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ECRKQ: Machine Learning-Based Energy-Efficient Clustering and Cooperative Routing for Mobile Underwater Acoustic Sensor Networks

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ABSTRACT The dynamic topology, narrow transmission bandwidth, and limited energy of sensor nodes in mobile underwater acoustic sensor networks (UASNs) pose challenges to design an efficient and robust network for underwater communications. In this paper, we propose a novel machine learning-based clustering and routing scheme, named energy-efficient clustering and cooperative routing based on improved K-means and Q-learning (ECRKQ), to reduce and balance energy consumption among sensor nodes in a mobile UASN and improve the bandwidth utilization. In the cluster head (CH) selection stage, ECRKQ modifies the K-means algorithm to dynamically select a CH based on the residual energy of the node and the distance from the node to the centroid in a cluster. In the clustering stage, ECRKQ adopts the Q-learning algorithm by incorporating the residual energy of the CH, the energy consumption of data transmission from the node to the CH, and the energy consumption of the data transmission from the CH to the base station into the Q-value function. In the data transmission stage, ECRKQ applies the dynamic coded cooperation (DCC) transmission to improve the bandwidth utilization and the robustness of the underwater communications. In the DCC transmission, cooperative nodes are also dynamically selected based on the residual energy and the energy consumption of transmitting a packet to their destinations. In the simulation, we apply the ocean current drifting model to emulate the position variation of nodes caused by ocean currents in a mobile UASN. The simulation results show that the proposed ECRKQ scheme can achieve more balanced energy consumption among sensor nodes in a mobile UASN than that of the existing scheme.

INDEX TERMS K-means, Q-learning, cooperative communications, clustering and routing, underwater acoustic communications.

I. INTRODUCTION

Applying underwater acoustic sensor networks (UASNs) is a key technique in realizing Internet of underwater things (IoUT), which can efficiently explore and utilize marine resources [1], [2]. UASNs can provide various functions, such as acoustic ranging, underwater positioning, and navigation, and a UASN has been widely used in marine data collection and underwater resource exploration activities, thus attracting much attention [3]. Many countries have established regional and international cabled seabed observation networks based on different scientific observation goals, such as the Neptune

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seabed observation network in Canada (NEPTUNE), the Mars observation network (MARS), and the Seaweb network in the United States [4], [5].

Due to the harsh marine environment, it is challenging to design a reliable UASN, where the energy consumption of sensor nodes in the UASN are balanced. In the dynamic topology of UASNs, some destination nodes will be further away from their source nodes due to the movement of ocean currents, leading to the source nodes consume more transmission energy. As a result, the energy consumption of the nodes in a UASN are unbalanced. In addition, due to narrow transmission bandwidth and high propagation delay of underwater communications, the wireless channels in UASNs always lead to very low utilization. All these characteristics require a high robustness underwater transmission protocol, which can improve channel utilization, balance the energy consumption of the nodes in a UASN, and extend the life time of the UASN.

Clustering can effectively improve the energy efficiency of UASNs by dividing sensor nodes into multiple clusters [6]. S. Souiki *et al.* in [7] proposed a clustering algorithm based on the fuzzy C-means mechanism, where each sensor node joins the cluster whose center to the sensor node is the shortest. After all the nodes join a cluster, the method then selects the node with higher residual energy as the cluster head (CH) for each cluster. All non-CH nodes send the data to their CH, and then the CH performs data aggregation and sends data to the base station (BS) in the single-hop or multi-hop modes. However, for each non-CH node, selecting a cluster based on the distance to a cluster center is not the optimal choice. K. Li *et al.* in [8] proposed the machine learning-based energy-efficient clustering (QLEC) algorithm for terrestrial wireless communications, which uses the distributed energy-efficient clustering algorithm in the CH selection stage and the Q-learning algorithm in the clustering stage. Non-CH nodes dynamically select a CH according to the reward function, which jointly considers the residual energy of the CH and the energy consumed by the non-CH nodes in sending data to the CH. This dynamic clustering method provides a new idea for underwater clustering to handle underwater nodes floating along with ocean currents. Cluster routing plays an important role in energy saving for sensor nodes. In most underwater routing techniques, data packets are transmitted from bottom to top in a multi-hop transmission mode, where CHs are responsible for the data aggregation and relay. Therefore, the energy of nodes and CHs close to the BS are easily exhausted, thus resulting in energy holes in UASNs [9].

Motivated by [8], we propose the **E**nergy-efficient **C**lustering and cooperative **R**outing protocol based on improved **K**-means and **Q**-learning (ECRKQ) to address the energy holes, nodes drift, and narrow bandwidth problem in a UASN. Basically, ECKRQ utilizes dynamic coded cooperation (DCC) [10] and machine learning techniques.

The main contributions of this paper are as bellow:

1) In the CH selection stage, the modified K-means algorithm is applied to dynamically select CHs, which takes the distance between nodes and centroid as well as the residual energy of nodes into consideration.

2) In the clustering stage, we modify the reward function for Q-learning in [8]. The new reward function incorporates the energy consumption of the CH in transmitting data to the BS, the residual energy of the CH, and the energy consumption of non-CHs in transmitting data to the CH. The new reward function will significantly improve the energy efficiency of the entire network.

3) As compared to the traditional single-hop or multi-hop transmissions, we introduce DCC in non-CHs to their CHs transmissions and CHs to the BS transmissions, thus saving energy and improving bandwidth utilization. The energy consumption of DCC based transmission is calculated by the energy consumption model of underwater acoustic cooperative transmission, and the cooperative nodes are dynamically selected by Q-learning to balance the energy consumption among the nodes.

4) Since underwater sensor nodes will change their locations along with the ocean currents in an ocean environment, we apply the ocean current drifting model [11] to simulate the position changes of the nodes, which can accurately reflect the performances of the proposed ECRKQ scheme and the comparison scheme in a real marine environment.

The rest of this paper is organized as follows. In Section II, we briefly introduce the related work of the clustering algorithm in UASNs. The system model is introduced in Section III. Section IV presents the proposed ECRKQ protocol, including the cluster head selection, clustering, and data transmission phases. The simulation results are shown and analyzed in Section V. Finally, Section VI concludes the paper.

II. RELATED WORK

In order to overcome the unreliability and large path loss of underwater acoustic channels, cooperative transmission as an ideal solution has been applied to underwater acoustic communications. For the relay-based cooperative communications, multiple relay strategies can be applied, e.g., amplify-and-forward (AF), decode-and-forward (DF), compression-and-forward (CF) and coded cooperation (CC) and dynamic coded cooperation (DCC) [10], [12]. H. Nasir *et al.* in [13] proposed cooperative depth based routing (CoDBR) for UASNs. In CoDBR, source node broadcasts its data to two relay nodes and a destination node. The relay nodes forward data to the destination node using AF technique. Three received copies are combined at the destination using diversity combining technique. The CoDBR consumes a significant energy due to the mechanism of one source and two relay nodes in forwarding packets. Also, the tradeoff between link availability and energy conservation has been discussed in CoDBR. In [14], an efficient cooperative opportunity routing (EECOR) protocol have been proposed to forward packets to the surface sink. The forwarding relay set is determined by the source node according to the relay nodes' local information, and then the fuzzy logic based relay selection scheme is adopted to select the optimal relay node according to the relay node's energy consumption ratio and the probability of transmitting packets.

Clustering technique is an appealing choice to construct a UASN and achieve an efficient routing. N. Javaid *et al.* in [15] proposed a region-based cooperative routing protocol (RBCRP) for AF technique in UASNs, where the clustering technique can convert the global communications into the local communications for saving energy. G. Liu *et al.* in [16] proposed a hierarchical multi-path routing-LEACH (HMR-LEACH) algorithm to optimize the CH selection by considering multi-hop transmissions. When selecting a transmission path, the HMR-LEACH algorithm takes the energy and distance of each hop into account. R. Hou *et al.* in [6] proposed an energy-balanced unequal layering clustering (EULC) algorithm to improve the energy efficiency of acoustic sensors. In the CH selection, the residual energy of the node, the distance to the sink node, and the node degree are considered. Meanwhile, the next hop for a node is also optimized according to the residual energy and distance of the neighboring nodes. Z. Zou *et al.* in [17] proposed a clustering-based adaptive routing algorithm (CBAR) to meet the needs of large-scale UASNs by optimizing the network structure. Inspired by the focused beam routing and hop-by-hop dynamic addressing routing protocols, the CBAR algorithm is designed to achieve better performance in large unmanned aerial systems, which can significantly reduce the energy consumption of the network and improve the life cycle of nodes. The purpose of energy utilization is not only to extend the network life, but also to mitigate the appearance of energy holes. In addition, J. Zhang *et al.* in [18] proposed an interference-aware data transmission protocol based on cellular clustering structure, which uses intra-cell hierarchical routing to achieve reliable data transmission for UASNs. K. G. Omeke *et al.* in [19] proposed a K-means clustering scheme based on distance and energy constraints (DEKCS) to select CHs for UASNs.

On the other hand, in the field of terrestrial wireless communication network, many clustering [20] and routing protocols [21, 22], which try to resolve the energy hole issue, have also been proposed in application scenarios. D. Zhang *et al.* in [22] proposed a new greedy forwarding improvement routing method for a mobile ad hoc network, where a forwarding path is determined by the quality of the link, the distance between the candidate node and the destination node, and the number of neighbor nodes. A. Khalid *et al.* in [23] proposed a life cycle maximization protocol based on the analytical hierarchal process and genetic clustering to solve the challenge of embedding energy-constrained devices in IoT. F. Fanian *et al.* in [24] used the shuffled frog leaping algorithm (SFLA) to propose a fuzzy multi-hop clustering protocol (FMSFLA). The FMSFLA considers parameters including energy, distance from the BS, the number of neighboring nodes, node distance from the BS, mean route load, delay, overlap, and the problem of hot spots, to achieve the best application-based performance.

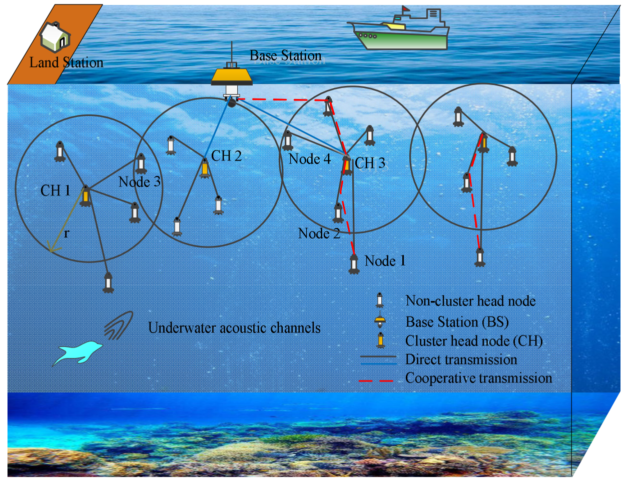

FIGURE 1. The model of cooperative UASNs for the proposed ECRKQ scheme.

In real ocean environments, dynamic routing of UASNs becomes a key technique due to the change of underwater topology causing by current movement. The Q-learning based clustering and routing algorithm has the potential to adaptively and dynamically optimize the network in response to environmental changes. The literatures [25]–[29] propose to apply Q-learning in designing routing protocols in the context of UASNs. V. D. Valerio *et al.* in [29] proposed a data forwarding scheme, i.e., channel-aware reinforcement learning-based multi-path adaptive (CARMA) routing, where a node, guided by CARMA, can adaptively switch between single-path and multi-path routing, thus optimizing route energy consumption and packet delivery ratio.

III. SYSTEM MODEL

In this section, we will describe the cooperative UASN model. The clustering structure is shown in Fig. 1, where underwater acoustic sensors with yellow colored indicate CH nodes, and the ones with white colored are non-CH nodes. A black and blue solid line represents the direct transmission from a non-CH node to a CH node and from a CH node to the BS, respectively, and a red dashed line represents the dynamic coded cooperation (DCC) transmission, which we will explain in Section III. A. We assume that the transmission radius of a sensor node is r, and so when the distance between a source and its destination node exceeds r, the DCC transmission will be adopted. For example, Node 1 uses the DCC transmission to send data to CH3 with the assistant of Node 2, while Node 2 uses direct transmission to send data to CH3; CH3 uses the DCC transmission to send data to the BS, while CH2 uses direct transmission sending data to the BS. Table 1 summarizes key symbols used throughout the paper.

TABLE 1. List of key symbols.

Symbol	Desription
CH	Cluster head
K	Number of cluster heads
ρ	Number of information bits
N_{li}	The length of listening phase
$N\text{-}N_{li}$	The length of cooperation phase
$\gamma(f)$	Absorption coefficient
$U(d)$	Attenuation of the power to the distance d
P	Transmission power
P_0	Receiving power
d	Distance between two nodes
f	Carrier frequency
ψ	Stream function
r	Radius of the tranmission range for a sensor node
M	Size of a network
N_{P}	Number of packet to be transmitted
N_{iter}	Iteration number of K-means to find the centroids
P_i^{CH}	Index of node i becoming the CH
$\varepsilon_i^{\mathrm{res}}$	Residual energy of the node i
$R_{i,k}$	Reward function of node i sends data to the CH of cluster k
$R_{i,BS}$	Reward function of node i sends data to the BS
$\varepsilon_k^{\mathrm{res}}$	Residual energy of the CH of cluster k
$\varepsilon_c^{\mathrm{res}}$	Residual energy of the cooperative node c
$\varepsilon_{i,k}^{\mathrm{con}}$	Energy consumption of transmitting a packet from node i to CH of cluster k
$\varepsilon_{c,k}^{\mathrm{con}}$	Energy consumption of transmitting a packet from cooperative node c to CH of cluster k
$\varepsilon_{k,BS}^{\mathrm{con}}$	Energy consumption of transmitting a packet from CH of cluster k to BS
$\varepsilon_{i,BS}^{\mathrm{con}}$	Energy consumption of transmitting a packet from node i to BS

A. THE COOPERATIVE TRANSMISSION MECHANISM IN THE UASNs

Cooperative transmission is to use a cooperative/relay node to assist the communications from a source node to a destination node. In general, there are three types of cooperative transmission, i.e., DF/AF cooperation, coded cooperation, and dynamic coded cooperation. As shown in Fig. 2, in DF/AF cooperation, a cooperative node decodes/receives the information bits and codewords from node i (i.e., the source node) in the listening phase, and then re-modulates/amplifies and retransmits them to node $i+1$ (i.e., the destination node) in the collaboration phase. Different from DF/AF cooperation, the cooperative node in the coded cooperation (CC) only relays the codewords in the collaboration phase, thus reducing the length of the collaboration phase. DCC is based on the rate compatible codes mechanism [12]; hence, the cooperative node will receive and decode the information bits and portion of the redundancy bits in the listening phase [10], [12], derive the rest of the redundancy bits based on the received bits, and

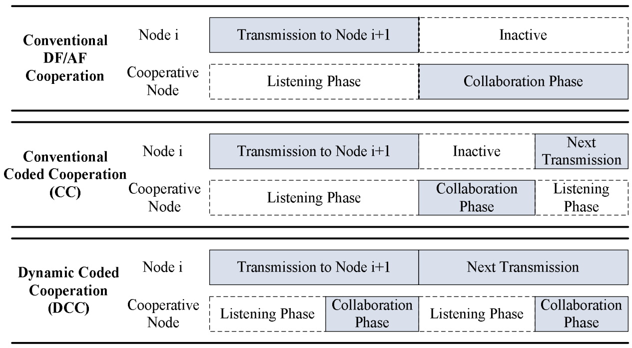

FIGURE 2. Bandwidth efficiency for different cooperative schemes [30].

relay the derived redundancy bits in the collaboration phase. Thus, node $i+1$ will receive the superimposed redundancy bits, one from node i and the other from the cooperative node. In DCC, the length of the listening plus collaboration phases for the cooperative node equals to the length of transmission time for node i. Hence, there is no extra transmission time scheduled, thus leading to much higher bandwidth efficiency than AF, DF, and CC [10], [30].

The listening phase of the cooperative node in DCC is adjustable. That is, if the channel condition from node i to the cooperative node is sufficiently good, the cooperative node can accurately decode all the information bits, and then derive all the redundancy bits based on the decoded information bits, and so the listening phase of the cooperative node is the same as the period of node i in transmitting information bits, denoted as ρ. If the channel condition from node i to the cooperative node is bad, the cooperative node has to decode not only information bits but also portion of the redundancy bits in order to derive the rest of the redundancy bits. Denote Δ and l as the total number of redundancy bits and number of redundancy bits that need to be decoded in the listening phase for the cooperative node, respectively. Thus, the size of the listening phase of the cooperative node in DCC, denoted as N_{li}, can be calculated as [12]

$$N_{li} = \rho + \frac{N-\rho}{\Delta} l, \tag{1}$$

where N is the size of the period for node i in transmitting data to node $i+1$. More detailed information of the DCC transmission model can be found in our previous work [10].

B. UNDERWATER ACOUSTIC ENERGY CONSUMPTION MODEL

The model to estimate the minimum transmission power in underwater acoustic communication is adopted based on the model in [19], [20]. Denote P_0 as the minimum received power to successful receive a packet. Let $U(d)$ be the attenuation of transmitting underwater acoustic signals between two nodes with the distance of d. Then, the minimum transmission power is [30]

$$P = P_0 \cdot U(d), \tag{2}$$

where

$$U(d) = (1000 \times d)^m \cdot [\gamma(f)]^d. \quad (3)$$

Here, m is the environmental coefficient (where we take $m = 1.5$ for shallow water acoustic channels) and $\gamma(f)$ is the absorption coefficient under carrier frequency f. We often use the Thorp's formula to formulate $\gamma(f)$, i.e.,

$$10\log_{10}\gamma(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75 \times 10^{-4}f^2 + 0.003. \quad (4)$$

The optimal choice of f is based on the empirical formula below [30]:

$$f_{opt} = \left(\frac{200}{d}\right)^{\frac{2}{3}}. \quad (5)$$

If cooperative nodes participate in the DCC transmissions, the total energy consumption of a transmission is the sum of the energy consumption of node i, node $i+1$, and the corresponding cooperative node. The formula for calculating the total energy consumption for transmitting a packet, denoted as E, is

$$E = P_0 \frac{U\left(d_{i,i+1}\right) + \lambda \times U\left(d_{c,i+1}\right)}{1+\lambda} \times T, \quad (6)$$

where $U(d_{i,i+1})$ and $U(d_{c,i+1})$ are the underwater sound attenuation between node i and node $i+1$ and between the cooperative node and node $i+1$, respectively, T is the transmission time of node i, and λ is a binary indicator to imply if DCC is needed, i.e.,

$$\lambda = \begin{cases} 0, & d_{i,i+1} < r_{\max}, \text{ for non DCC-cooperation}, \\ 1, & d_{i,i+1} > r_{\max}, \text{ for DCC cooperation}, \end{cases} \quad (7)$$

where $r_{\max}$ is the maximum distance between two nodes to determine if a cooperation node is needed for achieving the DCC transmission.

C. DRIFTING MODEL FOR UNDERWATER SENSOR NODES

The drifting model in [11] is to characterize the underwater sensor nodes' movement due to meandering sub-surface currents and vortices. This model considers sensors moving by the effect of meandering sub-surface currents and vortices. The domain model is representative of a large coastal environment, which is typically the marine environment where a UASN is deployed. Specifically, assume that rectangular coordinates are established on the sea surface, and the position of the underwater sensor node is denoted as $\Theta = (x, y)$. Then, the non-dimensional form of the meandering jet model is described by a stream function ψ [11]:

$$\psi(x, y, t) = -\tanh\left[\frac{y - B(t)\sin\left(\kappa(x - c_{phase}t)\right)}{\sqrt{1+\kappa^2 B^2(t)\cos^2\left(\kappa(x - c_{phase}t)\right)}}\right], \quad (8)$$

where $\tanh(\cdot)$ is the hyperbolic tangent function, t is the time in a day, κ is the number of meanders in the unit length, c_{phase} is the phase speed with which they shift downstream, and B(t) means the amplitude function of the meander. B(t) can be calculated by

$$B(t) = B_0 + \varphi \cdot \cos(\omega t), \quad (9)$$

where B_0 is the average width of the meander in km, φ is the amplitude in km, ω is the frequency.

IV. THE PROPOSED ECRKQ PROTOCAL FOR UASNS

In this section, we propose the ECRKQ protocol for cooperative UASNs. The algorithm comprises three stages, i.e., the CH selection, clustering, and data transmission stages. In general, in the CH selection, the CH for each cluster is selected based on the distance between a node and the centroid of the cluster (which is calculated according to K-means) and the residual energy of the node; in the clustering stage, Q-learning is utilized to group different nodes into different clusters. In the data transmission stage, a new DCC based routing method is proposed to select suitable cooperative nodes to enhance the reliability of the transmissions, while balancing the energy consumption among different nodes. ECRKQ is summarized in Algorithm 1.

A. CLUSTER HEAD SELECTION STAGE

The CH plays a key role in a UASN, and ECRKQ will dynamically clusters different nodes and select a CH for each cluster. Meanwhile, the number of clusters in a UASN is always tricky. That is, too many clusters created could waste of resources, and creating too few clusters may result in more isolated nodes and increase the burden of the BS. In order to compare the performance of the CH selection and routing methods for the two algorithms (i.e., QLEC and ECRKQ), the K-means method is also used in ECRKQ to calculate the centroid of a cluster. However, we slightly modify the CH selection based on the K-means method such that a CH is selected based on not only the distance between a node and the centroid of the cluster but also the residual energy of the node. Specifically, the number of clusters in a UASN, denoted as K, can be calculated by [8]:

$$K = \frac{3M^3}{4\pi \cdot r^3}, \quad (10)$$

where r is the radius of a node transmission range, M^3 indicates the size of a UASN, which is assumed to be a cube, and M is the length of an edge for the cube.

Once the value of K has been determined, all the N_u underwater nodes are first roughly divided into K clusters according to their positions. For each cluster a initialized centroid is randomly selected within a cluster. Accordingly, the Euclidean distance between the centroid of cluster k (where $k = 1,2,\ldots, K$) and node i (where $i = 1, 2, \ldots, N_u$), denoted as $D_{i,k}$, can be calculated by

$$D_{i,k} = \left\|\Theta_i - \Theta_k^{\text{centroid}}\right\|, \quad (11)$$

where $\Theta_k^{\text{centriod}}$ and Θ_i are the coordinate of the centroid for cluster k and node i, respectively. For each node i, it is

Algorithm 1 The Proposed ECRKQ Protocol Algorithm

```
**Stage 1**: **Distance calculation stage**
Initialized d(i, j), N_u, Θ.
Generate N_u nodes, and positions Θ are
   randomly generated
  The sink node broadcasts information.
**for** i, j = 1,2,3,..., N_u **do**
   Calculate the distance matrix d(i, j);
d(i, j) = sqrt([Θ(i, 1) − Θ(j, 1)]^2 + [Θ(i, 2) − Θ(j, 2)]^2);
**end for**
Calculate the number of CHs K based on the
network size according to Eq. (10).
**for** j_1 = 1, 2, 3, ..., N_P **do**
**Stage 2**: **CH selection stage**
    Initialize centroids.
    **for** j_2 = 1, 2, 3, ..., N_iter **do**
      Calculate the centroids using the K-means
      algorithm based on Eqs. (11), (12), (13) and (14);
      **end for**
      Find the CH based on the residual energy of the
      node and the distance from the node to
      the centroids based on Eq. (15).
      **for** k = 1,2,3,..., K **do**
   **Stage 3: Clustering stage**
      Initialize the Q table for each cluster.
      Calculate the energy consumption of each node
      in transmitting a packet to the CH according to
      Eq. (6).
      Calculate the energy consumption of each CH to
      transmit a packet to the BS according to Eq. (6).
      Calculate the Q value of node clustering
      according to Eqs. (16), (17) and (18).
      Form clusters according to the maximum
      Q value.
   **Stage 4: Data transmission stage**
      Data transmission in each cluster:
      Calculate the energy consumption of cooperative
      transmission from non-CHs to the CH, and select
      cooperative node according to Eq. (6).
      **end for**
      Data transmission from CH to the BS:
      Calculate the energy consumption of cooperative
      transmission from the CH to the BS according to
      Eq. (6), and select cooperative node according to
      Eqs. (19) and (20).
      Keep track of the residual energy of each node.
      Apply the ocean current drifting model to
      update node positions according to Eq. (8).
  **end for**
```

associated with the cluster, whose centroid has the shortest Euclidean distance to node i, i.e.,

$$\delta_i = \arg\min_{k} \left\{ D_{i,k} \,|k = 1, 2, \cdots, K \right\}, \tag{12}$$

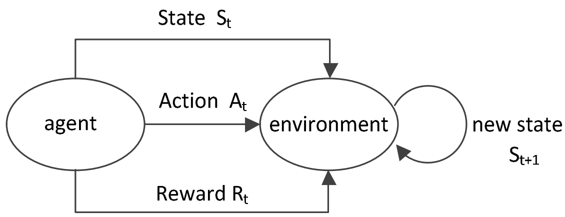

FIGURE 3. The agent-environment interaction in Q-learning.

where δ_i denotes node i belongs to which cluster. After each node has been associated with a cluster, the centroid of each cluster k needs to be updated based on

$$\Theta_k^{\text{centroid}} := \frac{1}{\left|\mathbf{C}^k\right|} \sum_{i \in \mathbf{C}^k} \Theta_i, \tag{13}$$

where $\mathbf{C}^k$ is the set of nodes that is currently in cluster k, i.e., $\mathbf{C}^k = \{i|\delta_i = k\}$, and $|\mathbf{C}^k|$ denotes the number of nodes in cluster k. In each iteration, each node is associated with a cluster based on Eq. (12), where the centroids are derived in the previous iteration. After all the nodes have updated their association to the clusters, each cluster would recalculate its centroid based on Eq. (13). The iteration continues until the value of

$$\sum_{k=1}^{K} \sum_{i \in \mathbf{C}^k} \left\| \Theta_i - \Theta_k^{\text{centroid}} \right\| \tag{14}$$

cannot be further increased or the maximum number of iterations N_{iter} is reached. The derived K centroids, i.e., $\mathbf{\Theta} = \{\Theta_1^{\text{centroid}}, \Theta_2^{\text{centroid}}, \ldots, \Theta_{\text{k}}^{\text{centroid}}\}$, will be used to select CHs. Basically, a CH is selected according to the distance from the candidate CH nodes to the centroid of its cluster and the residual energy of the candidate CH nodes, i.e.,

$$P_i^{\text{CH}} = \sigma_1 \cdot d_i^{\text{centroid}} - \sigma_2 \cdot \varepsilon_i^{\text{res}}, \tag{15}$$

where P_i^{CH} is the index of node i being selected as the CH, d_i^{centroid} is the distance between node i and the centroid (i.e., $d_i^{\text{centroid}} = D_{i,k}$, where $k = \delta_i$), $\varepsilon_i^{\text{res}}$ is the residual energy of node i, and σ_1 and σ_2 are the weights associated to the two items. Normally, a node with the minimum value of P_i^{CH} among all the nodes in a cluster will be selected as a CH.

B. CLUSTERING STAGE

After the centroids and CHs are calculated, the nodes in the network have to be reassociated to a specific CH/cluster by balancing the energy consumption among nodes, which is referred to as the clustering problem. We adopt the Q-learning algorithm to solve the clustering problem.

As shown in Fig. 3, the agent chooses an action in the current state. After interacting with the environment, the environment will give a reward feedback, and so the agent will transfer from one state to a new state.

Denote $Q(S_t, A_t)$ as the Q-value function, which represents the value of taking action A_t in state S_t under the policy:

$$Q\left(S_t, A_t\right) = R_t + \gamma \cdot \sum_{S_{t+1} \in \Phi} P_{S_t S_{t+1}}^{A_t} \max Q\left(S_{t+1}, A_t\right), \tag{16}$$

where R_t is the reward function, $\gamma \in (0, 1)$ is the discount factor, $P_{S_t S_{t+1}}^{A_t}$ is the probability of state S_{t+1} from state S_t, and Φ is the set of all the states.

Specifically, let Q table be a matrix with K rows and N_u columns. Action A_t represents the operation of associating node i ($i = 1, 2, \ldots, N_u$) to the CH of cluster k ($k = 1, 2, \ldots, K$) at time t, and S_t represents the environmental state at time t, including the residual energy of node i, the total energy consumption of node i in transmitting a packet to the CH of cluster k, and the CH of cluster k in transmitting a packet to the BS at time t. Under the policy based on Eq. (16), the agent repeatedly explores the actions of each node associating with the K CHs and finally selects the optimal clustering solution, which incurs the maximum Q-value.

Note that the reward function is critical to the design of Q-learning algorithm applied to a specific problem. In the proposed ECRKQ algorithm, when any non-CH node i sends data to the CH of cluster k, the reward function is defined as

$$R_{i,k} = -g + \alpha_1 \cdot \left(\varepsilon_i^{\text{res}} + \varepsilon_k^{\text{res}} + \lambda \cdot \varepsilon_c^{\text{res}}\right) - \alpha_2 \cdot \varepsilon_{i,k}^{\text{con}} - \alpha_3 \cdot \lambda \cdot \varepsilon_{c,k}^{\text{con}} - \alpha_4 \cdot \varepsilon_{k,BS}^{\text{con}}, \quad (17)$$

where $-g$ is a constant value to indicate punishment for a node in sending a packet since any transmission consumes the energy of the transmitter, the receiver, and the cooperative node, ${\varepsilon_i}^{\text{res}}$ and ${\varepsilon_k}^{\text{res}}$ are the residual energy of node i and the CH of cluster k, respectively, ${\varepsilon_{i,k}}^{\text{con}}$, ${\varepsilon_{c,k}}^{\text{con}}$, and ${\varepsilon_{k,BS}}^{\text{con}}$ are the energy consumption of node i in transmitting a packet to the CH of cluster k, the cooperative node c in transmitting a packet to the CH of cluster k, and the CH of cluster k in transmitting a packet to the BS, respectively, and α_1, α_2, α_3, and α_4 are the weights associated to the four items, respectively. Also, in order to prevent a node directly transmitting a packet to the BS, we assume the related reward function is negative infinity, i.e.,

$$R_{i,BS} = -\infty. \quad (18)$$

C. DATA TRANSMISSION STAGE

During the data transmission, we use DCC to reduce energy consumption of the nodes and enhance the reliability of the transmission. However, cooperative node selection is very critical. Always choosing the node with the lowest energy consumption for transmitting data to the CH as the cooperative node would lead to the cooperative node drain out quickly. Thus, we introduce to dynamically select cooperative nodes to balance the energy consumption among nodes. Specifically, we select the node with the maximum E_i among the candidates, where

$$E_i = \eta_1 \cdot \varepsilon_i^{\text{res}} - \eta_2 \cdot \varepsilon_{k,BS}^{\text{con}} - \eta_3 \cdot \varepsilon_{i,BS}^{\text{con}}. \quad (19)$$

Here, $\varepsilon_i^{\text{res}}$ is the residual energy for node i, $\varepsilon_{k,SB}^{\text{con}}$ and $\varepsilon_{i,BS}^{\text{con}}$ is the energy consumption of transmitting a packet from the CH of cluster k to the BS and from node i to the BS, respectively, and η_1, η_2, and η_3 are the weights for the three items. As mentioned before, the node with the maximum E_i

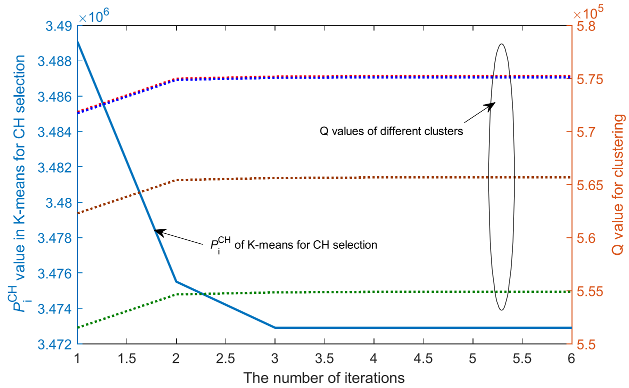

FIGURE 4. The convergence analysis of the K-means based CH selection and Q-learning based clustering algorithms in ECRKQ.

is selected as the cooperative node, i.e.,

$$c = \arg\max_i \{E_i\}, \quad (20)$$

where c is the index of the node that is selected as the cooperative node.

D. COST ANALYSIS OF THE PROPOSED ECRKQ

The number of iterations in the CH selection and clustering stages mainly determines the complexity of the ECRKQ. So, we measure the number of iterations for the K-means based CH selection and Q-learning based clustering algorithms in ECRKQ to analyze the complexity. As shown in Fig. 4, the blue solid line represents the convergence of P_i^{CH} as described in Eq. (15), and the four dashed lines represent the Q values (calculated by Eq. (16)) of different clusters under different iterations. We can see that the Q-learning based clustering algorithm can quickly converge after 2 iterations, and K-means based CH selection is converged after 3 iterations, thus demonstrating the low complexity of ECRKQ.

V. SIMULATION

Owing to some unresolved hardware challenges to achieve the underwater acoustic communications, most of the UASNs communications protocols are designed and validated their performance via simulations [6], [14], [18], [19], and so we also verify the efficiency of the proposed ECRKQ via the MATLAB simulator by comparing the performance of ECRKQ with QLEC.

A. SIMULATION SETUP

There are $N_u = 60$ underwater sensor nodes that are randomly generated in a 4 km×12.5 km area. These underwater sensor nodes have the same initial energy capacity and communications range. The initial energy of each node is 5,000 kJ. We assume that the BS can harvest the energy from solar or wind, and so its energy is sufficient. The data packet size is 50 bytes; the transmission rate is 1 kbps. The value of $r_{\max}$, which is the maximum distance between two nodes to determine if a cooperative node is needed for the DCC

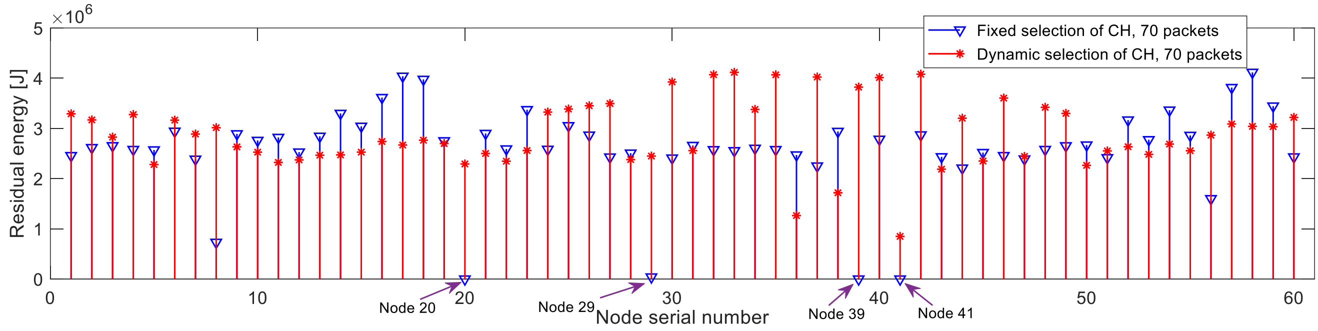

FIGURE 5. The residual energy of each node for dynamic selection of CH and fixed selection of CH after the 70th packet transmission.

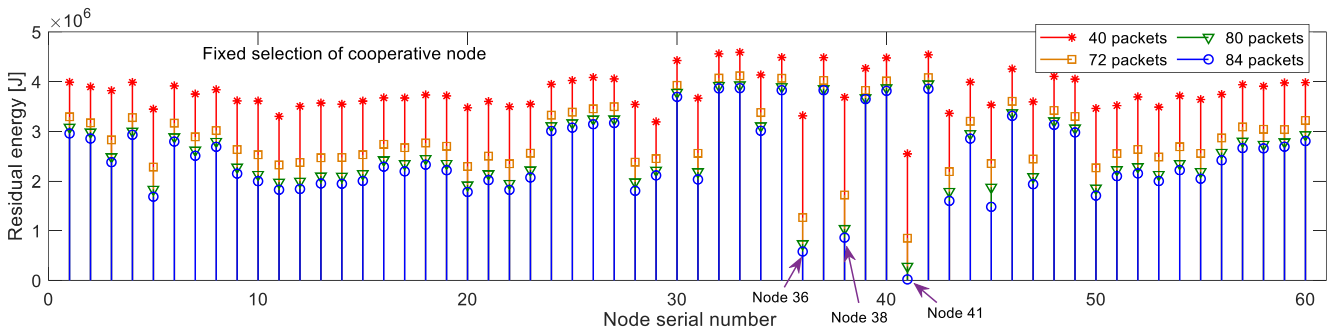

FIGURE 6. The residual energy of nodes with fixed selection of cooperative nodes after different packets' transmission.

transmission, is set to be $r_{\max} = 2.5$ km. For the drifting model, its parameters are as follows: $B_0 = 1.2$, $c_{phase} = 0.12$, $\kappa = 2\pi/7.5$, $\omega = 0.4$, and $\varphi = 0.3$.

B. THE IMPACT OF DYNAMICALLY SELECTING CH AND FIXED SELECTING CH ON ENERGY CONSUMPTION OF THE NETWORKS

The K-means algorithm divides nodes into different clusters based on their distances to other nodes. If the node that is the nearest to the centroid is selected as a CH, then the battery of this node will be quickly drained out. Hence, in the proposed ECRKQ, we select the CH according to the distance from the node to the centroid and the residual energy of the node. In this section, we will compare the performance in terms of the network energy consumption between the fixed CH selection and dynamic CH selection schemes.

Fig. 5 shows the residual energy of each node for dynamic CH selection and fixed CH selection after transmitting 70 packets from sensor nodes to their CHs. We can see that, for the fixed CH selection scheme, nodes 20, 29, 39, and 41 exhaust their energy after the 70th packet transmission. For the dynamic CH selection scheme, on the other hand, the energy consumption are more balanced among the nodes, and so no node is drained its battery after the 70th packet transmission. Therefore, the dynamic CH selection scheme in the proposed ECRKQ can balance the energy consumption of nodes and extend the life of the network.

C. THE ENERGY CONSUMPTION FOR DYNAMICALLY SELECTING COOPERATIVE NODES AND FIXED SELECTING COOPERATIVE NODES

The DCC transmission can improve bandwidth efficiency and enhance network reliability. Traditionally, the node with the lowest transmission energy consumption will be selected as the cooperative node, and so its battery would be quickly drained out. In order to better balance the energy consumption among the nodes, we dynamically select cooperative nodes, considering both residual energy and transmission energy consumption of the nodes.

We compared the residual energy of each node between the fixed cooperative node selection and dynamic cooperative node selection scheme at the 42nd, 72nd, 80th and 84th packet transmission. As shown in Fig. 6, the fixed cooperative node selection leads to nodes 36, 38, and 41 drain out their batteries after the 84th packet transmission. However, for the dynamic cooperative node selection in the proposed ECRKQ algorithm, the energy consumption among different nodes is more balanced and the average residual energy is higher than that of the fixed cooperative node selection, which can be demonstrated based on the results in Fig. 7.

Furthermore, Fig. 8 shows how the variance of residual energy changes with respect to the number of packet transmissions. It can be seen that due to the dynamic CH and cooperative node selection, the variance of residual energy for all the nodes in the proposed ECRKQ protocol is the smallest.

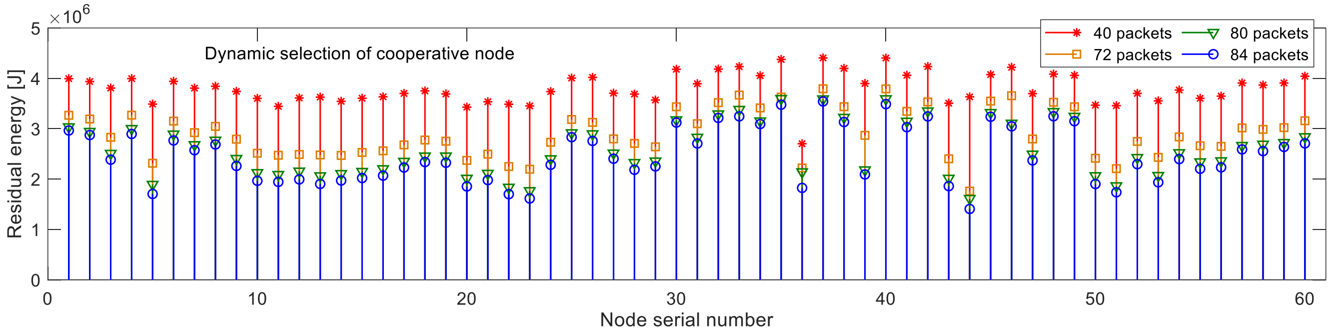

FIGURE 7. The residual energy of nodes with dynamic selection of cooperative nodes after different packets' transmission.

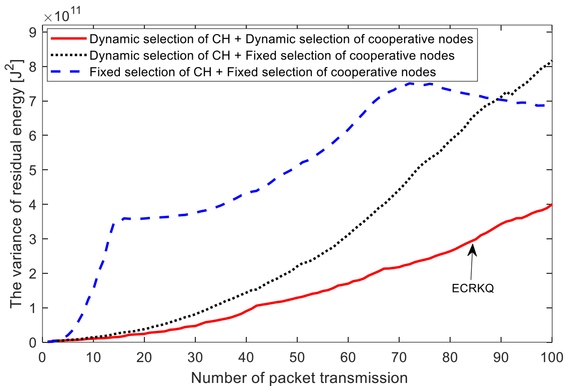

FIGURE 8. The variance of residual energy changes with the number of packet transmission.

Therefore, the proposed scheme has more balanced residual energy among the nodes, and thus can better avoid the energy holes.

D. THE PERFORMANCE COMPARISON BETWEEN THE PROPOSED ECRKQ AND THE QLEC

Based on the same parameter settings, Figs. 9 and 10 show the network clustering results and the corresponding transmission modes for the QLEC and ECRKQ schemes with and without node drifting, respectively. Here, a circle represents a sensor node, and different colors indicate different clusters. A circle with black cross symbol indicates the node is selected as a CH. Also, a circle with black triangular symbol implies the node requires DCC transmission.

From Figs. 9 (a) and 10 (a), we can find that after the clustering, all the nodes are using single-hop transmission to transmit data to the CH in each cluster in QLEC. Yet, from Figs. 9 (c) and 10 (c), after the clustering, some nodes in a cluster adopt DCC transmission in ECRKQ. On the other hand, with respect to the transmissions from the CH to the BS, as shown in Figs. 9 (b), 9 (d), 10 (b) and 10 (d), the CH uses single-hop transmission when transmitting data to the BS in the QLEC scheme; however, the CH uses the DCC transmission to send packets to the BS in the ECRKQ scheme.

By comparing with the results in Figs. 9 and 10, it can be found that, compared with the results after the 3rd packet transmission, the sensor nodes in the UASN drift due to the movement of ocean currents after the 80th packet transmission. It can be observed from Figs. 10 (b) and 10 (d) that, there are some isolated nodes after node drifting when adopting the QLEC scheme. However, there is no isolated node when adopting the ECRKQ scheme with no data loss.[1] This means that the proposed ECRKQ scheme can better maintain the integrity and reliability of data collection and transmission than the QLEC scheme.

In order to further analyze the variation of node energy holes, Fig. 11 shows the residual energy distribution of each node in the UASN after different packet transmissions. Fig. 11 (a) shows the results after the 40th packet transmission. In this case, the energy consumption of each node in the QLEC scheme and the ECRKQ scheme is relatively balanced. However, the residual energy of most of the nodes in the ECRKQ scheme is higher than that of the QLEC scheme. Fig. 11 (b) shows the results after the 72th packet transmission. Node 15 of the QLEC scheme has already been drained out, and the nodes 14 and 56 will be drained out very soon. Yet, the residual energy of all the nodes in the ECRKQ scheme is rather balanced, avoiding the energy holes. Fig. 11 (c) shows the results after the 100th packet transmission. It can be observed that a large number of nodes are drained out in the QLEC scheme, while all the nodes in the ECRKQ scheme have enough and balanced residual energy to properly conduct sensing and data transmission tasks.

Fig. 12 shows the number of dead nodes (i.e., the nodes whose batteries are drained out) changes with respect to the number of packet transmissions for the two schemes. It can be observed that the nodes in the QLEC scheme start to die after the 72nd packet transmission. As the number of packet transmissions increases, the number of dead nodes increases. After the 130th packet transmission, the number of dead nodes reaches half of the total. However, in the ECRKQ scheme, the first dead node appears in the 130th packet transmission. This is because the energy consumption of each packet transmission in the proposed ECRKQ scheme

[1]Isolated nodes are defined as underwater sensor nodes that cannot be clustered with other nodes in the network, and thus finally leads to data losses.

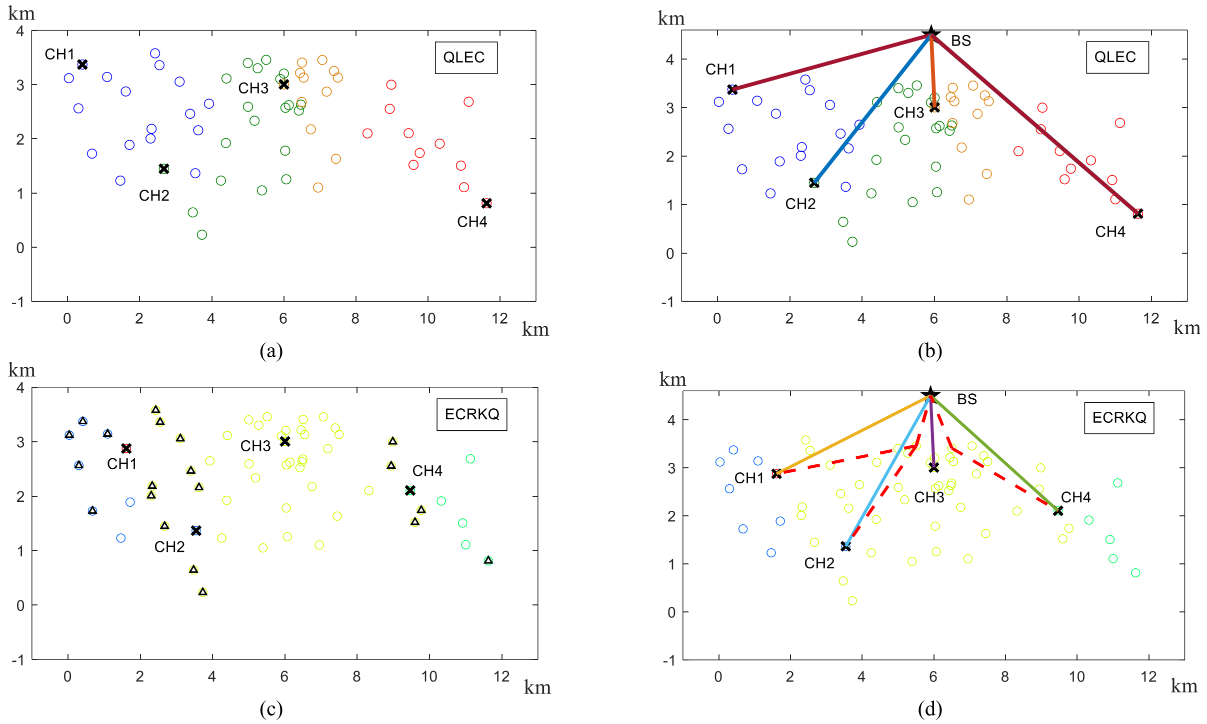

FIGURE 9. The results after the 3rd packet transmission when node drifting is applied: (a) clustering results of QLEC scheme; (b) transmission mode from CHs to BS in QLEC scheme; (c) clustering results of ECRKQ scheme; (d) transmission mode from CHs to BS in ECRKQ scheme.

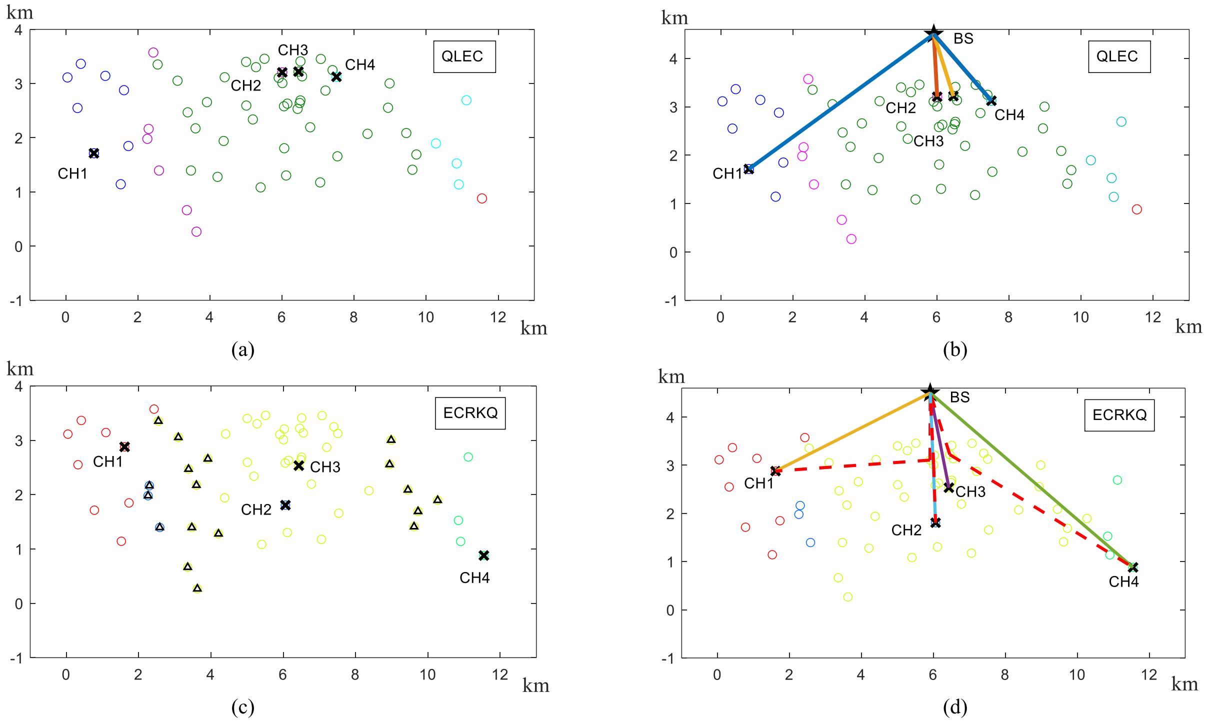

FIGURE 10. The results after the 80th packet transmission when node drifting is applied: (a) clustering results of QLEC scheme; (b) transmission mode from CHs to BS in QLEC scheme; (c) clustering results of ECRKQ scheme; (d) transmission mode from CHs to BS in ECRKQ scheme.

is much lower and the energy consumption is more balanced among the nodes.

Fig. 13 shows the variation of the total residual energy of the nodes with respect to the number of packet transmissions

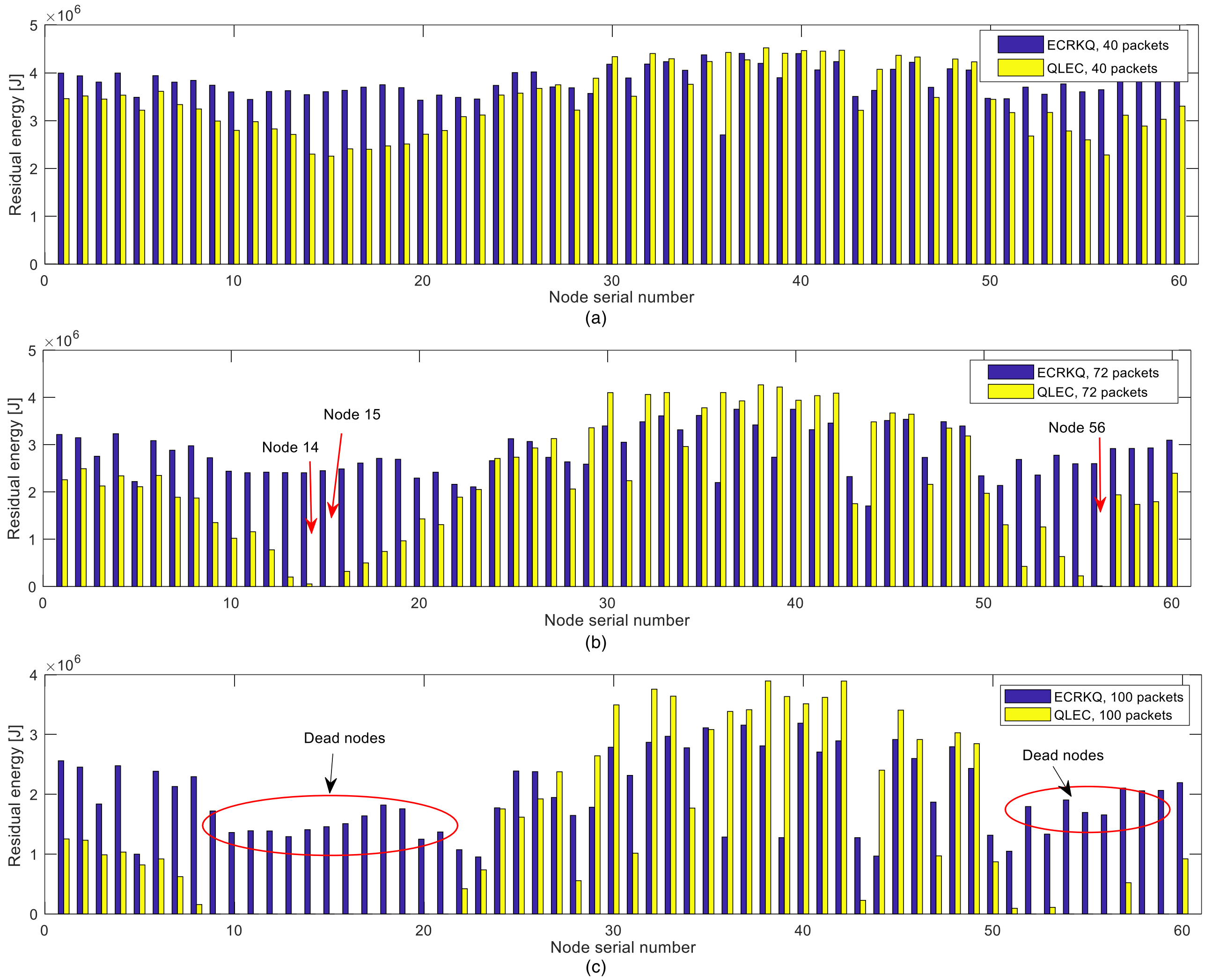

FIGURE 11. The residual energy of the nodes for the two schemes: (a) after 40th packet transmission; (b) after 72nd packet transmission; (c) after 100th packet transmission.

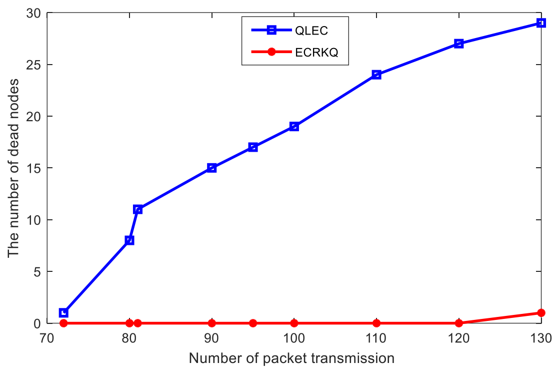

FIGURE 12. The comparison of number of dead nodes in the network varying with the number of packet transmission.

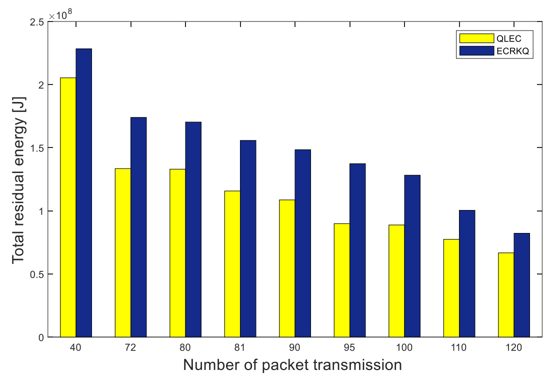

FIGURE 13. The comparison of total residual energy varying with the number of packet transmission.

for the two schemes. The total residual energy of the two schemes exhibits a decreasing trend as the number of packet transmissions increases, but the proposed ECRKQ scheme always has higher total residual energy than the QLEC scheme, which can hence extend the life time of the UASNs.

VI. CONCLUSION

To solve the issue of energy holes, floating of underwater nodes with ocean currents, and narrow bandwidth in UASNs, we proposed an energy-balanced clustering scheme, named ECRKQ. The proposed ECRKQ scheme modifies the K-means algorithm to dynamically select CHs based on the distance between the node and the centroid, and the residual energy of the node. The Q-learning algorithm is used to form clusters, where the Q-value function incorporates the residual energy of the CH, the energy consumption of the node in sending a packet to the CH, and the energy consumption of the CH in sending a packet to the BS. In the data transmission stage, DCC transmission is adopted. In addition, ocean currents model is introduced to simulate the influence of nodes' drifting in the proposed ECRKQ scheme. To accommodate the mobility of nodes, CHs and cooperative nodes can be dynamically selected. The simulation results show that the proposed ECRKQ scheme can balance the energy consumption of the entire network and extend the life cycle of network as compared to the existing scheme.

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