filled considering basic performance metrics [4]. The objective of this paper is to extend our previous study further by investigating the performance of the proposed approach in terms of data packets delivery, packet error rates, congestion, latency, throughput and energy consumption. In the following sections, the proposed scheme has been explained in detail (Table 1).

3. Proposed routing protocol (MERP)

The working procedure of MERP in underwater environments is explained in the subsequent sections.

3.1. Network model

The network architecture of our proposed protocol is described in Fig. 1. The entire network model consists of the main three different layers, namely the lower layer, middle layer and upper layer. In the lower layer, a 3D cube describes the underwater monitoring area, which is further divided into different layers such as the bottom layer ($N-1$), the intermediate layer (N) and the top layer ($N+1$). In the lower layer, a set of sensor nodes equipped with acoustic communication characteristics is randomly deployed for real-time monitoring underwater events. Generally, there are four types of events monitoring and reporting models, namely event-driven, query-driven, time-driven, and hybrid. We consider a hybrid model consists of the query and event-driven information delivery in UWSNs. In the middle layer, a surface sink equipped with acoustic and radio frequency communication is deployed in the middle of the cube. The sea surfaces sink is responsible to communicate with the ASNs for collecting or conveying user-defined information located in a remote location at the upper layer. The key aim of the ASNs deployed in a three-dimensional area is to collect events data and relay the data toward the sea surface sink. Taking into account the acoustic signal limited transmission range, the collected data is conveyed in multi-hop manners toward the sink. However, the ASNs can transmit their packets via short distance single hop transmission only if the sink is in their

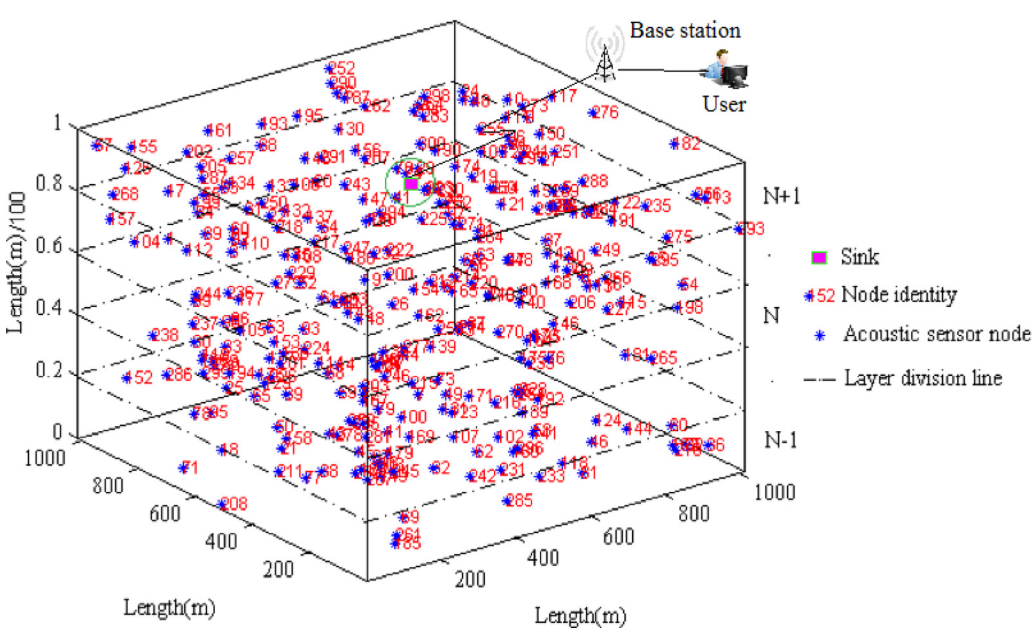


Fig. 1. A 3D view of MERP network model.

communication range. The sea surface sink operates to collect information from the ASNs then transmits the data to the end-user located in a remote location via an offshore base station. The proposed network model has the following properties: First, the surface sink and ASNs know their location using the technique presented in [28] for UWSNs. Second, the ASNs also know their current depth information and are homogenous in terms of data processing capability, buffer size, initial energy and communication range in UWSNs. Third, the surface sink and ASNs due to the water currents, randomly move in the horizontal and vertical direction in UWSNs. However, their movements in both horizontal and vertical direction are assumed negligible. Fourth, the link between ASNs are asymmetrical and can communicate with neighboring ASNs in a two-way manner only if they are in the communication range. In addition, the relative distance between a pair of ASNs can be obtained through the received signal strength values of the receiver. Fifth, the surface sink and offshore base station are rich in terms of energy and data processing capabilities. In addition, they have high data transmission rates over long distance highly stable communication links such as LTE-Advanced (4G) and Satellite communication technologies in the network. Moreover, the communication delay between the surface sink and offshore base station and, offshore base station and the remote user is assumed negligible compared to acoustic data transmission in UWSNs. Thus, by using these advanced communication technologies a remote user in a real-time can monitor, configure and control the entire UWSNs. In the end, we assume a time division multiple access (TDMA) technique to avoid packets collision in UWSNs.

3.2. Multi-objective bio-inspired computation

Generally, the existing traditional routing schemes follow some hard and soft rule, and in complex scenarios totally failed instead of providing the desired range of feasible solutions for multiple defined objectives in UWSNs. To this end, bio-inspired computing (BIC) has been the attraction of researchers due to solving complex problems in the fields of science and engineering for a long time. The BIC is based on the inspiration of the biological evolution of nature and has several consortiums such as artificial immune systems, swarm intelligence, evolutionary algorithms, and several others [29]. A BIC algorithm due to its intelligent behavior solves complex problems by searching the best or a set of near-optimal solutions in the given search space. Therefore, the BIC due to developing new and robust competing techniques explore a new era of computation for deciphering optimization problems in various UWSNs-based events monitoring applications. However, in traditional BIC techniques for finding a set of multiple objective values often affect each other in a nonlinear and complex way, which results in an optimization of the overall problem in the network [30]. Recently, the multi-objective BIC techniques have been widely adapted to the multiobjective optimization problem (MOP) for finding a wide range of solutions more rapidly compared to traditional techniques rely on mathematical programming or formal logics [31].

In BIC, the genetic algorithm (GA) because of its ability to select the fittest solution in a biological system, it has been successfully applied to MOP's as well as in several engineering and scientific domains [32]. Unlike in a single-objective, a GA in a multi-objective approach splits the complex task into several subtasks based on the fitness function intensity and provides optimization results simultaneously at the extremely fast convergence in a biological system. In addition, the key idea of 'Pareto rank' preserves the independence of individual objectives in the current solution of the initial population. In GA, it helps to distinguish the clearly superior individuals than others in all dimensions in the multi-objective problem search space. Because it might be possible that a superior solution by considering all under consideration objectives does not exist rather than a set of the solution with better quality to the remainder in the entire problem search space in a biological system. Moreover, it may also be possible that the genomic strings in a pair of solution results in a tie either both are non-dominated or dominated in the current solution of a problem search space in a system. To resolve such ties, we employ a niche-sharing concept presented in [33]. Thus, the non-dominated solutions saturated at a near-optimal point while rapidly advancing toward the global optimal in a biological system. However, this success resides in the general applicability of genetic representation and fitness evaluation of the designed GA in order to find an absolutely better solution than any other in the MOP field. Inspired by above-mentioned advantages of the multi-objective evolutionary method in the MOP, we propose a novel multi-objective evolutionary dynamic routing protocol for UWSNs. In MERP, the main purpose of the objective function (ϕ_{MERP}) is to decrease entire information collection cost in each individual round i for monitoring events in the underwater environments. The objective function formally can be denoted as

$$\varphi_{\text{MERP}} = \sum_{i=1}^{n} \Big(\text{Max}\big(\mathcal{R}_e + \mathcal{P}_{dr} + \mathcal{T}_p\big) + \text{Min}(\mathcal{D}_e + \mathcal{C}_{on} + \mathcal{P}_{er})\Big)^i \quad \text{for } \forall i = 1, 2, \ldots, n \tag{1}$$

in which $\mathcal{P}_{er}$, $\mathcal{C}_{on}$, $\mathcal{D}_e$, $\mathcal{P}_{dr}$ and $\mathcal{T}_p$ are, the packet error rate, the congestion, the delay, the packet delivery ratio and the throughput, respectively.

3.3. Multi-objective evolutionary implementation

In MERP to solve cluster-based routing problem for UWSNs-based events monitoring applications, we employ a numerical optimization version of the genetic algorithm containing tournament selection, arithmetic crossover and Gaussian mutation operators. In the first phase of the scheme, a chromosome ($\mathcal{C}_i$) with n number of genes, i.e., the sensor nodes represented by -1 for the inactive or dead sensor ($\mathcal{SN}_D$) having no remaining energy (E_0), 0 for non-cluster head nodes ($\mathcal{N}_{\mathcal{CH}}$), and 1 for the cluster head nodes ($\mathcal{CH}$) in underwater environments. On the contrary, in the second phase of our scheme, a chromosome ($\mathcal{C}_i$) is a routing path from the source toward the sink consists of n number of genes, i.e., the cluster head nodes represented by -1 for the dead or inactive cluster heads ($\mathcal{CH}_D$) with no remaining energy (E_0), 0 for non-cluster head nodes ($\mathcal{N}_{\mathcal{CH}}$), and 1 for the active cluster head nodes ($\mathcal{CH}_A$) in UWSNs. In the beginning, a sink by employing a random number generator $r \in [0, 1]$ is responsible to generate an initial population of n individuals in the network. Then, the fitness of each individual is calculated by employing a fitness function in UWSNs. The best individuals to form a mating pool are selected based on their fitness values from the current population and ranked by using the Pareto mechanism ($\mathcal{P}_r$) in decreasing order in the network. The vector form of the fitness values in a specific time interval (φ_t^i) for the current round r_i can be numerically denoted as

$$\mathcal{P}^i_{r(h)} = \begin{bmatrix} \varphi^1_{\mathbb{R}_e} & \varphi^1_{\mathbb{D}_e} & \varphi^1_{\mathbb{C}_{on}} & \varphi^1_{\mathbb{D}_a} & \varphi^1_{\mathcal{CH}} & \varphi^1_{\mathcal{S}p} & \cdots & \varphi^1_t \\ \varphi^2_{\mathbb{R}_e} & \varphi^2_{\mathbb{D}_e} & \varphi^2_{\mathbb{C}_{on}} & \varphi^2_{\mathbb{D}_a} & \varphi^2_{\mathcal{CH}} & \varphi^2_{\mathcal{S}p} & \cdots & \varphi^2_t \\ \varphi^3_{\mathbb{R}_e} & \varphi^3_{\mathbb{D}_e} & \varphi^3_{\mathbb{C}_{on}} & \varphi^3_{\mathbb{D}_a} & \varphi^3_{\mathcal{CH}} & \varphi^3_{\mathcal{S}p} & \cdots & \varphi^3_t \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \varphi^i_{\mathbb{R}_e} & \varphi^i_{\mathbb{D}_e} & \varphi^i_{\mathbb{C}_{on}} & \varphi^i_{\mathbb{D}_a} & \varphi^i_{\mathcal{CH}} & \varphi^i_{\mathcal{S}p} & \cdots & \varphi^i_t \end{bmatrix} \tag{2}$$

where the fitness values $\varphi^i_{\mathbb{R}_e}$, $\varphi^i_{\mathbb{D}_e}$, $\varphi^i_{\mathbb{C}_{on}}$, $\varphi^i_{\mathbb{D}_a}$, $\varphi^i_{\mathcal{CH}}$ and $\varphi^i_{\mathcal{S}p}$ are, the sensor residual energy, the packet transmission delay of a sensor to its single hop neighboring sensors, the possible cluster head node, the congestion management of a cluster head, the data traffic load of a cluster head, and the possible shortest routing path consisting of $\forall h \in \{1, 2, \ldots, \ell\}$ cluster head relay nodes from the source toward the destination at a specific time window φ_t^1 defined by the sink in the current round r_i in the network.

To improve the quality of the individual's crossover and mutation operators through the predefined probabilities (ρ_c) and (ρ_m) are applied in the network. After applying operators on each population individual's, we stored currthe ent population as the previous old population ($\mathcal{P}_{\mathcal{O}}$). Herein, the main purpose of the crossover operator is to allow new string formation by altering certain portions of a randomly selected string portion with another string in a chromosome. Thus, it preserves and combines the desirable features of the selected parents in the entire network. Generally, in the classical crossover mechanism, a single-point crossover sometimes is leading to an infeasible clustering and data path sequence after reproduction due to vertices duplication and omission in the network. To avoid this problem, we employ a simple multi-point crossover operator with high probabilities 0.96 and 0.98 to solve the combinatorial optimization problems because of its allowing good sequences of genes in a chromosome in the network. It simply adds various features to new offspring by swapping different sections of a chromosome in the population. To avoid redundancy, typically it maps the corresponding bits in the mate's absolute position and the remaining bits to the same absolute position in the genes of a chromosome in the network. Thus, it generates a set of child's chromosomes in the current mating pool in the population. Hence, new solutions are introduced more quickly into the population. On the other hand, the mutation operator determines the search directions and avoids premature convergence to suboptimal solutions by considering the lost or unexplored material into the population. Therefore, it is critical to the success of the MERP scheme. In mutation process, the randomly selected genes from the chromosome that form the population undergo a change of the value of each gene of a solution in a definite ratio. In MERP, mutation ratios 0.1% and 0.5% are applied to the chromosomes of the problems. This low mutation rates adequately change the chromosomes to provide better results of all the problems compared to the high mutation ratio in the network. The entire genomic alteration phenomenon in a chromosome is shown in Fig. 2. This mechanism iteratively refines and re-evaluates the new population according to the defined fitness function in the network. In addition, we employ a binary tournament selection ($\mathcal{B}_{ts}$) on each individual j from the previous generation to compare with the current generation individual's i based on the fitness value. If the fitness value of the ith individual is superior to the jth fitness, then it simply substitutes the jth individual in the current population. Thus, in the $\mathcal{B}_{ts}$ a set of best individuals is chosen to generate a pool for the k parents from the two randomly elite individuals of the population set, and this procedure repeats n times. The resultant survived population pass through the arithmetic crossover mechanism numerically given as follows:

$$\mathcal{P}_{\mathcal{O}}(j)_{yt} = \eta_w * \mathcal{P}_{\mathcal{O}}(j)_{yt} + (1 - \eta_w) * \rho_c * \mathcal{P}_{\mathcal{O}}(i)_{yt} \tag{3}$$

where $\mathcal{P}_{\mathcal{O}}(j)_{yt}$ is the yth solution parameter for each individual j, t is the iteration time, $\mathcal{P}_{\mathcal{O}}(j)_{yt}$ and $\mathcal{P}_{\mathcal{O}}(i)_{yt}$ are the parents offsprings. $\eta_w \in [0, 1]$ is a uniform random weight generated for each problem parameters y in each iteration i. The crossover probability ρ_c were set to 0.96 and 0.98. To maintain diversity in the population Gaussian mutation is applied which can be numerically indicated as

$$\mathcal{P}_{\mathcal{O}}(j)_{yt} = \mathcal{P}_{\mathcal{O}}(j)_{yt} + \ \rho_m * \beta * \ (\eta_{\max} - \eta_{\min}) \tag{4}$$

in which ρ_m is the variance parameter of the mutation operator fixed between 0.005 and 0.05, β is the Gaussian normal distribution where $\beta \in [0, 1]$ and, $\eta_{\min}$ and $\eta_{\max}$ are the lower and upper bound values of the desired solution set to 0 and 1, respectively. The new generated population ($\mathcal{P}^i_{new}$) for the current round r_i is ranked in decreasing order by using Pareto rank and niche-sharing mechanism ($\mathcal{P}_{rn}$) can be numerically indicated as

$$\mathcal{P}^i_{r(h)} = \begin{bmatrix} \overline{\varphi^1_{\mathbb{R}_e}} & \overline{\varphi^1_{\mathbb{D}_e}} & \overline{\varphi^1_{\mathbb{C}_{on}}} & \overline{\varphi^1_{\mathbb{D}_a}} & \overline{\varphi^1_{\mathcal{CH}}} & \overline{\varphi^1_{\mathcal{S}p}} & \cdots & \overline{\varphi^1_t} \\ \varphi^2_{\mathbb{R}_e} & \varphi^2_{\mathbb{D}_e} & \varphi^2_{\mathbb{C}_{on}} & \varphi^2_{\mathbb{D}_a} & \varphi^2_{\mathcal{CH}} & \varphi^2_{\mathcal{S}p} & \cdots & \varphi^2_t \\ \varphi^3_{\mathbb{R}_e} & \varphi^3_{\mathbb{D}_e} & \varphi^3_{\mathbb{C}_{on}} & \varphi^3_{\mathbb{D}_a} & \varphi^3_{\mathcal{CH}} & \varphi^3_{\mathcal{S}p} & \cdots & \varphi^3_t \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \varphi^i_{\mathbb{R}_e} & \varphi^i_{\mathbb{D}_e} & \varphi^i_{\mathbb{C}_{on}} & \varphi^i_{\mathbb{D}_a} & \varphi^i_{\mathcal{CH}} & \varphi^i_{\mathcal{S}p} & \cdots & \varphi^i_t \end{bmatrix} \tag{5}$$

where the new fitness value by using Pareto rank and niche-sharing mechanism $\overline{\varphi^i_{\mathbb{R}_e}}$, $\overline{\varphi^i_{\mathbb{D}_e}}$, $\overline{\varphi^i_{\mathbb{C}_{on}}}$, $\overline{\varphi^i_{\mathbb{D}_a}}$, $\overline{\varphi^i_{\mathcal{CH}}}$ and $\overline{\varphi^i_{\mathcal{S}p}}$ are, the residual energy of a sensor, the packet transmission delay of a sensor to its single hop neighboring sensors, the possible cluster head node, the congestion management of a cluster head, the data traffic load of a cluster head, and the possible shortest routing path consisting of k cluster head relay nodes from a source cluster head relay node toward the destination at a specific time window φ^1_t defined by the sink in the current round r_i by using Pareto rank and niche-sharing mechanism in the network. This entire optimization search proceeds until the predefined termination criterion is satisfied in order to find a chromosome containing the elite individuals as complete cluster-based routing solution from the source toward the destination in the current population. In a current population, the best individual fitness by using decision variables can be numerically indicated as

$$\mathcal{P}_{new}(j)_{yt} = \begin{cases} \mathcal{P}_{\text{new}}(j)_{yt} & if\ \mathcal{P}_{\text{o}}(j)_{yt} < \mathcal{P}^k_{C_j} \\ \mathcal{P}_{\text{o}}(j)_{yt} & otherwise \end{cases} \tag{6}$$

where C_j for $\forall j \in \{1, 2, \ldots, m\}$ is the current individual in the existing population $\mathcal{P}^k_{C_j}$ containg k iterations. The entire sensor node implementation has been divided into two basic sections explained below.

3.4. Multi-objective evolutionary cluster-based routing

Initially, the ASNs do not have information of the surrounding ASNs in UWSNs. Therefore, an efficient network initialization process (NIP) is essential for accurate neighbor discovery in the harsh nature underwater environment. The NIP process employes a package of basic four kinds of messages such as initialization, neighboring discovery, reply and acknowledgment messages indicated as $ireq\_msg$, ndr_msg, rp_msg and ack_msg, respectively in UWSNs. In the beginning, the BS based on the user-defined instructions sends a $ireq\_msg$ message to the sink in to begin the NIP in UWSNs. After receiving the $ireq\_msg$ message, the sink adjusts its transmission range and broadcasts a predefined number of $ireq\_msg$ messages in a specific region of the network. The key aim of $ireq\_msg$ message is to permit ASNs to discover neighboring ASNs in the underwater environment and compute the sink trajectory. Thus, the $ireq\_msg$ message consists of packet transmission time, location information and identity of the sink. After receiving the $ireq\_msg$ messages, the ASNs by using surface sink time synchronize their local time and identify the sink trajectory. Then, a neighboring information table is constructed by each ASN in UWSNs. In order to do this, the ASNs that receive the $ireq\_msg$ messages from the sea surface sink start to communicate with the nearby ASNs by disseminating neighboring discovery messages in their communication area in UWSNs. The ndr_msg message consists of ASN unique identity, position, angle information, $\mathcal{R}_e$ and signal-to-noise ratio value to neighboring ASNs that can be estimated by using a simple signal-to-noise radio formula

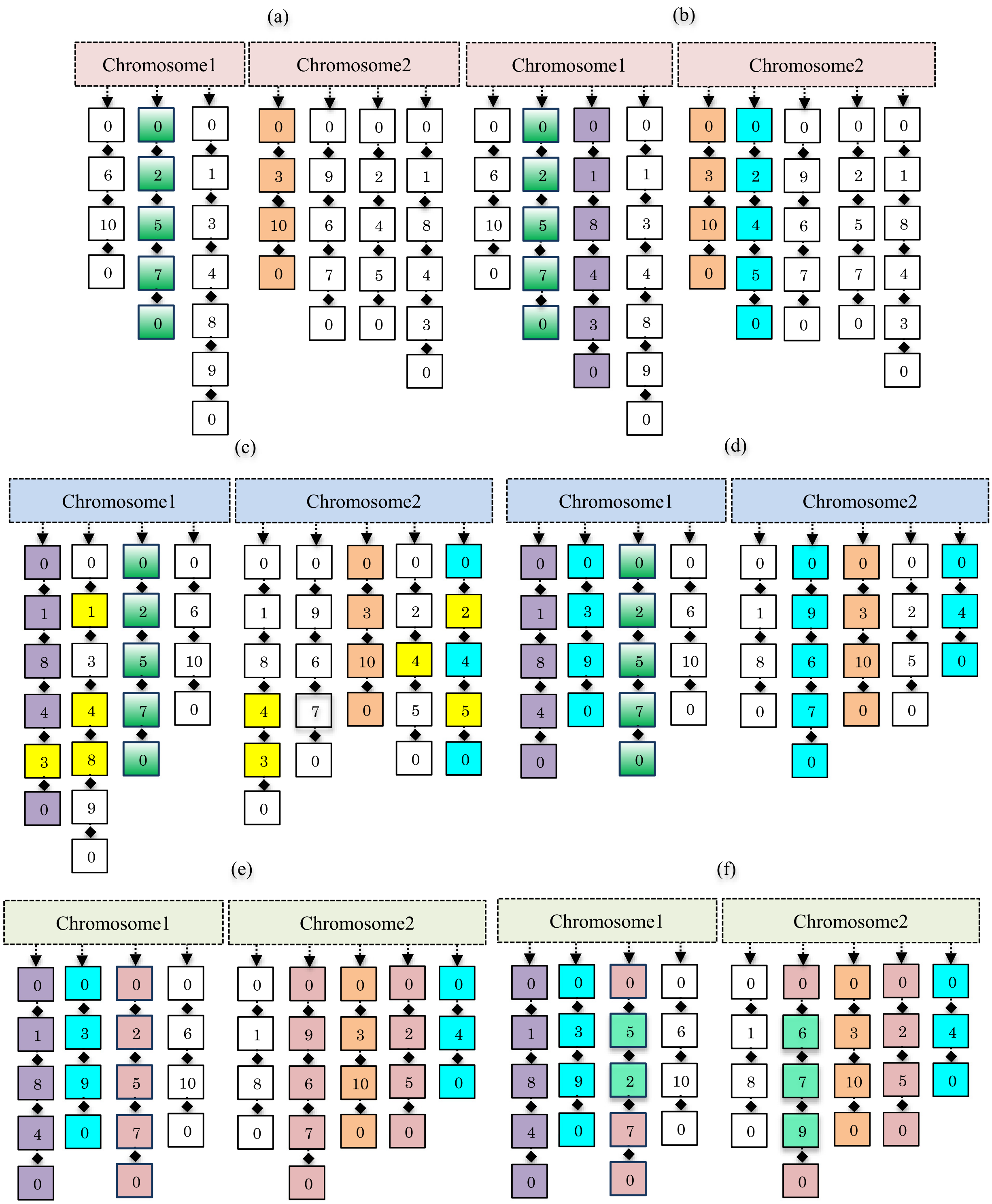


Fig. 2. The genetic representation of MERP in UWSNs. In representation, from 0 to 10 shows the different number of ASNs involved in the genomic process in UWSNs. (a) shows the selection of chromosomes in the current population. (b) represents the selection of chromosomes when new chromosomes information is added in the current population. (c) indicates the removal of duplications chromosomes after applying multipoint crossover operations. (d) shows the random shuffling of chromosomes by using a random number generator. (e) demonstrates the selection of the chromosome for mutation process. Finally, (f) illustrates the best individuals ASNs or CHs after mutation operations to find complete clustering and routing solution in UWSNs.

(p_{signal}/p_{noise}) in UWSNs. The p_{signal} and p_{noise} are, the expected signal strength value and the noise value in the network. In the neighboring discovery process, there might be message conflict issues if multiple ndr_msg messages are dissiminated by many ASNs concurrently in UWSNs. To tackle this issue, each ASN follows a time division multiple access (TDMA) procedure to avoid packets collision by in UWSNs. An ASN that receives the ndr_msg message saves the recent measurements in its recently created neighbor information table (NIT) if it does not exist before and measures the neighboring sender's ASN angle and distance information. This entire process reiterates till each ASN has neighboring ASNs recent information stored in its NIT in UWSNs. Herein, during exchanging informtion, each sender ASN receives an $\mathcal{ack\_msg}$ message from the receiver ASN that ensured the information delivery in UWSNs. Thus, all the links between ASNs are bidirectional tested in UWSNs. Later, the entire neighbor discovery information is forwarded to the sea surface sink in a multi-hop greedy fashion from all ASNs by using $\mathcal{rp\_msg}$ messages. The neighboring discovery procedure ends as soon as the ASNs located in different regions send $\mathcal{rp\_msg}$ messages to sea surface sink in UWSNs. Finally, the whole received information from the sea surface sink is delivered to the remote user.

In the proposed scheme, after network initialization, the cluster formation procedure begins as soon as the remote user sends a cluster discovery message ($\mathcal{cd\_msg}$) to the ASNs via sea surfaces sink. The ASNs after decoding the message precisely start to broadcast a predefined $\mathcal{cd\_msg}$ messages to the neighboring ASNs located in their communication range in the underwater environments. The $\mathcal{cd\_msg}$ message contains the information such as unique identity, signal-to-noise ratio, residual energy and location information in a specific area in the underwater environments. After decoding the $\mathcal{cd\_msg}$ message precisely, each receiver ASN via a reply message replies to the sender ASN, which consists of information such as unique identity, signal-to-noise ratio, residual energy and location information in a specific area. After receiving the reply message, each ASN updates its neighboring information table with the recent information only if it exists else a new entry is created in order to store the information of the sender ASN in UWSNs. Consequently, the routing table information is updated periodically at each ASN during the cluster discovery process and an $\mathcal{ack\_msg}$ is forwarded to the sender ASN in UWSNs. During updating the routing table, the neighboring information with decreasing priority is saved which is based on the high $\mathcal{R}_e$, $\mathcal{SNR}$ and smaller distance toward the sea surface sink. Remember that, the neighboring information is saved in the routing table opportunistically only if two or more ASNs have the identical priority in UWSNs. Moreover, in the proposed mechanism it is also possible that a receiver ASN might get multiple cluster discovery messages from the identical sender ASN in UWSNs. In this scenario, the ASNs just drop rest of the messages after receiving the first $\mathcal{cd\_msg}$ message from the same sender ASN in the network. On the contrary, if multiple $\mathcal{cd\_msg}$ messages are received from different ASNs then each receiver node responds to the sender ASNs by following First-Come-First-Serve (FCFS) policy in the network. Thus, the recent information is updated periodically in the routing table at each ASN during the cluster discovery process and an $\mathcal{ack\_msg}$ is forwarded to the sender ASN in UWSNs. At this stage, each sensor node has its neighboring sensor nodes information in UWSNs. Consequently, the sensor node j with genomic values -1 for the dead or inactive sensor node no remaining energy, 0 for non-cluster head nodes and 1 for the cluster head nodes in each set of a chromosome $\mathcal{C}_j$ numerically in the current round i can be shown as

$$ {}^{i}_{i} = \begin{cases} 1 & \text{if}\, \mathrm{E}_{(j)} \geq \mathrm{E}_0 \,\text{and}\, {}_{(j)} = C \\ 0 & \text{if}\, \mathrm{E}_{(j)} < \mathrm{E}_0 \,\text{and}\, {}_{(j)} = c \\ -1 & \text{otherwise} \end{cases} \tag{7} $$

For a required percentage of the cluster heads k in each set of a chromosome $\mathcal{C}_i$, each individual is initialized by a random number generator r_n with values 0 and 1 through a predefined probability (ρ_b), which numerically can be shown as

$$ \mathcal{C}^i_j = \begin{cases} 1 & \text{if } \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} \geq \mathrm{E}_0 \text{ and } r_n \geq \ \rho_b,\ \mathcal{CH}_h \\ 0 & \text{if } \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} < \mathrm{E}_0 \text{ and } r_n < \rho_b,\ \mathcal{N}_{\mathcal{CH}} \\ -1 & \text{otherwise} \end{cases} \tag{8} $$

This genomic type illustration implicitly assists the formation of a number of different size dynamic clusters ($\mathbb{C}_n$) throughout the individual or complete rounds for the entire set of chromosomes in UWSNs. This can be statistically denoted as

$$ \mathcal{C}^i_i = \begin{cases} 1 & \text{if } \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} \geq \mathrm{E}_0 \,\text{and}\, r_n \geq \ \rho_b,\, \mathcal{CH}_h \in \mathbb{C}_h \\ 0 & \text{if}\, \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} < \mathrm{E}_0 \,\text{and}\, r_n < \ \rho_b,\, \mathcal{N}_{\mathcal{CH}} \\ -1 & \text{otherwise} \end{cases} \tag{9} $$

For the superior quality clustering solutions, we employ a signal-to-noise ratio mechanism in order to provide highly stable and reliable links between sensors in the harsh underwater environments. A sensor node j with higher residual energy and signal-to-noise ratio ($\mathcal{SNR}$) values to its neighboring nodes i above the defined threshold has more chance to be elected as a cluster leader for the current round in UWSNs. In addition, the association of a set of cluster leaders to its member sensors in each chromosome $\mathcal{C}_j$ is also computed in highly stable clustering architecture in UWSNs. It measures the significance of a cluster leader with respect to the connectivity between other nodes based on the centrality measures in UWSNs. This can be numerically written as

$$ \mathcal{CH}_k = \begin{cases} 1 \ if \ \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} \geq \mathbb{R}_e \ and \ \mathcal{SNR}_{\mathcal{S}_{\mathcal{N}(j)}} \geq \ \mathcal{SNR}_{\mathcal{S}_{\mathcal{N}(i)}} \\ 0 \ if \ \mathrm{E}_{\mathcal{S}_{\mathcal{N}(j)}} < \mathbb{R}_e \ and \ \mathcal{SNR}_{\mathcal{S}_{\mathcal{N}(j)}} \leq \mathcal{SNR}_{\mathcal{S}_{\mathcal{N}(i)}} \end{cases} \tag{10} $$

After the cluster heads appointment, every cluster leader is responsible for broadcasting a predefined number of cluster head appointment messages ($\mathcal{chap\_msg}$) to its neighboring ASNs in UWSNs. The ASNs that precisely decode the cluster head appointment messages reply via a joining message ($\mathcal{jo\_msg}$) as a cluster member. Consequently, after precisely decoding the joining message, each cluster head node assigns a unique time slot by using TDMA mechanism and engaged them in a round-robin manner for the information sharing in the network. Thus, a predefined number of cluster heads with cluster members are dynamically constructed in the entire network. In a case, if an appropriate set of sensor nodes is not located in the range, then a cluster leader may adjust its transmission power to a high level in the network. This procedure finds a suitable neighboring sensor node even in a highly sparse network deployed for events monitoring in UWSNs. The average $\mathcal{SNR}$ of all ASNs to their associated clusters center in the underwater environments can be denoted as

$$ \mathcal{SNR}_{\mathcal{S}_{\mathcal{N}(n)}}\ (c)_n = \sum\nolimits_{j=1}^{\mathcal{N}_c} \left[\sum_{\forall \mathcal{S}_{\mathcal{N}(j)} \in \ c_{ij}} \mathcal{SNR}\left(\mathcal{S}_{\mathcal{N}(N)}, c_{ij}\right) \cdot Z_{ij} \right] / \left|c_{ij}\right| / \mathcal{N}_c \tag{11} $$

where

$$ \mathcal{SNR}\left(\mathcal{S}_{\mathcal{N}(n)},\ c_{ij}\right) = \sqrt{\sum_{k=1}^{\mathcal{N}_b} \left(\mathcal{S}_{\mathcal{N}(j)} -\ c_{ij}\right)^2} \tag{12} $$

in which $\mathcal{N}_c$, $\mathcal{N}_b$, $\mathcal{Z}_{ij}$, c_{ij}, $|c_{ij}|$ are, the total number of clusters, the sensors in each cluster, the components of the sensors belong to an associated cluster, the vector of the jth cluster center associated to the ith sensor node, the jth cluster node member of the ith cluster in the network. Consequently, we have the cluster head association $\mathcal{CH}_k(\mathcal{S}_{\mathcal{N}(j)})$ for a set of associated sensors far away to the sink as

$$ \mathcal{CH}_k\left(\mathcal{S}_{\mathcal{N}(j)}\right) = \sum_{i=1}^{n} \sum_{k=1}^{n-1} c_i(\mathcal{CH}_k) / \sum_{i=1}^{n} \sum_{j=1}^{n-1} \mathcal{CH}_k\left(\mathcal{S}_{\mathcal{N}(j)}\right) \tag{13} $$

A cluster leader association to its member sensors in a particular region ($\mathcal{R}_i$) near to the sea surface sink ($\mathbb{S}_{ink}$) can be numerically revealed as

$$ C_h\left({}_{(j)}\right) = \left(\sum\nolimits_{i=1}^{n} \sum\nolimits_{h=1}^{n-1} C_i(C_h) / \sum\nolimits_{i=1}^{n} \sum\nolimits_{h=1}^{n-1} (C_h)\left({}_{(j)}\right)\right)^{i} \cdot {}_{ink} \tag{14} $$

The probability of cluster leader coverage to the associated ASNs positioned in a specific area in UWSNs can be numerically shown as

$$\rho_r(\mathcal{CH}_k)_{\mathcal{R}_i} = 1 - \prod_{i=1}^{\mathrm{n}} \left(1 - \mathcal{CH}_k\left(\mathcal{S}_{\mathcal{N}(i)}\right)\right) \tag{15}$$

In the worst case, if a cluster head fails to find a predefined of sensors member in its range, then it could join its nearest cluster leader as a member node in UWSNs. As soon as the clustering process completes each ASN in a cluster senses the events and reports to its associated cluster leader in a timely manner in UWSNs. Note that, the key responsibilities of a cluster head in a cluster are, to periodically communicate with their member nodes for their residual energy, topology information and fuse the gathered information in UWSN. In the proposed scheme, for balancing the network E_c burden, a new cluster leader is elected at constant periodic time intervals in each constructed cluster in the network. A cluster leader schedules the activities and engaged sensor nodes in a round-robin order so that nodes can switch to transmission and reception to limit redundancy in coverage and prevent medium access collision in a cluster. Moreover, it also avoids the exchange of redundant data packets between sensors and conserves bandwidth for reliable communication by limiting the intra-cluster interactions to associated sensors in the network. In addition, cluster member nodes are responsible for not affecting any changes made at a high level while connecting with their cluster leaders. In this way, also it minimizes the topology maintenance overhead cost by maintaining the topology of the network at the sensor level in UWSNs. In the designed scheme, a clustering process re-initiated only if a cluster head loss its energy than the defined threshold value in UWSNs.

In the second phase, a set of fittest CHs is considered to relay events data between the source and sink. The routing path procedure begins as soon as route discovery message (rd_msg) received through the sea surface sink in the network. After precisely decoding the message, the receiver CHs limited broadcasts rd_msg messages to the neighboring CHs located in their communication range in UWSNs. The rd_msg consists of information of the sender CH such as unique identity, signal-to-noise ratio, residual energy and location information in UWSNs. The route discovery message is forwarded only in a specific direction $(\mathcal{D}_s)$ in a region $(\mathcal{R}_i)$ toward the sink, which can be numerically indicated as

$$r_e[_s] = \int_{\propto}^{s-(h+d_w)} {}_i\left(r_{eC(i,j)}\right) \cdot {}_{ink} \tag{16}$$

where $\propto$ is the origin of the route request, $r_{e\mathcal{CH}(i,j)}$ indicates the route request packet is transmitted from a cluster leader i to associated cluster leader j in a specific direction by avoiding horizontal (h) and downward (d_w) direction in UWSNs. The coverage probability (ρ_r) of a cluster leader $\mathcal{CH}_K$ to its associated cluster heads $\mathcal{CH}_i$ located in a region $\mathcal{R}_i$ can be numerically expressed as

$$\rho_r(\mathcal{CH}_K)_{\mathcal{R}_i} = 1 - \prod_{i=1}^{\mathrm{n}} (1 - \rho_r(\mathcal{CH}_i)) \tag{17}$$

Initially, the size of the space search is extremely large to find a feasible set of CH relay nodes from the source toward the sink, which can numerically indicate as

$$\delta_p = \prod_{i=1}^{n} Cr_i \tag{18}$$

where δ_p is the search space of the problem solution and Cr_i is the cluster based routing solution. In each iteration, the size of the search space iteratively reduces rapidly in order to find a feasible cluster head relay node, which can be written as

$$\delta_p = \prod_{i=1}^{n} \left(Cr_i - m_j\right) \text{ where } m_j < \delta_p \tag{19}$$

where m_j is the number of non-feasible clusters eliminated from the feasible cluster-based routing solution from the source toward the destination in UWSNs. Consequently, after decoding the route discovery message precisely a reply message is forwarded by the receiver CH to the sender CH in the UWSNs. The reply message consists of some basic information such as receiver CH identity, signal-to-noise ratio, remaining energy and location information in UWSNs. After receiving the reply message, each CH updates its neighboring information table with recent information only if it exists else a new entry is created in order to store the information of the sender CH. Accordingly, the routing table information is updated periodically at each CH during the route discovery process and an ack_msg is forwarded to the sender CH in UWSNs. This procedure continues until the CHs nearer to the sea surface sink are recognized in UWSNs. At this stage, the CHs have the knowledge to reach the sea surface sink via multiple routes over a set of CHs in UWSNs. Note that, the sink also follows the same direction architecture during forwarding instruction packets toward the destination in a specific region, which can be represented as

$$r_e[\mathbb{S}_{inr}] = \int_{\propto}^{s-(h+d_w)} \mathcal{R}_i\left(r_{e\mathcal{CH}(j,i)}\right) \cdot \mathcal{D}_s \tag{20}$$

During the route request forwarding process, the key aim to restrict data movement in various directions is to minimize overall network routing path size and routing path loops between the source and destination in UWSNs. In the information gathering process, the observed data from ASNs is collected in an active manner in UWSNs. In the beginning, a remote user is responsible to initiate the data collection process in the network. Consequently, predefined data collection messages (dc_msg) via sea surface sink and CHs are forwarded to the ASNs to explore the ocean environment. As soon as the dc_msg is decoded precisely, the ASNs start to monitor the underwater events. After monitoring the events each ASN sends its cached data to the linked CH in a timely fashion. After receiving the information, each CH fuses the data and sends it to the sea surface sink only if it is in the transmission range in the network. However, the CHs away to the sea surface sink start negotiating with neighboring CHs in order to discover an appropriate data forwarding CH node that is closer to the sink. Initially, a next hop relaying CH node toward the sink is selected based on its high higher residual, location and signal-to-noise ratio value in UWSNs. However, after a set of predefined iterations, a next hop CH node toward the sink is selected by employing the key idea of self-learning mechanism, which is based on prior history of buffer overflow time, location information, residual energy, low transmission distance and link quality values.

This self-instructed process extremely lowers the corrupted data packets caused by memory overrun issues in UWSNs. In a case, if a suitable cluster head relay sensor is not located in the vicinity, then it may change its transmission power to a high level. This process helps to locate a suitable next hop cluster head relay node to convey data traffic even in highly sparse network deployment. Consequently, each CH based on FCFS policy aggregates the events information coming from the ASNs and sends the fused data to the next hop forwarder CH node in a greedy fashion, which is closer to the sea surface sink. Upon receiving the data, the receiver CH node forwards the received information again to its neighboring CH node, which is further nearer to the sea surface sink. This process repeats until the CH node directly uploads the aggregated events data to the sink over a highly reliable link in UWSNs. At each hop after successful data transmission, the path counter length is decreased by 1 and reaches to 0 for the forwarder

CH, which is in direct communication range of the sea surface sink. On the other hand, at each hop after successful data transmission, the path counter length is increased by 1 and reaches to the predefined maximum value for the forwarder CH, which is in direct communication range of the destination CH node in the network. Finally, to allow memory for new events monitoring, the cached information at each CH along a route is removed immediately after successful packets transmission. The shortest path length between each set of a pair of cluster heads is important for the quality-aware communication efficiency in UWSNs. It reveals inter and intra-cluster separations of all cluster head pairs between the source and destination in UWSNs. In loops free shortest routing path by considering connectivity reliability at least an effective data path between the source and destination can be numerically indicated as

$$\mathcal{A}_{vg}(\mathcal{S}p) = \frac{1}{\mathcal{CH}_h(\mathcal{CH}_h - 1)} \sum\nolimits_{j,i\in\mathcal{CH}_h, h=1}^{n} \left(cr_{\mathcal{S}p(j,i)}\right) \cdot \mathbb{S}_{inh} \tag{21}$$

where $\mathcal{A}_{vg}(\mathcal{S}p)$ is the average shortest path, $\mathcal{CH}_k$ is the number of cluster leaders, $cr_{\mathcal{S}p(j,i)}$ shows the connective reliability between the source cluster leader j and destination cluster leader i toward the sea surface sink. The signal-to-noise ratio and the energy consumption of a cluster head toward the sink ($\mathcal{D}_{\mathbb{S}_{ink}\to C_i}$) numerically can be shown as

$$\mathcal{D}_{\mathbb{S}_{ink}\to\mathcal{CH}_i} = \min \frac{2}{\mathcal{R}^2} \int_0 \varepsilon_1(\mathrm{r}) h(,\mathrm{r})\mathrm{d} \tag{22}$$

where $\Re$, $h(\varkappa, \mathrm{r})$ and $\varepsilon_1(\mathrm{r})$ are, the radius of a cluster leader, the anticipated hops that cluster head packets need to make to reach the sink and the cluster head energy expenditure during single hop packets transmission at a specific distance in the network. Along with a specific routing path, i.e., $\mathcal{R}_{\mathcal{P}(i)}$, the probability of packets traveled between source and destination in the underwater environment is given in Eq. (23). The value of $i = 1$ means there exists a unique routing path i but the CHs are unaware of it while $i = 0$ means that there exists no routing path between source and destination in UWSNs. To this end, the exponent of utility is zero for the unavailable path while the limit is negative infinity for the log-of-zero in UWSNs.

$$\rho_{\mathrm{r}}\left(\mathcal{R}_{\mathcal{P}(i)}\right) = \mathcal{R}_{\mathcal{P}(j)} + \ln\ \mathcal{R}_{\mathcal{P}(i)} / \sum_{j\in\mathcal{R}_{\mathcal{P}(k)},\ j=1}^{n} \mathcal{R}_{\mathcal{P}(j)} + \ln \mathcal{R}_{\mathcal{P}(j)} \tag{23}$$

$$\delta_{\mathcal{R}_{\mathcal{P}(i)}} = \sum_{j\in\mathcal{R}_{\mathcal{P}(k)}} \frac{\ell_{1(\mathcal{CH}_i,\mathcal{CH}_j)}}{\mathcal{LR}_{\mathcal{P}(i)}} \frac{1}{\sum_{j\in\mathcal{R}_{\mathcal{P}(k)}} \left(\frac{\mathcal{R}_{\mathcal{P}(i)}}{\mathcal{R}_{\mathcal{P}(j)}}\right)^{\gamma} \delta_{\mathcal{R}_{\mathcal{P}\ell 1(j)}}} \tag{24}$$

Eq. (24) indicates that in $\ell_{1(\mathcal{CH}_i,\mathcal{CH}_j)}$ the value of γ is set to 1 while the link 1 has a maximum defined number of CHs along a routing path in the network. This ensures that a set routing path varies in length between source and destination is generated over a set of CHs in UWSNs. In addition, the data flow capacity of the shortest path by involving n number of cluster heads with links ℓ_{n-1} from the source toward the sink can be numerically computed as

$$\begin{aligned}\min_{v} Z = &\sum_{\ell_{ij}\in\mathcal{CH}_{(i,j)}} \int_{0}^{C_{ij}\left(v_{\ell f\left(\mathcal{CH}_{(i,j)}\right)\mathcal{S}d}\right)} C_{ij}(v)dv \\ &+ \lambda \sum_{\ell_{ij\in}\ \mathcal{CH}_{(i,j)}} \sum_{\mathcal{S},d} \left(v_{\ell f\left(\mathcal{CH}_{(i,j)}\right)\mathcal{S}d} - \mu\right)^2\end{aligned} \tag{25}$$

subject to

$$t_{\mathcal{S}d} = \sum_{\ell_{ij\in}\ \mathcal{CH}_n} v_{\ell f(\mathcal{CH}_n)\mathcal{S}d} - \sum_{\ell_{ij\in}\ \mathcal{CH}_{(i,j)}} v_{\ell f\left(\mathcal{CH}_{(i,j)}\right)\mathcal{S}d}\ \forall i;\ \mathcal{S} \neq d \tag{26}$$

$$\mu = \sum_{\ell_{ij\in}\ \mathcal{CH}_{(i,j)}} \sum_{\mathcal{S},d} v_{\ell f\left(\mathcal{CH}_{(i,j)}\right)\mathcal{S}d} \tag{27}$$

$$v_{\ell f(\mathcal{CH}_n)\mathcal{S}d} \geq \mu_{\ell f\left(\mathcal{CH}_{(i,j)}\right)\mathcal{S}d}\ \forall\ i,\ j; \mathcal{S}, d \tag{28}$$

So, the link flow $\ell f(\mathcal{CH}_n)$ though the link $\ell_{ij\in\ \mathcal{CH}_{(i,j)}}$ is

$$\ell f_{(\mathcal{CH}_n)} = \sum_{\mathcal{S},d} v_{\ell f(\mathcal{CH}_i + \mathcal{CH}_j +,\ldots,\mathcal{CH}_n)\mathcal{S}d} \tag{29}$$

where C_{ij} is the cost function for link $\ell_{i,j}$, $v_{\ell f}$ is the data flow rate from source cluster leader node i to destination cluster leader node j toward the sink, $t_{the\ \mathcal{S}d}$ is the time from the source toward the destination, μ is mean factor of the $(\mathcal{CH}_{i,j})\mathcal{S}d$ variables greater than 0, and λ is a constant set to 1. The amount of delay $(t_{\mathcal{S}d})$ for a set of cluster heads n using links ℓ_{n-1} with data traffic flow v from the source toward the destination can be numerically calculated as

$$\begin{aligned}\min_{\mathcal{S},d}(t, v) = &\sum\nolimits_{\mathcal{CH}_i\in\ell_{n-1}} \sum\nolimits_{\mathcal{CH}_j\in\ell_{n-1}} (t_i - t_i)\ddot{u}_{ij}\left(\bar{t}_i - t_i\right) \\ &+ \sum\nolimits_{u\in I_0} \sum\nolimits_{w\in\mathcal{A}_0} \left(\bar{v}_{ij} - v_{ij}\right)\ddot{w}_{ij}(\bar{v}_\ell - v_\ell)\end{aligned} \tag{30}$$

subject to

$$v_{ij} = \sum_{i\in\ell} t_i \sum_{j} p_{ij}\delta_{ij}^{k},\ \ \ell_{ij} \in \ell_{n-1} \tag{31}$$

where $t = \{t_i\ |i\ \in \ell\}$ is the vector containing the record of n cluster head links ℓ_{n-1} time matrix to be estimated, $\bar{t}_i$ is the vector containing the a priori time history matrix, $v = \{v\ |i, j\ \in \ell_{n-1}\}$ is the row vector containing the observed link flows in the network, v_{ij} is the data flow of a link l_{ik} from cluster head node i to j toward sink, and $\ddot{u}_{ij}$ and $\ddot{w}_{ij}$ are the precision matrices. Please also note that u and w are the subsets of I_0 and $\mathcal{A}_0$ associated with the observed information in time t, p_{ij} is the randomly selected path from the source toward the destination, and δ_{ij}^{k} is a constant value for the randomly selected path is 1 if the link ℓ_{ij} between cluster head node i and j belongs to selected path, otherwise 0. Consequently, the whole watched data is relayed over a set of highly reliable shortest multi-hop routing paths from the sensing field toward the sea surface sink in a greedy manner in UWSNs. The proposed protocol significantly minimizes the latency, packet collision and path loops because of its self-learning approach, which selects the best or near the optimal routing path from the source toward the sea surface sink in UWSNs. Moreover, the shortest path routing over a predefined number of hops further reduces the interference effects in UWSNs. In addition, the packets transmission by taking into account the high link reliability further improves the overall lifespan of UWSNs. The working mechanism of MERP protocol is shown in Fig. 3.

3.5. Dead or isolated node recovery

Throughout the data collection process, each cluster head periodically monitors its members ASNs by broadcasting a predefined number of neighboring alive (al_msg) messages. The ASNs that receive the al_ms messages update their neighboring information table and each of them replies by sending an ack_msg message. Upon receiving the ack_msg messages, the neighboring table of each CH is updated in the network. However, if a cluster head did not receive any ack_msg message from its member ASNs in a given time, then it is supposed to be inactive in the network. The inactive ASN information is forwarded to the sink over a predefined routing path in UWSN. After receiving information, the sink generates a predefined number of limited broadcast instruction ndr_msg messages and sends via associated cluster heads it to ASNs located in a specific region nearer the inactive node in the

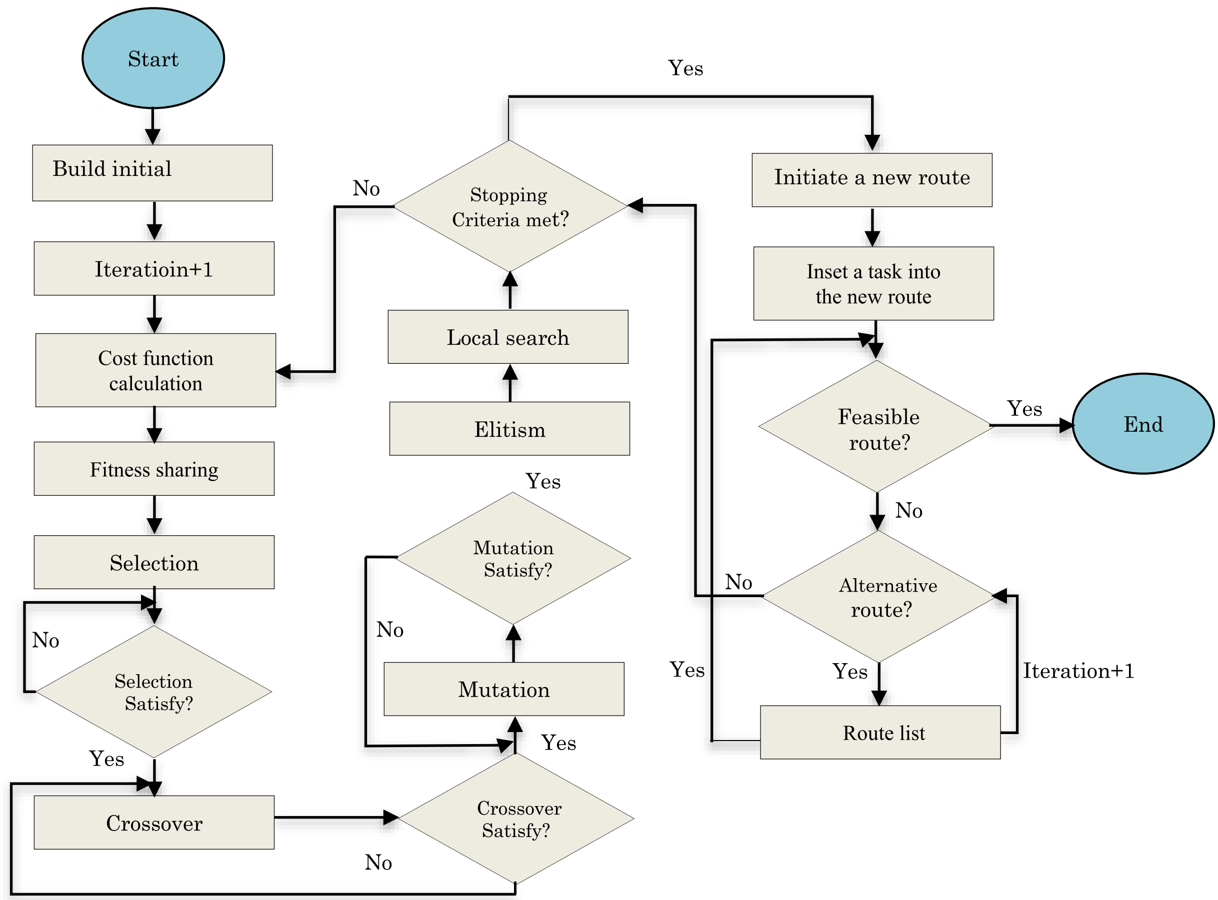


Fig. 3. Entire working mechanism of MERP.

network. As soon as the information is received, the specific set of ASNs starts to communicate with the inactive ASN by periodically sending a predefined number of ndr_msg messages. The assumed inactive ASN is alive only if at least one of the neighboring ASNs receives an ack_msg message, otherwise it is declared as a dead ASN in UWSNs. This recent information is sent to the sink, which initiates the route construction process only if the ASN was a cluster head or relay node in UWSNs. The whole data path construction procedure is similar as explained above in detail. In the case of an isolated ASN, if an acoustic node A is interested to send its information to node B but there is no route information exist in the routing table. Then, the acoustic node A sends a $rreq\_msg$ message to the neighboring ASNs, including its recent location, residual energy and unique identity in UWSNs. The receiver ASNs forward this information to its associated cluster head, which is forwarded to the sink in UWSNs. Upon receiving the $rreq\_msg$ message, the sink computes the location of the isolated neighboring ASN in UWSNs. As soon as the computation process finishes, the sink forwards the neighboring ASNs information to the isolated node in the network. Then, isolated ASN based on the received information starts to communicate with the neighboring ASNs by sending a $rreq\_msg$ message in UWSNs. In a case, if an isolated ASN receives the $rreq\_msg$ messages from neighboring ASNs. Then, first, it looks into its neighboring table for each sender ASN information and creates a new entry only if it does not exist and saves updated information in the neighboring table. After that, it joins a neighboring ASN as a leaf node by sending an ack_msg message, which is delivered to the associated cluster heads. Later, the cluster head assigns a unique time slot to new leaf node for transferring data packets in the network. On the other hand, if an isolated ASN did not receive any $rreq\_msg$ message from the neighboring ASNs then it uploads its sensed data by using the high transmission power to the neighboring ASNs without guaranteeing the data delivery in the harsh nature underwater environment.

4. Performance analysis

The underwater path loss and energy consumption models are given as below.

4.1. Underwater path loss model

The acoustic path loss model described in [34] is used in our simulation studies. The average path loss ($\mathcal{PL}$) can be numerically computed as

$$\mathcal{PL}(d, f) = \kappa \log(d) + \alpha(f)\, d \times 10^{-3} \tag{32}$$

in which d, f, α and κ are the distance, frequency, absorption coefficient and spreading factor. This spreading factor is due to energy spreading and bit error rate (BER) which can be calculated as

$$P_b^{16\text{QAM}} = \frac{3}{2\kappa}\, erfc\left(\sqrt{\frac{\kappa}{10}\frac{\mathcal{E}_b}{\mathcal{N}_0}}\right) \tag{33}$$

where

$$\mathcal{E}_b/\mathcal{N}_0 = \text{SNR}\frac{\mathcal{B}_n}{\mathcal{D}_r} \tag{34}$$

and

$$\text{SNR} = 10^{\text{SNR}(d,f)/10} \tag{35}$$

Table 2
Performance metrics.

Sr no.	Metrics	Definition
1	Packet delivery ratio	is the total number of data packets successfully received at the sink to the total number of data packets generated in the deployed UWSNs
2	Congestion	is the attempt of a sensor to handle more information than its maximum capacity.
3	Packet error rate	is the total number of corrupted data packets received at the sink to the total number of data packets generated in the deployed UWSNs.
4	Throughput	is the amount of data moved between a sensor and mobile sink or pair of sensors in a certain time period measured as bits per second (bps).
5	Delay	is the time difference between a data packet sent from an ASN to the time when it receives successfully to the sea surface sink.
6	Residual energy	is the amount of remaining energy after energy consumed during a successful transmission of data packets by the sensors in UWSNs. On the other hand, energy consumption is the amount of energy consumed during successfully transmitting and receiving a data packet in the network. The energy consumption is the sum of idle listening, data aggregation, packet transmission and reception in UWSNs.
7	Network lifetime (*NLT*)	is the time when a set of ASNs run out of energy and fail to deliver data packets to the sink.

in which QAM, κ, $\mathcal{E}_b/\mathcal{N}_0$, $\mathcal{D}_r$ and $\mathcal{B}_n$ are, the Quadrature Amplitude Modulation (QAM), κ is 4, the energy per bit to noise power spectral density ratio, data rate in bits per seconds (bps) and the noise bandwidth in Hz, respectively.

4.2. Energy consumption model

The energy consumption model described in [16] is used, which can be numerically indicated as

$$E_{T_x}(K,d) = E_{\mathrm{elec}} \times K + E_{\mathrm{amp}} \times K \times d^2 \quad < d_0 \tag{36}$$

$$E_{T_x}(K,d) = E_{\mathrm{elec}} \times K + E_{\mathrm{amp}} \times K \times d^4 \quad \geq d_0 \tag{37}$$

$$E_{R_x}(K) = E_{\mathrm{elec}} \times K \tag{38}$$

in which K, d, d_0, E_{elec}, E_{amp}, E_{R_x} and E_{T_x} are, the sum of bits, the distance between sea surface sink and an ASN, the threshold distance of the ASNs, the packets transmitting or receiving E_c of circuitry, the amplifier coefficient for static signal, the E_c during sending a packet, and the E_c during receiving a packet in UWSNs. In underwater environment, the performance of the MERP protocol is compared with recently proposed data collection protocol, namely E-CARP [16] using MATLAB R2017a. The performance evaluations of both MERP and E-CARP data collection protocols is computed in the underwater environment by using the metrics shown in Table 2.

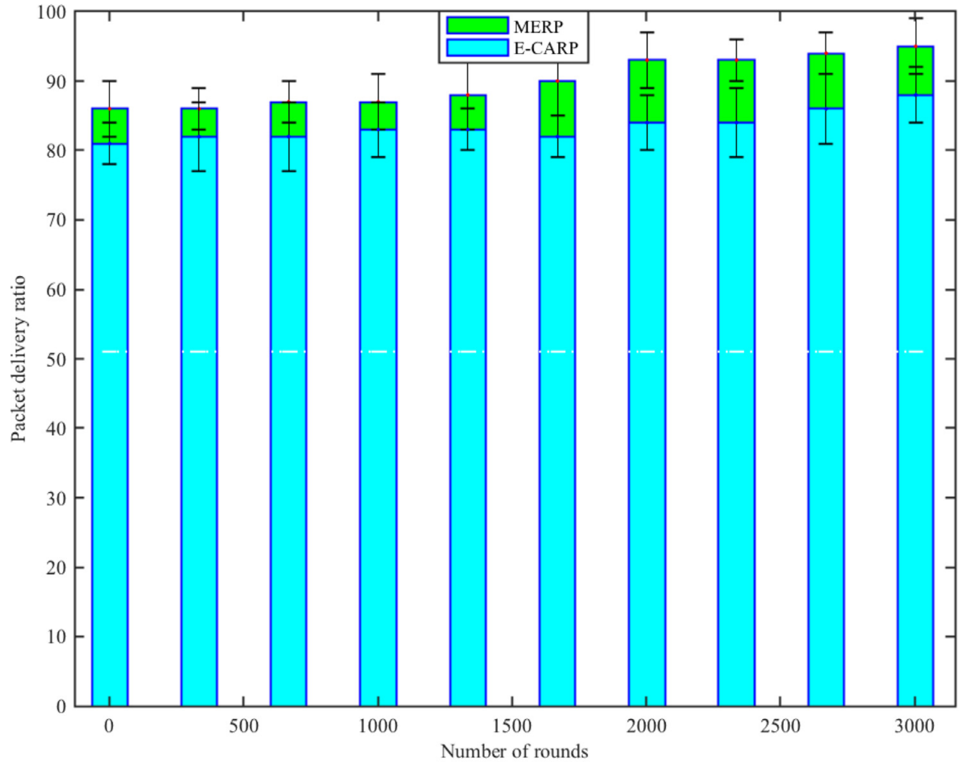
In our simulations, we consider a 3D underwater area (length × width × depth) with values (1000 × 1000 × 100) m containing 300 ASNs. The upmost velocity of sea surface sink and ASNs is set to 0.05 m/s, which is assumed negligible (see Section 4 for detail). In addition, the maximum and minimum numbers of clusters were defined between 23 and 42 in UWSNs. Lastly, 59 sets of simulations with 95% confidence intervals are performed for providing steady results in the underwater environment. Further parameters and values used in our simulation studies are given in Table 3.

Table 3
Simulation model parameters values and description.

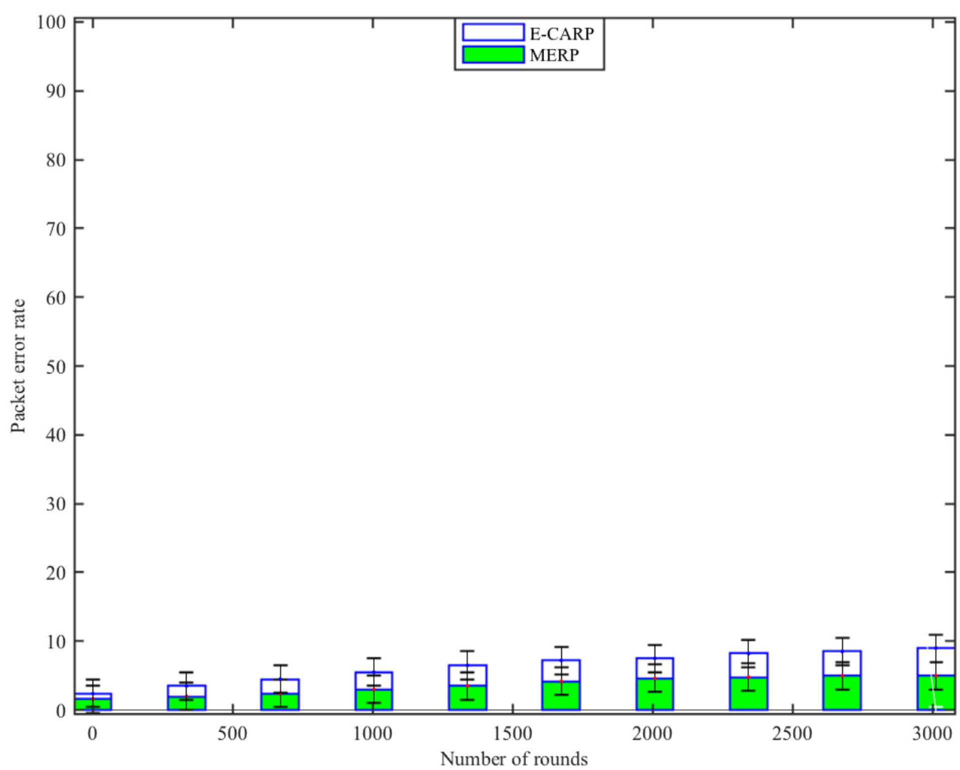
Simulation Model Parameters	Values
Initial energy of ASNs	15 J
Initial energy of sink	12 kJ
Maximum hop distance	85 m
High transmission power	0.99 W
Low transmission power	0.93 W
Packet receiving power	0.25 W
Ideal listening	0.13 W
Sleeping power	3×10^{-6} W
Data aggregation	0.035 W
Packet length	1500 bits
Topology	Random
ASN data rate	16 kbps
Frequency	40 KHz
Memory size	3 Mb
Maximum distance between ASNs and sink	0.81 km
Antenna	Omnidirectional
Set of simulations	59

The obtained experimental facts during simulations reveal that the $\mathcal{P}_{dr}$ in both schemes increases with the increase in the number of rounds in UWSNs. As clearly seen from Fig. 4(a), with the increase in a number of rounds between 1 and 3000 increases the $\mathcal{P}_{dr}$ ranging from 85% to 94.3% representing low and high packets delivery rate cases, respectively. The simulations results reveal that data delivery success rate upto 88.5% is realized by the sink when the round numbers are around 1000, which results in low delay and subnetwork coverage between 90.2% and 92.3% in MERP. The data success rate is sharply increased to 92% and then to 94.3% with subnetwork coverage ranging from 91.6% to 93% and from 94.6% to 98.2% in round numbers 2000 and 3000 in UWSNs. On the contrary, in E-CARP the data success rate is reported around 81%, 83.5% and 88% with subnetwork coverage between 83.2%, 85%, and 86%, respectively, in UWSNs. This low coverage between 81% and 86% in E-CARP means that an average of more than 8% of ASNs are not effectively covered by the neighboring ASNs in UWSNs. Fig. 4(b) makes it clear that with the increase in the number of ASNs between 1 and 300 increases the $\mathcal{P}_{er}$ ranges from 1% to 9% representing minimum and maximum error rate cases, respectively. In MERP, the $\mathcal{P}_{er}$ rapidly drops up to 2.7% when the when the ASNs around 50 in round number 550, are involved to gather information in UWSNs. However, the $\mathcal{P}_{er}$ increases up to 4.2% when the ASNs around 200 in round number 2000 are involved to gather information in UWSNs. This data loss rate (DLR) further increases maximum up to 5.1% when the ASNs around 300 in round numbers between 2800 and 3000 are involved to gather information in UWSNs. On the contrary, the $\mathcal{P}_{er}$ in E-CARP is observed close to 4.1%, 7.2% and 8.3%, when the ASNs around 50, 200 and 300 are involved in round number 550, 2000 and 2800, respectively, to gather information in UWSNs.

Fig. 4(c) indicates that the network congestion increases with the increase in the number of ASNs between 1 and 300 in UWSNs. In MERP, the $\mathcal{C}_{on}$ rapidly drops up to 95% when the when the ASNs around 100 in UWSNs. However, the $\mathcal{P}_{er}$ decreasing rate is observed up to 88% when the ASNs around 200 are involved to gather information in UWSNs. This decreasing rate is found up to 86.4% with ASNs around 300 used to gather information in UWSNs. While, the $\mathcal{C}_{on}$ decreasing rate is found nearly 91%, 84% and 81%, when the ASNs around 100, 200 and 300 in round number 1000, 2000 and 2800, respectively, are involved to gather data in UWSNs.

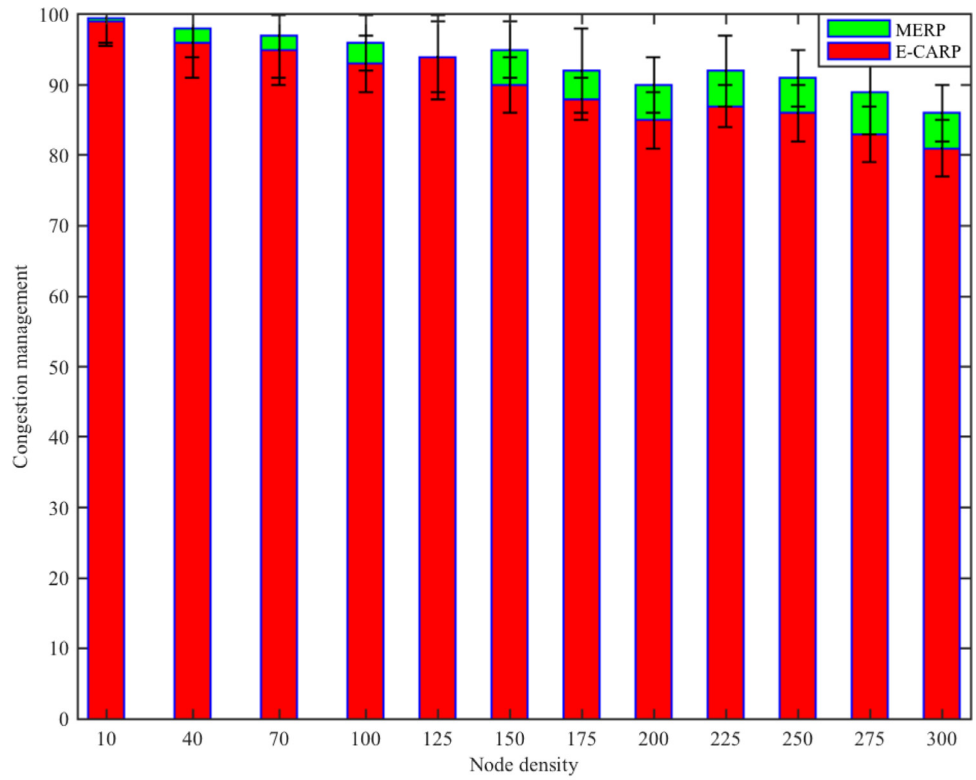


(a)

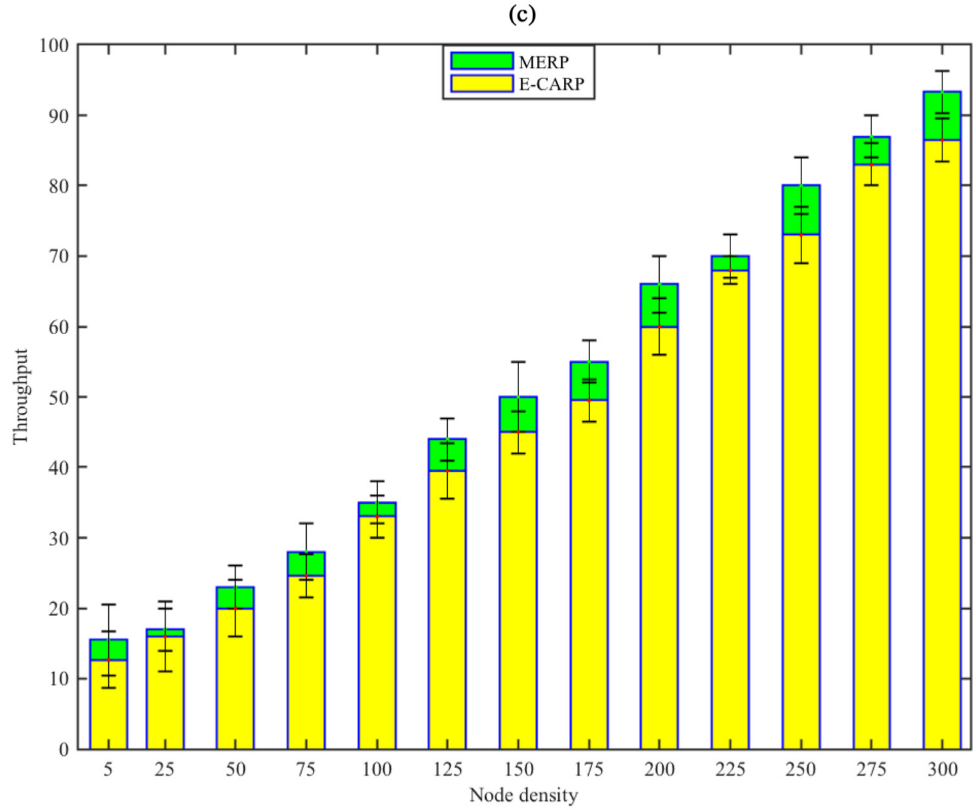


(b)

Fig. 4. (a) shows the packet delivery ratio vs number of rounds between 1 and 3000. (b) indicates the packet error rate vs number of rounds between 1 and 3000. (c) expresses the congestion management vs number of ASNs between 1 and 300. (d) illustrates the network throughput vs number of ASNs between 1 and 300. (e) indicates the network delay vs number of ASNs between 1 and 300. (f) depicts the ASNs residual energy vs number of rounds between 1 and 3000 in UWSNs.

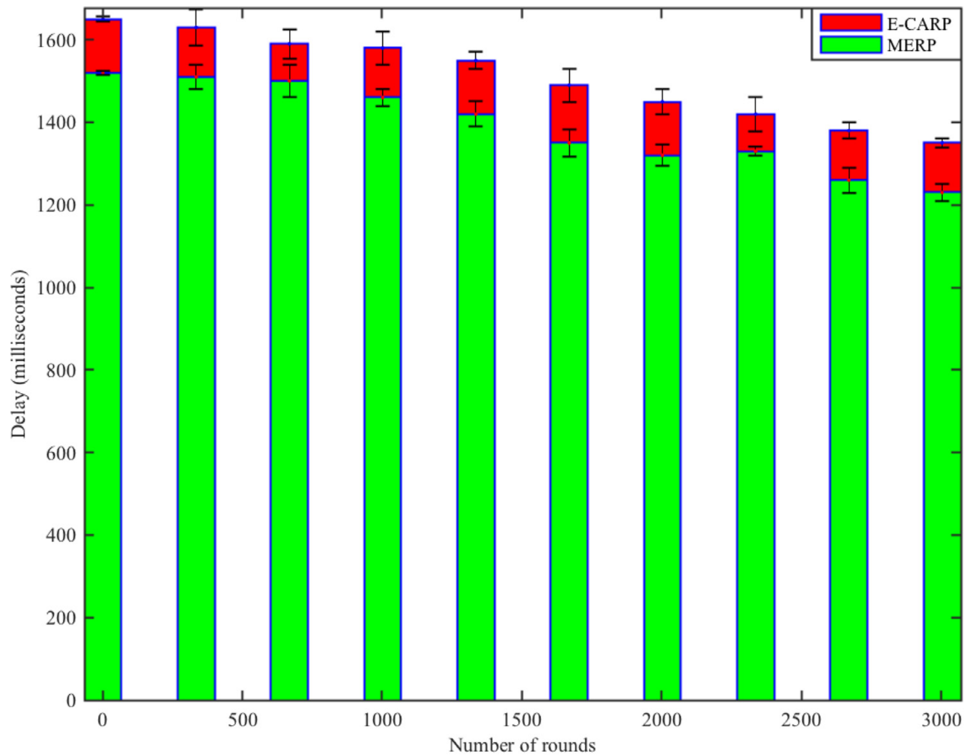


(c)

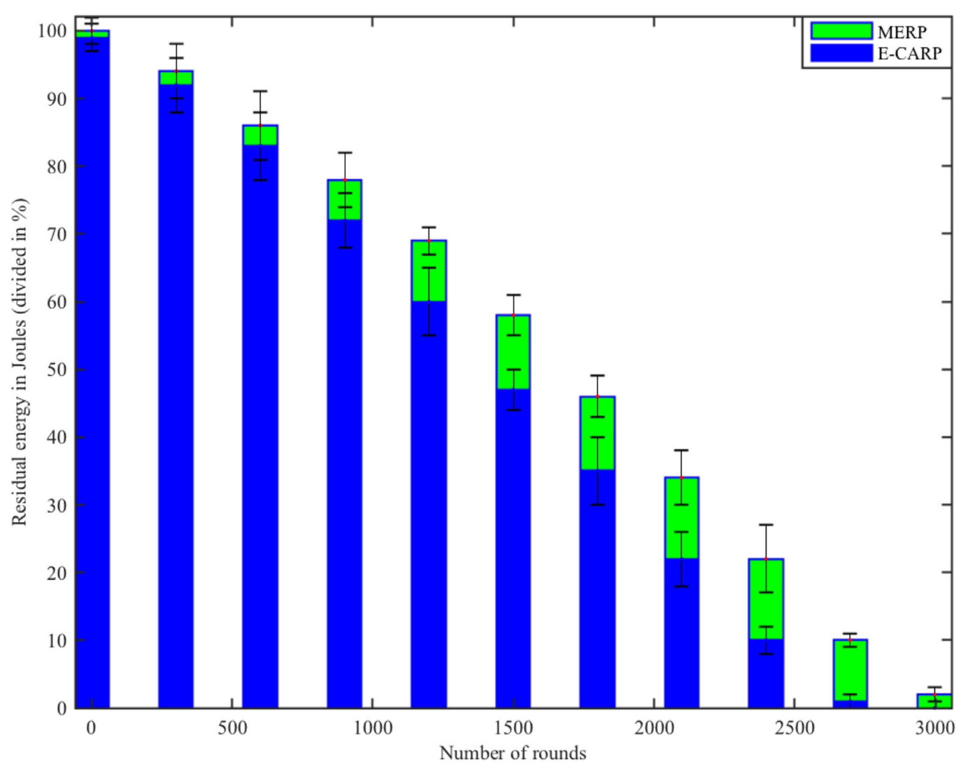


(d)

Fig. 4. Continued



(e)



(f)

Fig. 4. Continued

Herein, it is noticed that both $\mathcal{P}_{er}$ and $\mathcal{C}_{\sigma n}$ significantly decreases as the efficient memory utilization of an ASN increases during monitoring events in UWSNs. The overall cache overflow is found lower in MERP compared to E-CARP in UWSNs. In MERP, the cache emergence data from all ASNs is collected by the sink within a certain predefined time in UWSNs. In addition, the ASNs with respect to their overflow times in MERP are better distinguished in UWSNs. Moreover, the periodic scheduling of CHs in MERP offers a way to observe the predictability of ASNs that generate data at higher rates in various areas in UWSNs. This significantly helps to reduce hotspot problems of the CHs located in various regions in the network. This result in excessive information packets forwarding to the sea surface sink. All these measurements indicate that compared to E-CARP, the DLR in MERP reduces at higher rates during events monitoring in UWSNs. Thus, each ASN in MERP compared to E-CARP gathers additional time-critical information of the underwater events in UWSNs. This result in high throughput in MERP compared to E-CARP as revealed in Fig. 4(d).

As can be seen in Fig. 4(d), the $\mathcal{T}_p$ values in MERP and E-CARP protocols varies between ASNs 1 and 300 in UWSNs. Nevertheless, the $\mathcal{T}_p$ in MERP is found high around 92% when compared to E-CARP, which is around 87% in UWSNs. In E-CARP, the key issue is that ASNs closer to sea surface sink are facing energy hole/hotspot issues because of relaying a massive information coming from nearby ASNs in UWSNs. Hence, the collected information in some senarios entirely cannot be conveyed to the sea surface sink. This minimizes the $\mathcal{T}_p$ performance in E-CARP in UWSNs. In addition, each ASN in E-CARP routing protocol during the information collection process from neighbroing ASNs requires a significant amount of time due to poor network coverage issues in UWSNs. Fig. 4(e) demonstrates the latency between MERP and E-CARP data collection mechanisms in UWSNs. It clearly indicates that the $\mathcal{D}_e$ values in MERP and E-CARP routing protocols reduces when the rounds number increases between 1 and 3000. Initially, the values of $\mathcal{D}_e$ is found around 1550 ms in MERP during monitoring events in UWSNs. However, it decreases rapidly up to 1270 ms around round numbers 2000 in UWSNs. The values of $\mathcal{D}_e$ is found nearly 1210 ms in rounds number 2800 and 3000 during monitoring events in UWSNs. On the contrary, for the identical number of rounds the values of $\mathcal{D}_e$ in E-CARP are noticed around 1630 ms, 1440 ms, and 1372 ms, respectively. In E-CARP, the frequent route failures and bottlenecks due to relaying massive information with limited memory results in high data gathering latency. In addition, the E-CARP compared to MERP routing protocol fails to identify alternative routing paths instantly and thus resulting in delaying information at the sea surface sink. This increases the invalid data packets in E-CARP compared to MERP because of not reaching at the sea surface sink in a certain time.

In E-CARP an ASN entirely discovers a routing path before the actual data packets transmission in UWSNs. During the route discovery process, the E-CARP discovers more than one routing paths to a given destination by using small query packets relies on a scoped flooding mechanism in UWSNs. At each hop, E-CARP employs the 3-way handshaking mechanism to provide routing paths and thus is facing high signaling overhead in the network. This control message overhead increases with the increasing number of hops along a routing path in UWSNs. In addition, in E-CARP the quality of the selected paths is impossible to know in advance prior to call setup and requires fewer nodes to participate in forwarding a packet to the sink. Hence, as the hop-distance increases leading to poor link quality in E-CARP. This poor link quality leads to excessive rerouting due to a data route break down during monitoring underwater events in the large-scale UWSNs. In E-CARP, most of the time, the ASN are facing disconnectivity issues and frequent disconnects and reconnects releases a link state update message each time for each such change, which floods the network and causes excessive overhead. Depending on the update period, these update messages consume a considerable amount of bandwidth as the acoustic network size grows large in UWSNs. On the other hand, the excessive messages exchange for a route repairing brings cache ineffective issues when traffic load is high in the network. This excessive route failures and maintenance lead to excessive control message overheads, which increases the routing table maintaining cost and overall residual energy consumption performance, especially when the number of ASNs are huge in a highly dynamic underwater environment. These overheads consume a notable sum of ASNs energy and hence, shorten the lifetime of the whole acoustic sensor network.

On the contrary, the high stable links among ASNs and CHs during relaying information from the source node to the sink avoids the above problem in MERP. In MERP, a set of highly reliable clustering architecture is created to gather data from the ASNs in UWSNs. The precise knowledge of the routing path in a hop-by-hop manner over best links among neighbors progressively becomes more accurate as the packet gets closer to sink. More precisely, the data paths constructed by MERP over a set of CHs relay nodes help to send packets on the path that is highly stable and requires less energy consumption in UWSNs. Moreover, in case of a route failure, the routing table helps to find a robust forwarding CH relay node for conveying information to the sink, which greatly reducing the control message overheads in UWSNs. In fact, based on the local information of the neighboring nodes stored in the routing table is used in the handshake procedure between upstream and downstream ASNs to recover a node or path failure in the network. Generally, MERP employs a multicast mechanism to discover better next hop relay CH along a routing path and thus it prevents the packet from being flooded into the whole network compared to the E-CARP. Thus, MERP avoids the extra work of finding the neighboring relay nodes by retaining a routing entry for each destination node. In addition, by using different exchange periods for different entries reduces the routing update overhead in MERP. More accurately, within the smaller scope, the CHs entries corresponding to neighboring CHs are propagated at a higher frequency while the rest of the entries are sent out with the lower frequency in UWSNs. As a result, a considerable fraction of control message overheads of maintaining the routing table and states at each ASN is further minimized especially in the large-scale UWSNs. Hence, the MERP without compromising route computation accuracy keeps overhead low in large-scale UWSNs. These low communication and routing table overheads help to reduce the burden of energy consumption in MERP. Consequently, the E-CARP achieves high energy efficiency and uniform energy distribution, and thus, prolongs the lifetime of the acoustic sensor network compared to the E-CARP scheme.

The $\mathcal{R}_e$ profile of MERP and E-CARP is shown in Fig. 4(f). As seen clearly, the overall energy consumption of both schemes increases as the number of ASNs increase in UWSNs. However, the energy depletion profile is found lower in MERP than E-CARP routing protocol in UWSNs. In MERP, the $\mathcal{D}_e$ and E_c of information collection is highly affected by the shortest routing paths in UWSNs. Over a defined route, this reduces the data gathering period of ASNs and thus leads to low $\mathcal{D}_e$ and E_c for information collection in UWSNs. This low E_c influences on the network lifespan in the MERP routing scheme. In fact, both bio-inspired dynamic clustering and routing mechanism play important roles for reliable data delivery with low energy consumption in UWSNs. In MER, the designed clustering mechanism generates unequal size clusters in which each member is selected based on its high SNR value in the underwater environment. Generally, the clusters generated near to sink are small in size and have a lower distance to the sink in order to prevent them from prematurely dying due to a heavy energy consumption burden. Consequently, a set of forwarder candidates closer to the sink in the clusters is appointed by following the location information and higher residual energy for gathering and relaying packets in the network. Generally, these CH nodes have a notable holding time and forward the packets as soon as it receives from the neighboring CHs. Moreover, self-learning based CHs data gathering pattern from ASNs also helps to minimize information collection $\mathcal{D}_e$ in UWSNs. Thus, the CHs gather time-sensitive data from ASNs by using their previous history information at the required time. Usually, the CHs one-hop or two-hops away to the sea surface sink directly uploads their cached data via short distance communication. The CHs away to the sea surface sink send their stored information over a specific data path containing a set of CHs in UWSNs.

During forwarding packets, the average latency trend is reduced with the increase in the number of CHs in the highly dense network. This is because of the more potential forwarder, which provides an opportunity to find a path with higher link quality results in reducing the average latency. Consequently, the observed information is conveyed in the upward and downward direction by restricting excessive horizontal transmission over a restricted routing path in UWSNs. This hop-by-hop information conveying along a predefined shortest routing path with maximum seven CHs relays toward the sea surface sink decreases the packets delivery $\mathcal{D}_e$ in MERP. This mechanism extensively avoids data path loops in UWSNs. Moreover, it also reduces the impact of interference and corrupted data packets due to selecting appropriate packets forwarder from the source toward the sink. Hence, the entire cache emergence information is routed toward the sea surface sink from ASNs over eminently stable communication links in a greedy manner in UWSNs. This effectively balances the E_c and data traffic load and increases the successful information delivery probability in UWSNs. Moreover, if a link failure occurs then CHs quickly detect and reconfigure the demaged data path in UWSNs. Therefore, once the link is interrupted the MERP still has another reliable path to forward packets successfully in the network. Moreover, during the route recovery process, it notably minimizes the E_c of ASNs by minimizing network $\mathcal{C}_{m\sigma}$ and therefore help to increase the network timespan of MERP in UWSNs. Hence, MERP shows higher $\mathcal{P}_{dr}$, and low DE and EC than E-CARP routing scheme in UWSNs. On the contrary, this is not the case in E-CARP. The ASNs in E-CARP are facing long $\mathcal{D}_e$ due to the limited coverage of the network that limits distinct regions as outside-of-service, where several ASNs exist in UWSNs. Thus, none of the ASN in E-CARP gather neighboring ASNs data in those areas in UWSNs.

Generally, in E-CARP, the routing path among ASNs are created without considering the appropriate distance information to the sink. Therefore, the ASNs near to the sink die prematurely due to excessive energy burden during relaying entire network data. The packets forwarding over many ASNs by considering their excessive low transmission distance between the source and the sea surface sink is another main reason. This might assist to balance E_c of the network, however, it depletes a prominent sum of $\mathcal{R}_e$ at each ANS in the UWSNs. In addition, due to these factors the probability of corrupted data packets, uneven E_c and $\mathcal{D}_e$ due to data path loops increases in E-CARP compared to the MERP routing protocol. Most interestingly, some distant ASNs employ direct data transmission toward the sink. Therefore, they consume more than one energy level in sending one data packet and deplete their energy earlier in UWSNs. Thus, no more packets can be received at the sink, consequently, low throughput is observed in UWSNs. Moreover, this long-distance transmission faces high attenuation and creates interference, which probably increases the chances of packets error in the UWSNs. In some cases, the E-CARP routing mechanism repeatedly selects the same forwarding ASN each time as a next hop forwarder in UWSNs. As a result, for data forwarding over the same relay ASNs leading to the ultimate death of ASNs causing energy instability in UWSNs. The packets also may drop to void nodes, resulting in a low delivery ratio in UWSNs. This also results in a communication void problem in UWSNs. Hence, the packet failure increases as soon as the void areas appear in the routing paths, which lowers the $\mathcal{P}_{dr}$. On the other hand, in some scenarios, it utilizes the high transmission power to forward the packets with the expensive of higher E_c in UWSNs. Therefore, it faces the problem of highly imbalanced energy consumption during backward data transmissions where few forwarding ASNs deplete very high energy while maximum ASNs have high $\mathcal{R}_e$ in the routing paths. Consequently, the information delivery rate slightly decreases in E-CARP compared to the MERP routing protocol in UWSNs. Lastly, discovering a new data path also needs excessive communication overheads that depletes $\mathcal{R}_e$ of forwarding ASNs and therefore the network lifespan reduces quickly in E-CARP compared to MERP routing protocol in UWSNs. In sum, the MERP routing protocol due to its bio-inspired multi-object clustering and routing mechanism achieves the best performance during monitoring events than E-CARP, and therefore is extremely suitable for UWSNs-based applications.

5. Conclusion

The underwater wireless sensor network with the advancement in the Internet of underwater smart things has emerged as a promising networking technique to facilitate the discovery of vast unexplored ocean environments. However, the unique characteristics of an underwater environment pose a number of constraints on reliable data transmission in UWSNs. Thus, the performance of ASNs for QoS-aware data gathering is hampered in UWSNs-based underwater applications. Therefore, designing a quality-aware data gathering protocol to monitor and explore oceans is challenging for UWSNs. Hence, this paper proposed a novel bio-inspired multi-objective evolutionary routing protocol for UWSNs-based events-driven applications. In the proposed scheme, the clustering mechanism provides highly stable unequal size dynamic clusters for balancing data traffic load in the network. On the other hand, the proposed routing mechanism preserves high stable link quality among a set of cluster heads for robust data delivery data in UWSNs. The proposed scheme avoids data path loops and unnecessary multi-hop packet transmission by restricting data movement in the upward and downward direction in the network. Moreover, it significantly reduces the energy consumption, corrupted data packets and prolongs the lifetime of the network. The extensive simulation results show that the proposed scheme attains its defined goals compared to existing UWSNs-based routing schemes during monitoring and exploring aquatic environments. Future work of this study includes investigating the impact of node mobility for efficient packet delivery in UWSNs.

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Declaration of Competing Interest

We declare that the authors have no significant competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

We have described our potential competing financial, professional, and/or personal interests in the acknowledgments.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adhoc.2019.101912.

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