Indonesian Journal of Electrical Engineering and Computer Science
Vol. 38, No. 1, April 2025, pp. 254~261
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v38.i1.pp254-261

Development of clustering with Bayesian algorithm for optimal route formation in software-defined radio underwater WSN

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Article Info

Article history:

Received Jun 19, 2024
Revised Oct 8, 2024
Accepted Oct 30, 2024

Keywords:

Bayesian algorithm
Bayesian algorithm
Clustering
Slap swarm optimization algorithm
Software-defined networking
Underwater wireless sensor network

ABSTRACT

Underwater wireless sensor networks (UWSNs) have recently offered chances to investigate oceans and thus enhance the underwater world. WSNs are imperative for discovering the ocean region. Software-defined networking (SDN) improves flexibility and uses the clustering method to improve lifespan. This article introduces the Development of a clustering process with a Bayesian algorithm (CPBA) for optimal route formation in software-defined radio UWSN. The clustering concept improves energy efficiency; however, cluster head (CH) selection is challenging. The present clustering mechanisms could be more successful in suitably assigning the node's energy. This mechanism utilizes a slap swarm optimization algorithm to pick out the optimal CH by node energy and distance among inter-cluster as well as intra-cluster. In addition, the Bayesian algorithm selects the best forwarder from sender to base station. Thus, enhances efficiency. The simulation results demonstrate that the UWSN improves both the 23% packet forward ratio and 0.014 joule energy. Furthermore, it minimizes the 30% network delay.

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1. INTRODUCTION

Underwater wireless sensor networks (UWSNs) plays a significant role in helping humans investigate data under the ocean. UWSNs have been formulated as helpful methods for a variety of applications that take place underwater, such as admitting enology observation, surrounding observation, tsunami monitoring [1], and underwater observation [2]. UWSNs contain several sensor nodes distributed in the underwater surroundings to collect data and forward it to the base station (BS) via the controller. However, UWSNs face many disputes, such as rough underwater surroundings, restricted transmission range, and lower data rates [3]. A metaheuristic optimization technique is developed in response to the collective behavior of salps, a sea creature. The choice of cluster heads (CHs) in UWSNs is essential for effective data routing and collecting [4]. The slap swarm optimization might be modified as follows for CH selection in UWSNs:

- Identify the objective function: as certain which objective function requires optimization. In the context of CH selection, this might include increasing network longevity, reducing energy usage, or improving data transmission efficiency [5]. Each possible CH selection solution should be represented using the encoding solution representation. This might be a binary vector, with each entry denoting whether or not a sensor node has been chosen to be a CH. Establish a swarm of salp agents at random locations in the solution space as the initialization step.

- Assess fitness: using the objective function as a guide, assess each salp's fitness within the swarm. The performance of the relevant CH selection is shown by this fitness value [6]. Update location: using its current location, velocity, and the positions of other salps, each salp in the swarm should have its position updated. The best solution developed so far has a weighted effect that directs this update. Iterate: continue until a stopping requirement (such as convergence or a maximum number of iterations) is satisfied by continuing the process of updating locations, assessing fitness, and looking for better solutions. Choose CHs: Based on the locations of salps with the highest fitness values, choose CHs when the algorithm reaches the maximum number of iterations [7].

Optimal route options and evading the route difference are necessary for transmission to achieve the receiver suitably and accumulate energy. An optimal routing method is demanded to transmit data from sensors in the clusters and to the base station via the controller. The major focus is decreasing energy utilization and increasing lifetime. Choosing the best forwarder is essential to effective data transfer in UWSNs, where communication is difficult because of the underwater environment. Probabilistic reasoning may be used to inform judgments via Bayesian decision models. Here, it refers to choosing the optimal forwarder node from a range of choices in a UWSN clustering situation. Identify the factors that affect the best forwarder choice [8]. These include the distance to the sink node, the amount of energy left, the data transfer's dependability, and the connection's quality. Model the distributions of these parameters using Bayesian inference based on existing data or past knowledge. For example, the utility function may prioritize energy efficiency and dependable data transmission. Select the forwarding node that optimizes the anticipated utility [9]. The node with the greatest predicted utility value would be this one. SDN is an assuring method that changes flexible direction by dissociating the data plane from the control plane.

A fuzzy logic-based SDN mechanism (FPO-MST) using a fuzzy path optimization and a fuzzy cut-set optimization algorithm to improve the routing efficiency. Furthermore, using a spanning tree algorithm minimizes the complexity and raises the accessibility of underwater nodes. To solve these issues, the development of a clustering process with a Bayesian algorithm for optimal route formation in SDN underwater WSN is proposed. The CPBA mechanism is summarized as follows.

Clustering primarily groups the sensor nodes together. Following the cluster growth, the CH is chosen by the slap swarm optimization algorithm. The node distance between inter and intra cluster, energy, and delay are also considered. The response of this article is structured as follows: section 2 describes the proposed mechanism. Section 3 shows the simulation outcomes. Section 4 presents the conclusion as well as the future scope.

An SDN is proposed to make networks more quick and flexible. SDWSN is realized by infusing an SDN model in a WSN [10]. Software-defined energy harvesting WSN to minimize the sensor nodes overhead. A reinforcement learning algorithm to maximize the long-term signal-to-noise ratio (SNR) performance and prove the algorithm's convergence [11]. SDN differentiates the data plane from the control plane to make a network structure. Initially, launch the SDN and then inquire about the underwater node and the surface controller. Next, the clustering is built, and the data is forwarded [12]. The selection of CH was established using the spider monkey optimization (SMO) algorithm to solve the issues of cluster routing. It enhances the system's energy utilization, lifetime, stability, and quality [13].

Several clustering algorithms picked out the nearest sensor nodes to the best position, which were determined as CHs during selection. As a result, the clustering process may initiate optimal CH positions that differ from the definite node locations. In addition, the network load raises the nearest nodes after determining the CHs, increasing energy consumption and shortening the network's lifetime. SMO and an energy-efficient CH selection mechanism are picked out to improve stability and lifetime [14].

The particle swarm optimization (PSO) mechanism employs the positions of the optimal CHs, and the nodes nearest to these positions are determined as CHs [15]. The PSO algorithm raises energy efficiency and lifespan. However, choosing the CH is lacking regarding distance, which minimizes energy efficiency. A PSO-based energy efficient CH selection that covers the lifetime by varying the way each node selects a CH, which allows control of the number of nodes going to every cluster [16]. Thus, energy consumption can be controlled during data response from every CH. Choosing a CH necessitates great computational energy and raises energy utilization [17]. PSO algorithm in clustering with routing into different segments along with the vertical distances. Separating these layers assists in describing the energy utilization in several layers to evaluate the energy-utilizing balance and initialize the particle hierarchically; thus, it increases the speed of the particle convergence and handling the long lifespan. An optimal CH selection mechanism is established based on multiple constraints such as delay, distance, security, and risk. For CH selection, the chimp integrated osprey optimization process minimizes the network delay [18]. A salp swarm optimization algorithm (SSOA) selects the CH animatedly for the clustering technique. The quality of the service is measured regarding lifespan, energy utilization, and throughput [19]. The adaptive node clustering mechanism utilizes a dragonfly optimization algorithm (DFO) to determine the perfect cluster. It improves the network performance [20].

Clustering-based routing mechanism [21] utilizing UWSNs established parameters like residual energy, locality and distance between CH and BS. However, a re-clustering method to handle traffic load and energy raises the delay. A vector-based forwarding algorithm is utilized to enhance the routing. This position-based approach is especially calculated to enhance the delay and rate of data transmission. However, the disadvantage of this mechanism is that delay is very high [22]. The route deviation is pollard via the Bayesian algorithm that utilizes the subsequent distribution incrementally while verification occurs [23]. The Bayesian algorithm computes the probability of conditional utilizing the earlier information to decide the route difference and optimal route [24]. A probabilistic method was established on Bayesian inference to facilitate proficient routing [25]. The fractional border collie optimization (FBCO) method builds the routing procedure more proficient; it is important to create the cluster by applying the Bayesian fuzzy clustering method. It computes the fitness function by Delay, link lifetime, distance, as well as energy. The FBCO mechanism improves energy utilization and lifespan [26]. Internet of things (IoT)-driven image recognition system use convolutional neural networks to notice and quantify microplastics in water samples [27]. This mechanism is more scalable and receptive owing to IoT data capture and remote observing of water infrastructure [28].

2. PROPOSED METHOD

Suppose we install a UWSN in a prepared underwater area, and all sensor nodes are inexpensive, small, and light arbitrarily distributed via ship or unmanned aircraft. Afterward, a node dips into the water; it scales the anchor chain to a certain length according to the depth guess. Sensors bind the buoy to build a 2D sensing space. The sink node that transmits with the seaside BS and underwater nodes are pre-set via sail wheel, unmanned underwater vehicle (UUV). In SD-UWSN, the sink nodes are set as controllers as well as underwater nodes virtual switches. Thus, a software-defined UWSN is built. Figure 1 explains the structure of clustering UWSN.

The UWSN contains three main elements: underwater sensor nodes, sink nodes that play controller, and the BS. The sensor node is climbed on the buoy, and the anchor series links to the buoy. To construct the data plane, underwater sensor nodes are planned as OpenFlow switches are executed by applying SDN. The controller is located on the water outside, and the OpenDayLight is established to make the control plane. The controller handles all transferring routes, recognizes centralized management, and merges resource scheduling. The controller transmits a radio signal, while the sinks underneath the water are sensor nodes that can identify the sound. Based on such features, a radio signal is applied to associate the data-collecting hub and sink nodes; also, an audio signal is applied to link the sensor nodes. Controllers are weapons with airbags, buoys, GPS, and RF. The linked applications run on the BS in an application plane.

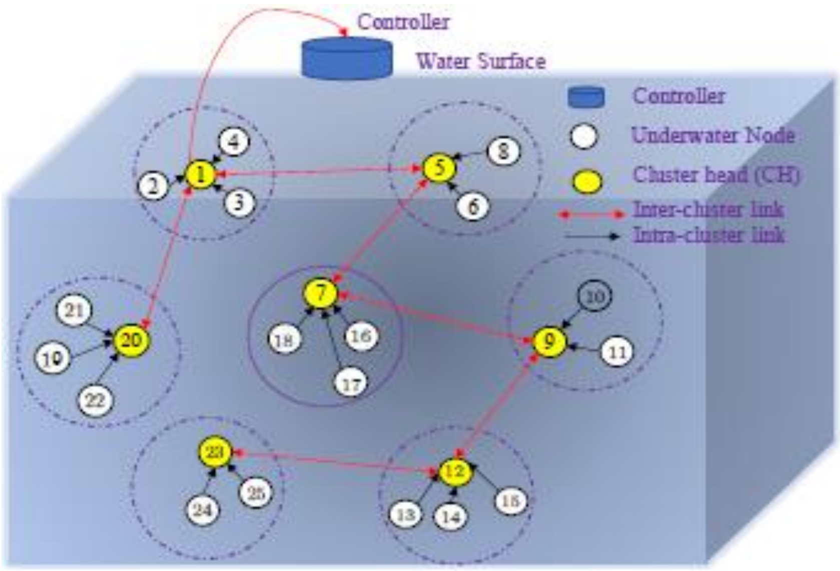

Figure 1. Structure of clustering UWSN

Single-hop transmission is applied for control transmission, and multi-hop transmission is utilized for data transmission. The RF signal is employed to communicate among controllers and BSs. The controller activates all sensor nodes in the region during control transmission. At a specified time, the sensor nodes are linked to the controller through one-hop control transmission and next information on their status details, for example, the position and status of the resource. When the underwater node forwards a route request, the controller performs the routing algorithm, allowing the routing conclusions to the representing node.

2.1. Clustering operation

Single-hop transmission is applied based on the control message during the clustering process. This message consists of node ID, node location, time to live, remaining energy, and resource residence. The willing sensor nodes send a request message to the controller. Then, the controller decides the CH based on the slap swarm optimization algorithm. Salps have poured into the area of deep waters called the Salp series, helping to improve foraging mobility. The statistical formula for the WSSA is assigned.

$$SL_m^n = \begin{cases} FS_m + a_1[(UB_m - LB_m)a_2 + LB_m]a_3 \geq 0 \\ FS_m + a_1[(UB_m - LB_m)a_2 + LB_m]a_3 < 0_m \end{cases} \tag{1}$$

Where SL_m^n represents the preliminary salps position in the m dimension, FS_m indicates the Food Origin position, UB_m, LB_m indicates the upper as well as lower bound a_1, a_2 and a_3 denotes the random interval established on the interval among 0 and 1. The important property is a coefficient a_1 applied to the equilibrium of the exploration and utilization of food as in the equation. Where a_1 indicates a significant coefficient, PC refers to the current hop, e denotes the exponential function, and TC represents the overall hop count:

$$a_1 = 2e^{-\left(\frac{4PC}{TC}\right)} \tag{2}$$

After CH selection, the selected CH distributes a join-request message to communication range sensor nodes. Within the communication range, nodes forward the join-reply messages to CH. Then, CH groups the near-sensor nodes. In this method, each and every CH registry with the controller is sensible. After certain rounds, CHs will inform the controller of the registration details. Thus, the controller constantly maintains the updation. Sometimes, several CHs may not work suitably; therefore, the registration threshold for CH rests on the controller. If the registration expires, the controller decides which representing CH fails. Currently, the controller distributes a CH Failure message that admits the ID of the mistake CH. Then, immediately, the controller chooses a better CH from the surrounding region. Later, the controller disseminates a Cluster-Rebuild message that admits the ID of the unique CH and the innovative CH.

2.2. Optimal path selection and UWSN communication

The CHs maintain their radios turned on to obtain data from CMs, and they execute a filtering process to minimize duplicate and unnecessary data. Once a CH obtains data from its CMs, it executes data aggregation and forwards it to the controller. As the BS is characteristically positioned a long distance away, applying these approaches will ensure a manageable amount of energy transmission since forwarding to the BS on the ground would result in high energy utilization and heavy data loss. This method forwards the data via the controller to the BS to preserve energy and transmission costs. The Naive Bayes technique is established on the Bayesian theorem. Accepting training data R, the later possibility of a theory S, P(S|R), traces the Bayesian theorem. It applies the knowledge of prior events to forecast future events.

$$P(S|R) = P(R|S).P(S)/P(R) \tag{3}$$

The naive Bayesian algorithm chooses the next hop as a CH from within the communication range node, and these transfer the data to the controller. Finally, the controller effectively transfers data to the BS. Throughout this route, the data from the sensor nodes may be securely and rapidly forwarded to the BS. The optimal path selection for data transmission in an efficient routing consequence in lesser energy utilization and improves the cluster's lifetime.

3. RESULTS AND DISCUSSION

We utilized the Network Simulator-3 to execute the simulation of the clustering method [29]. The experiment is carried out in a consistent arrangement, where the preliminary energy of all nodes is the same. The introduced scenario imitates underwater sensor nodes functioning in a three-dimensional space. The nodes were distributed arbitrarily in a 450×550×500 m^3 with an identical allocation, and the transmission rate is 10 Kbps [30]. The transmission range of every sensor node is pre-set to 50 meters, and the topography of the network changes habitually [31]. To prove the execution of the CPBA, four simulation metrics are evaluated with FPO-MST. These performance metrics are the ratio of packet forward to BS, lifetime, remaining energy, and Delay [32]. The result demonstrates that the lifetime of the Cluster round is enhanced since employing the cat swarm optimization algorithm. The communication range also involves cluster stability as if extra members are in the cluster. This, in turn, minimizes the probability of the cluster being ignored. Figure 2 explains the cluster round based on the network size.

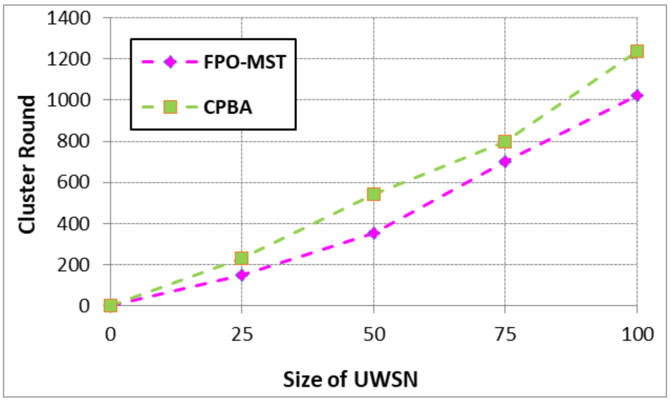

Figure 2. Cluster Round versus size of UWSN

From Figure 2, when raising the UWSN sensor node count, the CPBA mechanism has the highest cluster round since the Bayesian algorithm chooses the best forwarder. Furthermore, SDN can improve routing efficiency. However, the conventional FPO-MST mechanism has a 215 smaller cluster round because it increases network complexity. The capacity of energy that remains in the node is related to the remaining energy. The initial energy of every underwater sensor node is 0.5 joule. After data forwarding, receiving, and sensing the data, the sensor node energy is minimized [33]. Figure 3 demonstrates the Remaining Energy versus the size of UWSN.

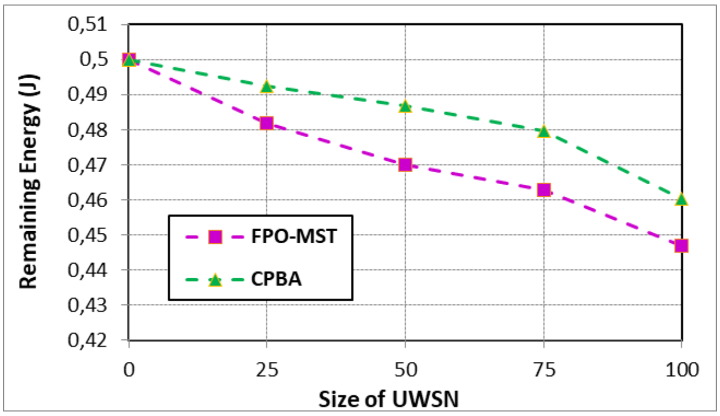

Figure 3. Remaining energy versus the size of UWSN

Figure 3 illustrates that the proposed CPBA and FPO-MST mechanisms minimize the remaining energy when the size of UWSN is increased. The CPBA utilizes less energy than an FPO-MST since it reaches the data fusion and the least energy conveyed to spread data from the CHs to the BS via the controller with the best route. In addition, the Bayesian algorithm selects the best forwarder from sender to base station. Thus, the CPBA mechanism enhances 0.014 Joule energy efficiency. Figure 4 explains a Packet Forward Ratio versus the size of UWSN.

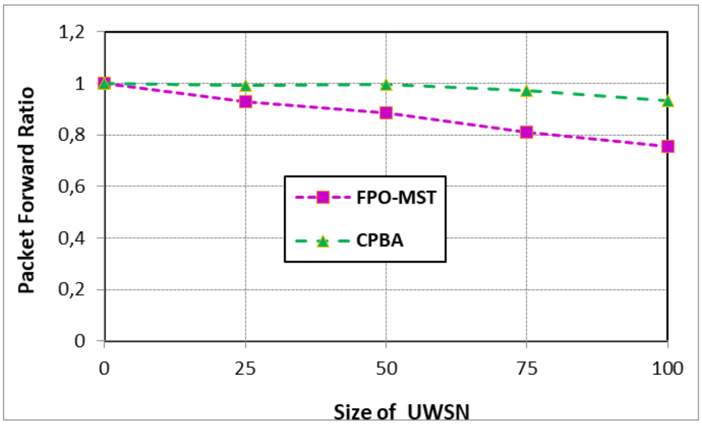

Figure 4. Packet Forward Ratio versus the size of UWSN

Figure 4 shows the ratio of packets forwarded to the BS, demonstrating that CPBA can forward more packets compared with FPO-MST since it executes a lengthier period. It can simplify the extremely useful linearity execution, which assures the development of data packet forwarding. This mechanism utilizes a slap swarm optimization algorithm to pick out the optimal CH by node energy and distance among inter-cluster as well as intra-cluster. Hence, the CPBA mechanism enhanced the 23% packet forward ratio. Figure 5 demonstrates the delay versus the size of UWSN.

The UWSN size increased from 25 to 100, and the data transmission delay was also raised since the data was transmitted via multiple hops [34]. A slap swarm optimization algorithm will be used to pick out the optimal CH to reduce the unwanted data aggregation time. Furthermore, the Bayesian algorithm selects the best forwarder from the sender to the base station. As a result, the CPBA mechanism has a 30% lesser delay compared to FPO-MST.

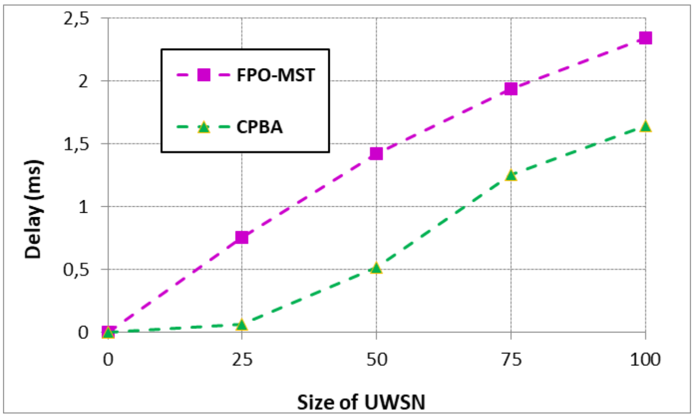

Figure 5. Delay versus the size of UWSN

4. CONCLUSION

In UWSN, CH selection is vital to ensure energy efficiency. In several research studies, the near nodes were chosen as CHs after discovering the perfect CH location. Thus, it easily dead the CH and raises the CH burden. In this work, we introduced the development of the clustering process with a Bayesian algorithm for optimal route formation in SDN UWSN. Greatly high difficulty consequence in fast energy reduction in underwater nodes. However, this mechanism minimized the unwanted energy utilization since it used the slap swarm optimization to choose the best CH and minimize the CH overhead. The simulation outcomes demonstrated that the CPBA algorithm provides an additional 215 cluster round lifetimes, and it reaches a 23% greater packet forward ratio than an FPO-MST protocol. The CPBA outperforms FPO-MST in terms of longer lifetime, lesser energy dissipation, better CH selection, and network efficiency. Furthermore, it minimizes the 30% delay and increases the 0.014 joule energy. The proposed mechanism is used to investigate oceanology, environment supervision, and military functions. However, resource allocation is not provided efficiently. In the future, we will allocate the network process and integrate cross-layer optimization technology.

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