Hybrid charging scheduling schemes for three-dimensional underwater wireless rechargeable sensor networks

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ABSTRACT

Recent breakthrough in wireless power transfer provides a new paradigm for enabling wireless energy replenishment for wireless rechargeable sensor networks, especially in the underwater environment. In this paper, we first propose the concept of UWRSNs (underwater wireless rechargeable sensor networks) and then develop a series of 3D charging schemes for enhancing charging efficiency, using underwater charging robot mules in three-dimensional charging scenarios. Through constructing the architecture of UWRSNs, we develop a basic charging scheme SCS (Shortest-path Charging Scheme), which minimizes the traveling cost for the charging mules in the 3D underwater environment. Then, ECS (Emergency Charging Scheme) is proposed, which concentrates on serving emergency nodes. After that, a charging algorithm that combines ECS and SCS to collaboratively solve the charging problem, namely, HOCS (Hybrid Optimal Charging Scheme) is developed. At last, experimental simulations are conducted to show the outperformed merits of the proposed scheme. Experimental results demonstrate that our schemes not only save energy and time, but also ensure effective utilization of resources.

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1. Introduction

WSNs (Wireless sensor networks) are composed of a large number of cheap micro sensor nodes, which are deployed in specific areas for monitoring events (He et al., 2014b, 2016; Obaidat and Misra, 2014; Chen et al., 2017). Sensors in WSNs are powered by batteries which have constrained energy capacity, leading to limited network lifetime. Therefore, issue of constrained energy capacity has been acting as a longlasting bottleneck that forbids large-scaled deployment of WSNs.

Fortunately, recent breakthrough of WPT (wireless power transfer) technology provides a promising alternative for extending equipment life, especially for battery powered embedded devices. Now, this technology has already been applied for energy replenishment in health care (Yang and Wang, 2015), wireless communications (He et al., 2013b; Zhao et al., 2014), and so on. Different from traditional energy harvesting technology, WPT together with a number of mature and inexpensive mobile robots, such as mobile WCVs (wireless charging vehicles), creates a controllable and perpetual energy source, with which power can be replenished proactively to meet the charging requirements (Deng et al., 2016). Based on these, Xie et al. (2013a, 2012a, 2013b) put forward the concept of WRSNs (wireless rechargeable sensor networks) (Xie et al., 2012b). Nowadays, great progress has been achieved in the research field of WRSNs. The energy supplement of WRSNs has no longer become the main problem, which largely broadens the application prospects for WSNs.

However, all traditional charging methods concentrate on charging applications in the air or on land (Lin et al., 2016c; Xie et al., 2013a, 2012a, 2013b), with little attention paid in the underwater environment. In fact, UWSNs (underwater wireless sensor networks) Davis and Chang (2012) and Zhang et al. (2014a,b) have already been widely used for decades, and it is necessary to focus on energy replenishment for them. In Phamduy et al. (2016),

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magnetic resonance-based WPT is firstly used for energy replenishment in the underwater environment. Therefore, it is possible that WPT can be applied for energy provisioning for UWSNs in the near future, and UWRSNs (underwater wireless rechargeable sensor networks) become promising.

After taking a careful investigation, we found that due to the complex characteristics of the underwater environment (Peleato and Stojanovic, 2007; Xu et al., 2014), energy charging for 3D UWRSNs is facing some challenges (Yong and Pei, 2012).

1. Usually, underwater environment is complicated. Interferences, such as water flotage, resistance and other factors have huge impacts on the charging process, resulting in big latency, low transmission rates, and dynamical channel conditions. It is difficult or even impossible to replace the energy source (i.e.batteries) for sensor nodes. Moreover, due to harsh environmental conditions, traditional energy harvesting technology is infeasible. Therefore, WPT for underwater wireless charging becomes a promising way to achieve energy provisioning (Xu et al., 2014).
2. A charging task taken in an underwater environment should be modeled in three-dimensions, which has never been investigated before (Lin et al., 2016a,b, 2015; Xie et al., 2013a, 2012a, 2013b). No available charging scheduling algorithm for 3D underwater sensor nodes is suitable to refer, because nearly all charging scheduling algorithms can only be used in a planar/2D network.
3. The widespread applications of UWSN require a feasible and effective charging design for prolonging the lifetime, such as system architecture, charging model, charging scheme, and so on. Hence, scheduling strategy for charging has become a prominent issue.

Therefore, studying how to replenish UWRSNs effectively has a great significance, specifically for underwater monitoring and applications. In this paper, we focus on how to effectively schedule mules (i.e. underwater WCVs) to replenish underwater sensor networks. We propose a HOCS (Hybrid Optimal Charging Scheme), which is a feasible solution for the charging scheduling of UWRSNs with high energy efficiency and scheduling flexibility. First of all, we develop a basic charging scheme SCS (Shortest-path Charging Scheme), which minimizes the traveling cost in the underwater environment. Then, ECS (Emergency Charging Scheme) is proposed, which concentrates on timely serving the emergency nodes. After that, a charging algorithm named HOCS is devised, combining ECS and SCS to serve the common nodes and emergency nodes as well as enhance the charging performance. In HOCS, two kinds of mules are used under different charging circumstances. To determine the working regions of all mules, an improved $k-means$ clustering algorithm is employed, which designates every mule to work within pre-allocated area. At last, experimental simulations are conducted to show the outperformed merits of the proposed schemes.

The contributions of this paper can be summarized as follows.

1. To the best knowledge of the authors, this is the first study of using underwater charging robots in three-dimensional charging scenarios. We pay close attentions to designing dynamic collaborative scheduling with on-demand charging architecture and modeling the charging behaviors of mules.
2. To reduce energy consumption and maximize the energy utilization rate, we develop a series of charging algorithms SCS, ECS, and HOCS for enabling energy replenishment. Through network segmentation, target selection, infeasibility testing and target updating, tasks can be assigned to each energy mule for high charging and energy efficiency. (In addition, a cross-region collaboration mechanism is devised to allow busy mules to dispatch additional tasks to nearby mules.)

3. To demonstrate the advantages of the proposed schemes, simulation experiments are carried out. Simulation results reveal that the proposed schemes are able to save energy and save time, and ensure effective utilization of resources.

The rest of this paper is organized as follows. Section 2 gives a brief overview of related works. In Section 3, we detail related background knowledge. In Section 4, we propose four charging algorithms and analyze relationships among them. In Section 5, related characteristics of the proposed schemes are analyzed in detail. We evaluate the algorithm through simulation experiments in Section 6. Finally, Section 7 concludes and points out future works.

2. Related works

UWSNs (Underwater wireless sensor networks) is an emerging research area. Chu et al. (2011) proposed a cross layer link transmission algorithm to enhance the scare resource effective utilization, which respectively paid close attention to characteristics of physical layer, the functionalities and characteristics of the underwater devices. Davis and Chang (2012) presented a survey of various UWSN architectures. Li et al. (2012b) proposed an efficient deployment of surface area for UWSNs, they provided background informative data about the structure and the trajectory of the sinking node. Elmannai et al. (2014) presented a new solution for UWSNs, which deals with the ionization properties of seawater. With respect to the wireless charging issue in underwater environment, although few art has been proposed, issues of wireless rechargeable sensor networks are still deserved to be mentioned.

Wireless charging has been investigated in rechargeable sensor networks in general (Guo et al., 2013; Peng et al., 2010). Xie et al. proposed a SES (Smallest Enclosing Space) solution (Welzl, 1991) to deal with the path planning problem (Xie et al., 2013b). Then Fu et al. (2013) developed a concentric structure to work out the appropriate stop locations for WCV from the overlapping area in SES. A dynamic path planning method for WCV considering Nearest Job Next with Preemption was proposed for better throughput and charging latency (He et al., 2014a, 2013a). They devised a charging scheduling method based on a tree structure to simply charging scheduling and path planning, lowering both the energy consumption and charging latency. Later on, Li et al. (2011) combined routing protocol and charging strategy for high efficiency of WCV, updating the global energy state without any restriction. A collaborative charging method can succeed in dealing with the influence caused by uncertainties in WRSN efficiently (Li et al., 2012a). However, demand for reliability and instantaneity of charging was ignored all the time, lowering network reliability (Yang et al., 2017). Jiang and Cheng addressed its performance by analyzing the optimal scheduling problem of WRSN appropriately. Based on QoM (Quality of Monitoring) (Dai et al., 2013a,b), they took application view of WCV's behavior, data transmission protocol into account to optimize system performance.Zhang et al. (2015, 2012) proposed a theory that WCVs can transfer energy freely.

Lin et al. (2016a,b, 2015) proposed several charging algorithms for WRSNs. In Lin et al. (2016b), two charging algorithms HCCA (i.e. Hierarchical Clustering Charging Algorithm) and HCCA-TS (i.e. Hierarchical Clustering Charging Algorithm based on Task Splitting) were proposed which aim at shortening charging time and distance via merging and splitting charging tasks. Lin et al. (2015) proposed a Double Warning Thresholds with DWDP (Double Preemption) charging scheme, in which double warning thresholds were used when residual energy levels of sensor nodes fall below certain thresholds. In Lin et al. (2016a), a temporal and distantal related priority charging scheduling algorithm TADP was proposed for WRSNs. TADP merged temporal and

Table 1
Symbols and definitions.

Symbol	Definition
L_i	Location of node i.
C_{ij}	Energy cost between two nodes i and j.
X_{ij}	Distance between i and j.
k	A constant for energy and distance.
w_{ij}	Energy cost on the distance between i and j.
β	A constant for energy and distance in underwater environment.
N	Vertical resultant.
F_1	Water flotage.
F_2	Water resistance.
ξ	A weight for evaluating the quality of the $k-means$ cluster.
ζ	Vertical cross-sectional area.
τ	Drag coefficient.
D_{ij}	Degree of arcsine of h_{ij} / X_{ij}.
v	Speed of an energy mule.
V	Volume of an energy mule.
m	Weight of an energy mule.
h_i	Depth of node i.
h_{ij}	Vertical distance between node i and j.
Q_{ij}	Energy cost on the depth between i and j.
α	A constant for total energy and distance.
γ	A constant for total energy and force.
e	Remaining energy of a node.
R	Remaining energy of a mule.
R_m	Initial energy of a mule.
P	Energy capacity of a node.
S	Energy charging threshold.

distantial related priority into a mixed priority to achieve better scheduling performance. However, it was still a 2D charging scheme, which is not suitable for 3D scenario, especially in the underwater environment (Lin et al., 2016c).

Compared to the above prior arts, we proposed an efficient charging scheme for UWSNs named HOCS. We divided the nodes into two categories for processing, emergency nodes and common nodes. Accordingly, two kinds of mules, emergency mules and common mules were assigned to improve energy efficiency.

3. Preliminaries

In this section, related preliminaries are given for better comprehending our schemes.

3.1. Symbols and definitions

We summarize the notations used in this paper in Table 1.

3.2. Network model

The UWSN network model usually has the following components: underwater sensor nodes, surface base station, ship-based receiving stations, satellites, and ground receiving stations. There are two types of underwater sensor nodes. The first type is beacon nodes, which can obtain their own reliable position coordinates through global positioning system. In UWSN, a few number of beacon nodes are evenly distributed, to locate the exact positions of underwater sensor nodes. The second type is ordinary nodes, which are responsible for the entire monitoring environment. Ordinary nodes are randomly deployed in the monitoring area. In order to cover all events, they usually float at different depths. Ordinary nodes move with the flow of seawater within a small area and form networks in a self-organization manner. They send out charging requests to the base station in a hop-by-hop way, which contains coordinates and id when their remaining energy fall below a certain threshold. Upon the receptions of the charging requests, the water surface base station will designate an energy mule to travel to the position recorded by the node at the previous charging time. Through the close-distance communication with the node, the exact position of the node can be determined, and the accurate coordinates will be delivered to the base station and updated.

3.3. Energy consumption model

We model the distribution of sensor nodes as a graph $G(V, E)$. $V = \{V_1, V_2, \ldots, V_n\}$ denotes the set of nodes' locations and E denotes the set of edges. To express the energy cost of traveling from node i to j (i.e. $C_{i,j}$), we have:

$$C_{ij} = k \cdot X_{ij}. \tag{1}$$

Here, X_{ij} is denoted as the distance between i and j. In our model, C_{ij} is proportional to X_{ij} and k is a constant value. Without loss of generality, we have:

$$w_{ij} = \beta \cdot X_{ij}. \tag{2}$$

Here, w_{ij} is the energy cost on the distance from node i to node j. β is a proportional constant value for energy and distance in underwater environment. Since the water environment is totally different from the ground, we additionally take relevant factors into account. For instance, given the same distance, the cost of moving upward is quite different from downward. The traveling cost is relevant to distance, relative depth and so on. We define the vertical sum force as N, thereby, N can be formalized as:

$$N = G - F_1 - F_2. \tag{3}$$

Here, $G = m \cdot g$, where m refers to the weight of an energy mule and g stands for the acceleration of gravity. F_1 means flotage, which can be obtained as:

$$F_1 = \rho g V. \tag{4}$$

ρ and V indicate the density of sea water and the volume of energy mule, respectively. F_2 means resistance, which can be obtained as:

$$F_2 = \frac{1}{2} \tau \rho v^2 \zeta. \tag{5}$$

c and v indicate the drag coefficient of sea water and the speed of energy mule, respectively. ζ designates the vertical cross-sectional area of the energy mule. Then we have:

$$N = mg - \rho g V - \frac{1}{2} \tau \rho v^2 \zeta. \tag{6}$$

We define h_{ij} as the vertical difference of two nodes i and j, which can be calculated as:

$$h_{ij} = h_j - h_i, \tag{7}$$

where h_i and h_j indicate the depth of i and j, respectively. Therefore, in the vertical direction, the relevant energy cost of total force is:

$$Q_{ij} = N \cdot h_{ij}. \tag{8}$$

The traveling cost from node i to node j is computed as Eq. (9), where α and γ are constants, satisfying $\alpha/\gamma=10$.

$$C_{ij} = \alpha \cdot w_{ij} + \gamma \cdot Q_{ij}. \tag{9}$$

After replenishing, the energy mule should have sufficient energy to go back to the base station. We define the remaining energy of an energy mule as R and the remaining energy of a charging candidate node as e. The energy capacity of a node is P, hence, the following equation should always be satisfied:

$$C_{ij} + C_{j0} + (P_j - e_j) \leq R. \tag{10}$$

Only in this case will the energy mules charge node j. Furthermore, each time when the energy mules are replenishing nodes,
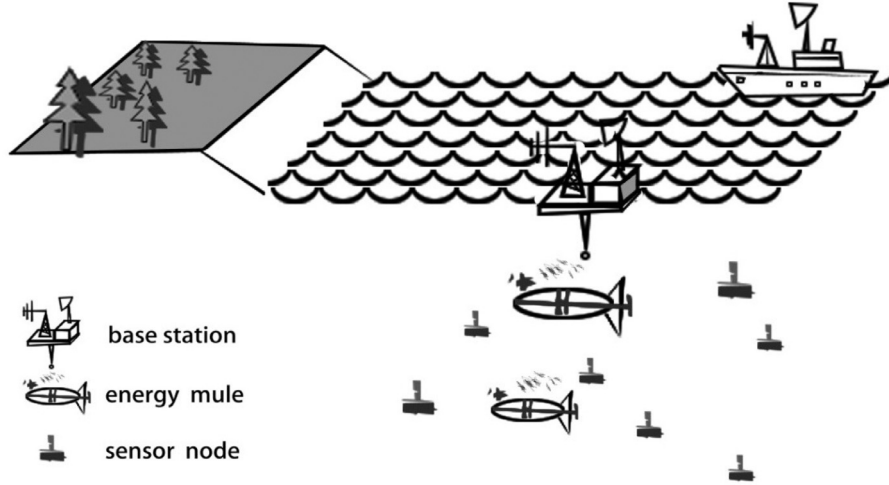
Fig. 1. System overview.

Eq. (14) should be satisfied. Otherwise, it will immediately go back to the base station to get charged for itself. As for the influence of physical equipment on the charging efficiency of mule, the simulation results of the latter can also be seen that the effect of the angle on the charging result is negligible, but the underwater glider cannot rise or fall sharply because in the actual physical situation. When the angle of the glider moving under water is set too large, the flotage force of the underwater vehicle will increase. In that case, the flotage pressure of the underwater glider on the vertical plane will become large, which may cause deviation of the running track of the aircraft. When the angle of motion is set too small, the energy loss of the glider to the same depth will increase, which will reduce the charging efficiency. Therefore, considering the above factors and at the same time to facilitate the simulation experiment, in our method, we additionally put a 30 degree restriction, if a mule moves from node i to node j, it should meet the condition that:

$$D_{ij} < 30°. \tag{11}$$

3.4. Problem statement

As shown in Fig. 1, we consider a scenario that a UWRSN is composed of a number of homogenous sensors, energy mules, and a base station. Sensors periodically report their sensory data to the base station through pre-determined routing protocols. When the remaining energy of a sensor falls below a threshold S, it will send a charging request to the base station. The base station collects, aggregates, and analyzes data, so as to monitor the underwater environment, when it receives a charging request, it will mark that node as an emergency node.

At the same time, a number of homogenous mules armed with WPT are located at the base station, which are ready to move out for replenishing nodes. Mules are two-folds based on their functionalities: common mules and emergency mules. A common mule is designated to replenish common nodes within a fixed area. An emergency mule is used for saving emergency nodes. When an emergency node appears, an emergency mule will be immediately set out to replenish it. Mules have limited energy capacity, after the remaining energy drops below a threshold, it will come back to the base station to get recharged.

Our problem here is *how to improve throughput without investing additional the energy cost?* The answer is to design an effective charging scheduling method for mules, which minimizes the cost of mules in traveling without degrading the charging effi-

ciency. Subsequently, we propose several schemes to achieve energy replenishment for underwater rechargeable sensor networks (Lin et al., 2018).

We define $S_N(i)$ as the state of a node. A sensor has two states: alive ($S_N(i) = 1$) and dead ($S_N(i) = 0$), which is expressed as:

$$S_N(i) = \begin{cases} 0 & T \le T_D(i) \\ 1 & T > T_D(i) . \end{cases} \tag{12}$$

T refers to the current time and $T_D(i)$ refers to the deadline of node i. Then the objective of our scheme (i.e. minimizing the number of dead nodes $\mathcal{N}_D$ and maximizing the energy efficiency η of mule during the whole lifetime of sensor networks) can be formalized as:

$$\min \quad \mathcal{N}_D = \sum_{i=0}^{N} S_N(i), \tag{13}$$

$$\max \quad \eta = \frac{\sum\limits_{i=0}^{n} E_i}{\sum\limits_{i=0}^{n} E_i + \sum\limits_{i=0}^{n} \omega_{n,n-1}}. \tag{14}$$

Subject to:

$$t_{i+1} = t_i + \frac{D_{i,i+1}}{v}, \quad 0 \le i \le \epsilon. \tag{15}$$

$$T_R(i) = T_D(i) - T. \tag{16}$$

$$T_R(i) = \frac{E_C(i)}{V_M(i)}. \tag{17}$$

$$E_e = \sum_{i=0}^{N} (V_M(i)T(1 - S_N(i)) + V_M(i)T_D(i)S_N(i)). \tag{18}$$

Eq. (15) describes the charging process between two adjacent nodes, where t_i denotes the arrival time when mule reaches node i, $X_{i,i+1}$ is the distance between node i and $i+1$ and v is the speed of mule. The remaining time of node i depends on its remaining energy $E_C(i)$ and energy consumption rate $V_M(i)$, and it can also be calculated by dead time $T_D(i)$ and current time T according to Eqs. (16) and (17). The effective energy of mule E_e refers to energy which is eventually received by nodes and is given by Eq. (18). If node i is alive, which means $S_N(i)$ is 0, it gets $V_M(i)T(1 - S_N(i))$ energy, otherwise, $E_e = V_M(i)T_D(i)S_N(i)$.

4. The proposed scheme

We develop four charging scheduling algorithms for solving the charging scheduling problem for UWRSNs, namely CCS, SCS, ECS, and HOCS.

CCS is used to schedule ordinary charging requests. To further minimize the traveling cost, SCS is applied. Whenever an emergency is detected, ECS will designate emergent mules to save emergent nodes. Finally, HOCS combines SCS and ECS to further improve network performance.

4.1. Clustering charging scheme (CCS)

As the charging capability of a single mule is limited, it is not realistic to arrange only one mule to replenish all nodes in a large-scale network. In our scenario, sufficient mules will be employed to serve. Therefore we designate fixed areas for each of them. We apply an improved $k - means$ clustering algorithm for dividing the charging areas for both common mules and emergency mules. First of all, we divide the whole region so that each sub-region is managed by an emergency mule. Then we further divide the sub-regions into smaller parts, in which a common mule is designated to replenish energy periodically. Here, an emergency energy mule can communicate with several common energy mules within a local sub-region.

The improved $k - means$ clustering algorithm is described in Algorithm 1.

Fig. 2. Nodes distribution in underwater environment.

Fig. 3. Clustering results after using CCS.

Algorithm 1 Improved $k - means$ clustering algorithm.

1: **Input:** All nodes' location L_i
2: **Output:** The number of mules p
3: Initial: $j \leftarrow 2$
4: **while** true **do**
5:     $k - means$ clustering algorithm, $l \leftarrow 0$
6:     **for** each cluster **do**
7:         $\xi \leftarrow \sum_{i=1}^{n} P_i + \sum_{i=1}^{n} \sum_{j=1}^{n} \log_n C_{ij}$
8:         **if** $\xi < R_m$ or $\xi > 2R_m$ **then**
9:             $l \leftarrow 1$, break
10:         **end if**
11:     **end for**
12:     **if** $l = 1$ **then**
13:         $j \leftarrow j + 1$
14:     **else**
15:         $p \leftarrow j$, break
16:     **end if**
17: **end while**
18: **Return:** p

As shown in Fig. 2, a couple of nodes are randomly deployed in the underwater environment. After applying Algorithm 1, all sensors are grouped into two categories as shown in Fig. 3 (i.e. circles and rectangles). Two emergency mules are responsible for replenishing each type. Then to determine the working region of common mules, $k - means$ clustering algorithm is executed again, which further divides the former two groups into four smaller clusters (see Fig. 3). Then, we only need to designate four common mules to charge them.

After cluster partitioning, we explore the dynamic behaviors of common nodes under the constraints of the water flow law. When node i sends a charging request to the base station, the base station will record its position and update the information of the corresponding cluster.

When the node's location information in cluster is updated, we calculate the ξ to estimate whether the old cluster are still suitable
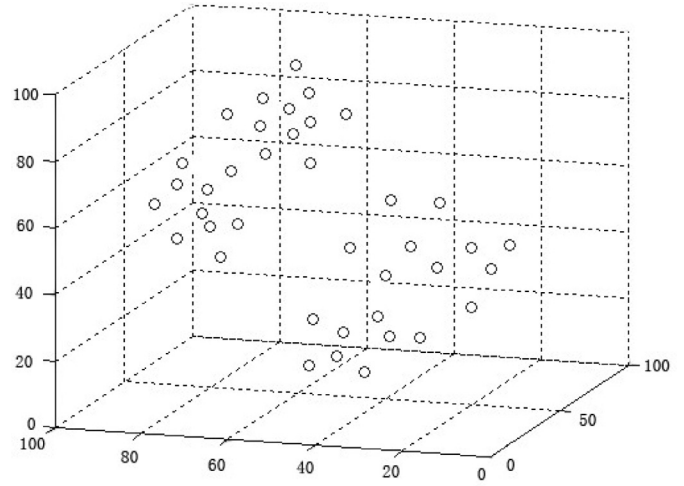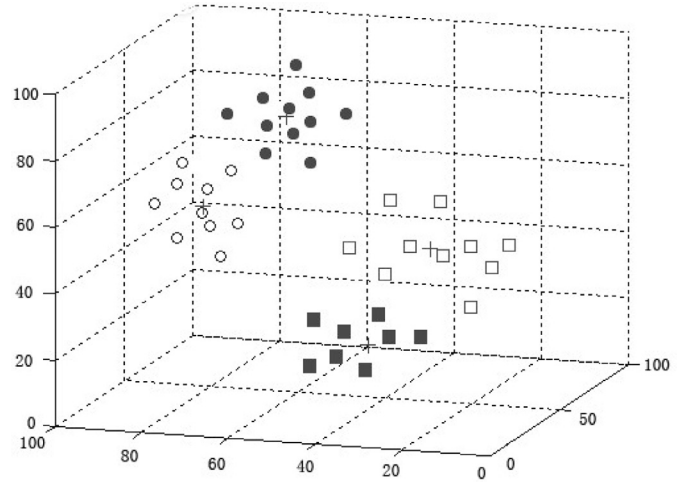
for the node's new location. If $\xi < R_m$ or $\xi > 2R_m$ are satisfied, it is necessary to re-invoke the Algorithm 1 to divide the network and arrange the schedule based on the newly-divided network.

On the contrary, if $R_m \leq \xi \leq 2R_m$, then the division of improved $k - means$ clustering algorithm is still effective, and there is no need to repartition the clusters.

4.2. Shortest-path charging scheme (SCS)

SCS is the basic algorithm of our schemes. In SCS, we assume that the remaining energy of any node will never fall below the threshold S. Therefore, only common mules are used here. We thereby mainly focus on how to reduce the traveling cost by using the Shortest-path Charging Scheme (SCS). In SCS, every time, a common mule selects the node j as the next node to be charged, which has the least C_{ij} from current node i while satisfying Eqs. (14) and (11).

The Shortest-path Charging Scheme can be described as Algorithm 2.

Algorithm 2 proceeds as follows. Originally, a charging candidate list D is input as parameter. SCS chooses a node j with the minimum value of C_{pj} in D while satisfying Eq. (11) as the objective. We define p as the number of current charged nodes. At this time, if Eq. (14) is satisfied, an energy mule will charge node j, then SCS will add j into Q and remove it from D. This process repeats
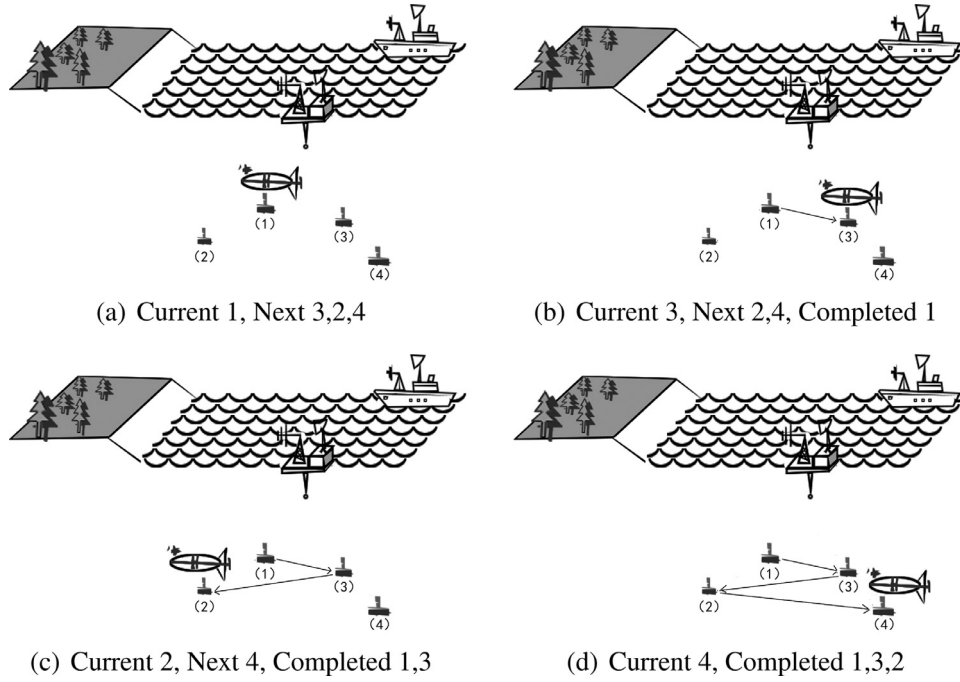
(a) Current 1, Next 3,2,4

(b) Current 3, Next 2,4, Completed 1

(c) Current 2, Next 4, Completed 1,3

(d) Current 4, Completed 1,3,2

Fig. 4. Charging process of SCS.

Table 2
Traveling cost and degree when using SCS.

Node Number/Cost and Degree	$C_{i1}/(D_{i1})$	$C_{i2}/(D_{i2})$	$C_{i3}/(D_{i3})$	$C_{i4}/(D_{i4})$
1	0	10.3a/48.5	11.6a/15.6	12.9a/37.9
2	12.7a/48.5	0	21.3a/8.5	23.6a/11.6
3	12.4a/15.6	20.7a/8.5	0	8.3a/50.5
4	15.1a/37.9	22.4a/11.6	9.7a/50.5	0

Algorithm 2 Shortest-path charging scheme (SCS).

1: **Input:** Charging candidate list D
2: **Output:** Charging sequence Q
3: Initial: $p \leftarrow 0$
4: **for all** $i \leftarrow \{0 \cdots n\}$
5: Find a node j with minimum C_{pj} in D **do**
6:    **if** Eq. (11) and Eq. (14) are satisfied **then**
7:       $Q \leftarrow Q \bigcup \{j\}$
8:       $D \leftarrow D \setminus \{j\}$
9:       $p \leftarrow j; n \leftarrow n - 1$
10:    **else**
11:       Find the next node with minimum C_{pj} in D
12:    **end if**
13: **end for**
14: **Return:** Q

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until no node exists in D. Finally, SCS outputs list Q as the charging sequence.

To better clarify the notion of SCS, we give a simple example in Fig. 4. Four nodes, node 1, node 2, node 3 and node 4 are given in a UWRSN. A mule, which locates at position 0, is designated to replenish for them. Table 2 list related values and Fig. 5 shows the charging timeline. When using SCS, each time a node with the minimum traveling cost will be selected. Obviously, C_{01} is the smallest. Hence, node 1 will be charged first (Fig. 4(a)). This process repeats until all nodes are served. The final charging sequence is $1 \rightarrow 3 \rightarrow 2 \rightarrow 4$ as shown in Fig. 4(b), Fig. 4(c), and Fig. 4(d).

4.3. Emergency charging scheme (ECS)

In SCS, we consider that all nodes are common nodes and the emergency case will never happen. In practice, nodes may deplete energy at any time. To solve this problem, we employ an on-demand charging architecture (He et al., 2013a). Once a node's remaining energy is lower than a threshold S, it will send a charging request to the base station, and then an emergency mule will be immediately designated to serve it. Obviously, the purpose of emergency energy mule is to save the emergency node so as to prolong lifetime of network. Here, a priority list is used for recording the remaining lifetime of nodes. Basically, a shorter lifetime leads to a higher priority. The detailed design of Emergency Charging Scheme (ECS) is described in Algorithm 3.

Algorithm 3 proceeds as follows. Originally, a charging candidate list D and a list M for recording newly added nodes are input as parameters. In ECS, a mule firstly chooses a node with the minimum lifetime l_j while satisfying Eq. (11) in D as the charging target. If Eq. (14) is satisfied, it will add node j into list Q and delete it from D. In the meanwhile, the mule updates values of p and t, and checks whether there exists a node requesting to join D. If so, it will be added into D. This process repeats until all requests are served. At last, a sequence of nodes which have been served will be output.

Similar to SCS, we present an example for illustrating the charging process of ECS in Fig. 6. Related information, such as remaining lifetime and charging timeline is given in Table 3 and Fig. 7, respectively.

Fig. 6 exemplifies the charging process of ECS. Fig. 6(a) depicts the original state in emergency sequence. Fig. 6(b) shows that two
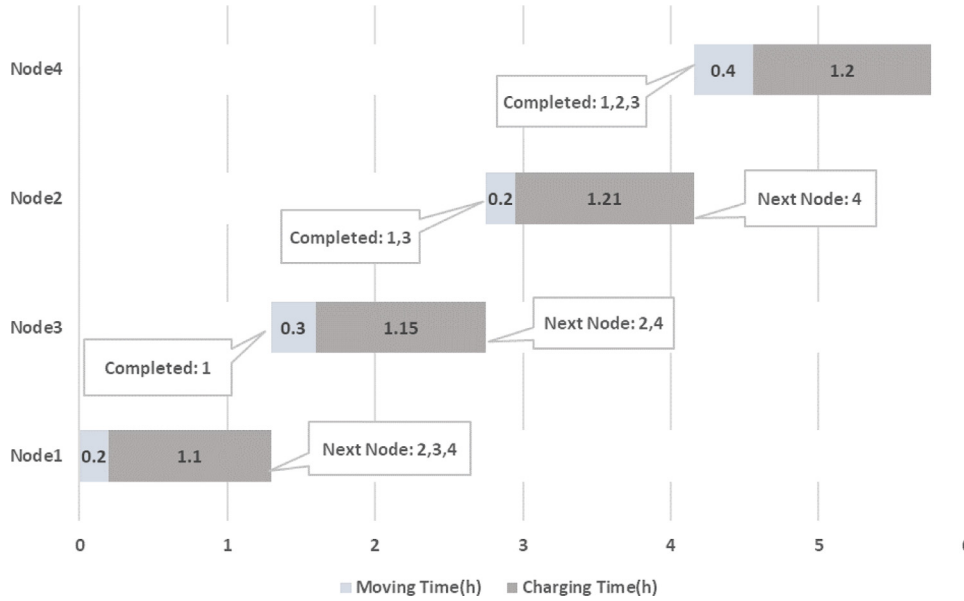
Fig. 5. Charging timeline of SCS.

Algorithm 3 Emergency charging scheme (ECS).

1: **Input:** Charging candidate list D, a node list M
2: **Output:** Completed node sequence Q
3: Initial: $t \leftarrow 0$, $p \leftarrow 0$, $k \leftarrow 0$
4: **for all** $i=\{0 \cdots n\}$ **do**
5:     Find a node j with minimum l_j in D
6:     **if** Eq. (11) and Eq. (14) are satisfied **then**
7:         $Q \leftarrow Q \bigcup \{j\}$
8:         $D \leftarrow D \setminus \{j\}$; $n \leftarrow n - 1$
9:         $p \leftarrow t, t \leftarrow t + t_j$
10:        **if** k requests are waiting to be served from M_p to M_t **then**
11:            Add k requests into D and $n \leftarrow n + k$
12:        **end if**
13:    **else**
14:        Find a node with minimum l_j in D as the charging target
15:    **end if**
16: **end for**
17: **Return:** Q

Table 3
Information on charging sequence and remaining lifetime.

Time	Next node ID	Lifetime(s)
t0	1	2000
t1	2	3000
t1	3	2500
t2	2	2500
t2	4	3000
t3	4	2500

nodes, node 2 and node 3 are added. Fig. 6(c) indicates that the energy mule chooses node 3 as the next charging target owing to the shorter lifetime which satisfies Eqs. (14) and (11). In Fig. 6(d), the mule chooses node 2 as the target and finally in Fig. 6(e), node 4 gets charged.

4.4. Hybrid optimal charging scheme (HOCS)

Next, we mainly analyze how to schedule the charging sequence of mules when both common nodes and emergency nodes exist (Duan et al., 2017). We also intend to focus on how to designate energy mules so as to enhance the charging performance.

In our scheme, we merge SCS and ECS into a Hybrid Optimal Charging Scheme (HOCS). Similar to SCS and ECS, every mule maintains a node list as charging candidates. Each time, when finishing the charging task, a common mule will update the information of the node list. When the node's energy is lower than S, it will be deleted from the common mule's list and will be added into the emergency mule's list. For instance, after finishing charging node a, the common mule updates the information of node list. At that time, node b is regarded as an emergency node due to decrement of remaining energy. In that case, information of node b will be informed to emergency mules and ECS will be applied.

The HOCS algorithm is described in Algorithm 4.

Algorithm 4 proceeds as follows. At first, a node j which has the minimum C_{pj} while satisfying Eq. (11) in D is selected as the charging target. If Eq. (14) is satisfied, HOCS will add j into Q_{v1} and deletes node j from D. Then HOCS checks whether there is a value e_h less than S. Here, e_h stands for the remaining energy of node h. If so, node h will be added into M, and deleted from D. From list M, HOCS chooses node j which has the least lifetime l_j

Table 4
A case study of HOCS.

Node Number	$C_{i1}/(D_{i1})$	$C_{i2}/(D_{i2})$	$C_{i3}/(D_{i3})$	$C_{i4}/(D_{i4})$	$C_{i5}/(D_{i5})$
1	0	14.2a/30.2	13.5a/27.8	22.8a/39.5	14.3a/82.6
2	15.8a/30.2	0	28.3a/5.8	33.6a/11.5	16.1a/29.8
3	14.5a/27.8	27.7a/5.8	0	8.3a/25.6	16.8a/31.3
4	25.2a/39.5	34.4a/11.5	9.7a/25.6	0	19.5a/6.5
5	17.1a/82.6	17.9a/29.8	21.2a/31.3	20.5a/6.9	0

(a) Next 1

(b) Current 1, Next 3,2

(c) Current 3, Next 2,4, Completed 1

(d) Current 2, Next 4, Completed 1,3
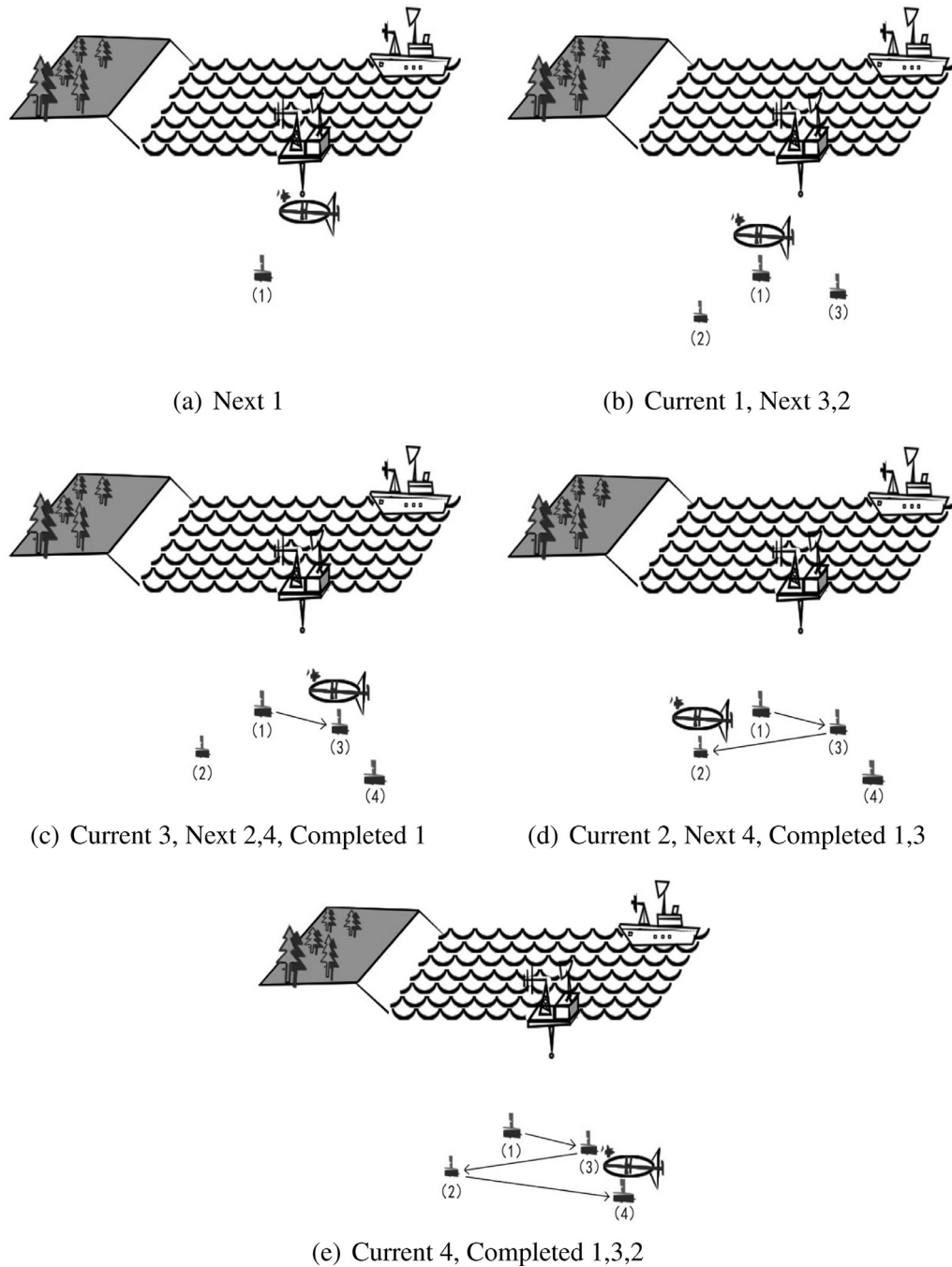
(e) Current 4, Completed 1,3,2

Fig. 6. Charging process of ECS.

satisfying Eq. (11) as the charging target. Then if Eq. (14) is satisfied, HOCS will add node j into list Q_{v0} and delete it from M. At last, HOCS outputs list Q_{v0} and Q_{v1}. Here, Q_{v0} stands for a sequence of emergency nodes, which have been served, and Q_{v1} stands for a sequence of common nodes which have been replenished.

An example of HOCS is given in Fig. 8. Related data are listed in Table 4 and Fig. 9. Originally, five nodes, node 1, node 2, node 3, node 4, and node 5 are deployed under the water. They are waiting to be charged at $t0$ and none of them is an emergency node. By applying HOCS, node 1 and node 3 will be charged. After that, the remaining energy of node 5 falls below the threshold S and becomes an emergency node. At that time, an emergency energy mule is available, and it will be designated to charge node 5 at once. In latter charging process, node 2 is also regarded as an emergency

node, and the emergency mule will be appointed to replenish it.

4.5. Relations among algorithms

In this section, the relation among algorithms proposed in this paper is presented.

As shown in Fig. 10, to determine the working region of emergency mules and common mules, improved $k - means$ clustering algorithm is applied. Each mule is able to work in pre-determined working area for energy replenishment (namely CCS). SCS aims to minimize the traveling cost, where mules select the node with the minimum traveling cost as the target node. ECS ensures that when an emergency node appears, an emergency mule can be called im-
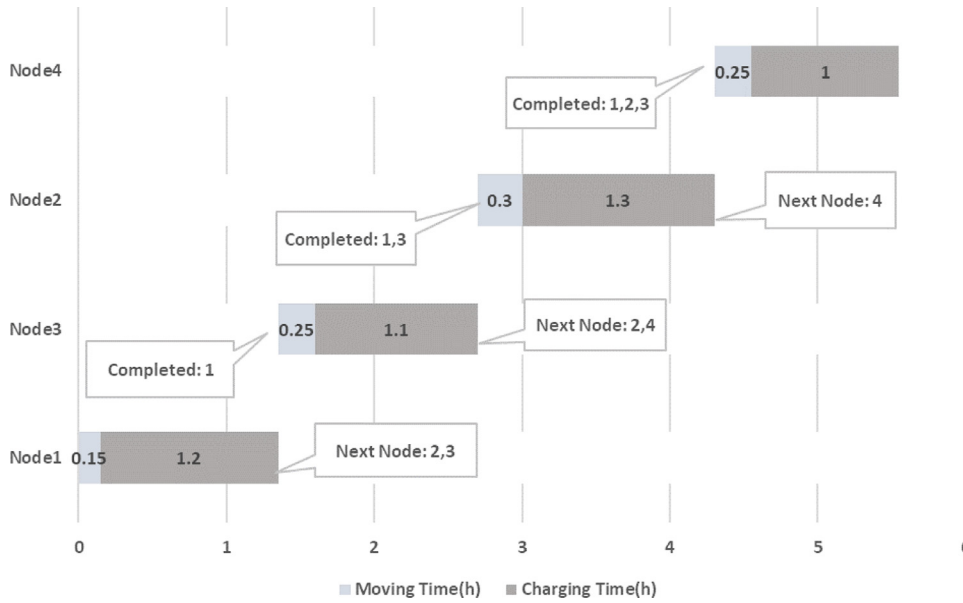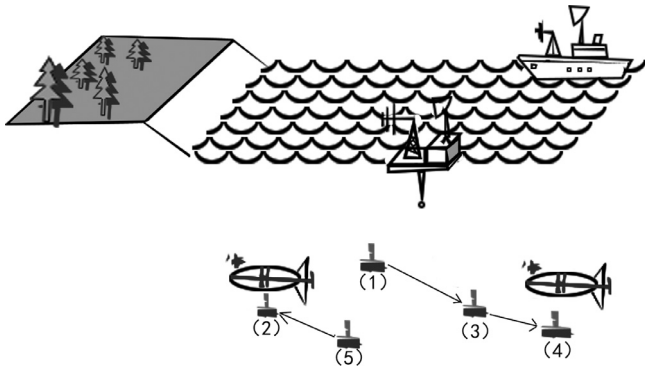
Fig. 7. Charging timeline of ECS.

Fig. 8. Charging process of HOCS-common mule: 1,3,4, emergency mule: 2,5.

mediately. Moreover, nodes are prioritized by their remaining life-time in ECS. A node with a shorter lifetime will be served earlier,

guaranteeing the survival of the network. Finally, HOCS combines SCS and ECS to enhance network performance.

5. Characteristic analysis

In this section, related characteristics of the proposed schemes are analyzed in detail.

For ease of simplicity, in our model, each energy mule is designated in a specific area by the improved $k - means$ clustering algorithm. When Eq. (14) is not satisfied, the energy mule will return to the base station at once. During its returning period, another energy mule which is located at the base station will start working instead of it. Hence, the charging model can be formalized as a queueing problem of energy mules.

The charging process of energy mules can be formalized as an $M/G/1$ queueing model (Elshabrawy, 2014; Harrison and Patel, 1993). Here, the inter-interval time between any two energy mules follows the negative exponential distribution. Meanwhile, the serving time has a general distribution. Besides, the length of time be-
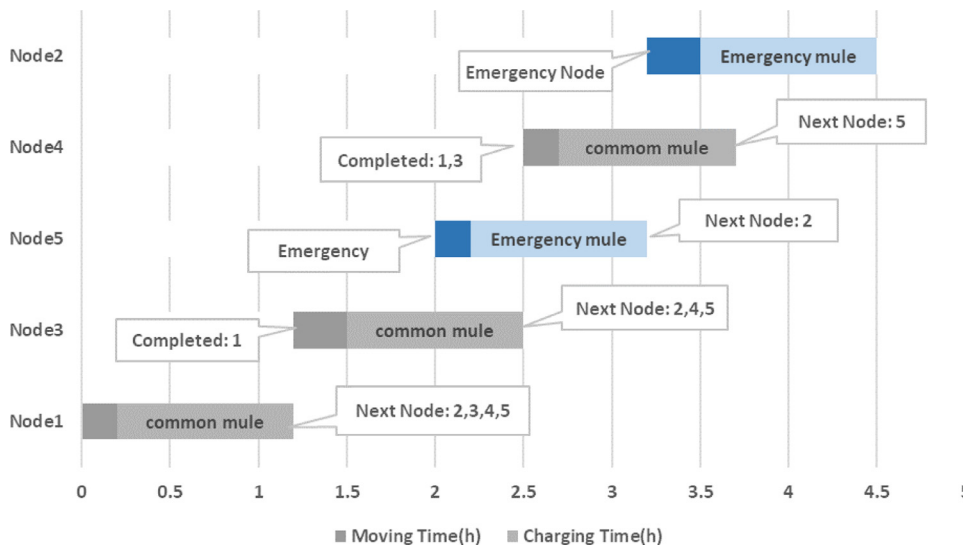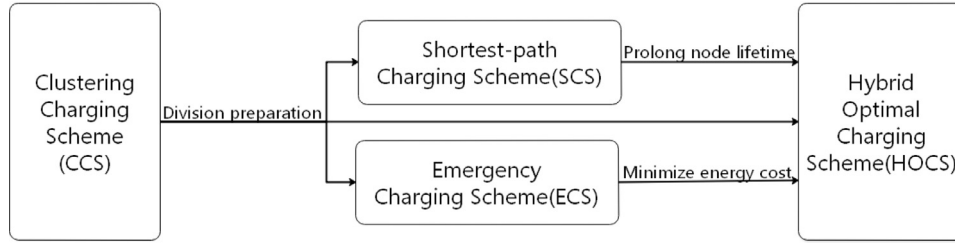

Fig. 9. Charging timeline of HOCS.

Fig. 10. Relations among CCS, SCS, ECS, and HOCS.

Algorithm 4 Hybrid optimal charging scheme (HOCS).

1: **Input:** Candidate list D, emergency node list M, charging threshold S
2: **Output:** Completed node sequence Q_{v1} of common mules, completed node sequence Q_{v0} of emergency mules
3: $k \leftarrow 0, j \leftarrow 0, m \leftarrow 0$
4: **for all** $i \leftarrow \{0 \cdots n\}$ **do**
5:　　Find a node j with minimum C_{kj} in D while satisfying Eq. (11)
6:　　**if** Eq. (14) of V_1 satisfies **then**
7:　　　$D \leftarrow D \setminus \{j\}$
8:　　　$Q_{v1} \leftarrow Q_{v1} \bigcup \{j\}$
9:　　　$k \leftarrow j; n \leftarrow n - 1$
10:　　　**for all** $h \leftarrow \{0 \cdots n\}$ **do**
11:　　　　**if** $e_h < S$ **then**
12:　　　　　$M \leftarrow M \bigcup \{h\}$
13:　　　　　$D \leftarrow D \setminus \{h\}$
14:　　　　　$n \leftarrow n - 1; m \leftarrow m + 1$
15:　　　　**end if**
16:　　　**end for**
17:　　**end if**
18: **end for**
19: **for all** $p \leftarrow \{0 \cdots m\}$
20: Find a node j with minimum l_j in M while satisfying Eq. (11) **do**
21:　　**if** Eq. (14) of V_0 satisfies **then**
22:　　　$M \leftarrow M \setminus \{j\}$
23:　　　$Q_{v0} \leftarrow Q_{v0} \bigcup \{j\}$
24:　　　$m \leftarrow m - 1$
25:　　**end if**
26: **end for**
27: **Return:** Q_{v0}, Q_{v1}

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tween arrivals and service periods are random variables, which are assumed to be statistically independent. Moreover, we define λ as the intention of steady flow. Therefore, we use *PollaczekKhinchine* (van de Liefvoort, 1990) formula, which states that the relationship between the queue length and service time distribution is Laplace transform to an M/G/1 queue (where jobs arrive according to a Poisson process and have general service time distribution).

The mean queue length L can be expressed by:

$$L = \rho + \frac{\rho^2 + \lambda^2 \sigma_H}{2(1 - \rho)}, \tag{19}$$

where λ is the arrival rate of the Poisson process, and $1/\mu$ is the mean value of the service time distribution H. $\rho = \lambda/\mu$ denotes the utilization. σ_H is the variance value of the service time distribution H.

We define W as the mean time a customer spends in the queue, then $W = W' + \mu^{-1}$, where W' is the mean waiting time (the time spent in the queue waiting for service) and μ is the service rate. According to Little's law (Gao et al., 2010; Obaidat and Boudriga,

2010):

$$L = \lambda W, \tag{20}$$

where L is the mean queue length and λ is the arrival rate of the Poisson process. W is the mean time spent in the queue for both waiting and being served.

Therefore, we have:

$$W = \frac{\rho + \lambda \mu \sigma_H}{2(\mu - \lambda)} + \mu^{-1}. \tag{21}$$

The mean waiting time can be expressed as:

$$W' = \frac{L}{\lambda} - \mu^{-1} = \frac{\rho + \lambda \mu \sigma_H}{2(\mu - \lambda)}. \tag{22}$$

We define $\pi(z)$ as the probability-generating function of the number of customers in the queue, then we have:

$$\pi(z) = \frac{(1 - z)(1 - \rho)g(\lambda(1 - z))}{g(\lambda(1 - z)) - z}, \tag{23}$$

where $g(h)$ is the Laplace transform of the service time probability density function.

Define $W^*(h)$ as the Laplace–Stieltjes transform of the waiting time distribution, then we can obtain:

$$W^*(h) = \frac{(1 - \rho)h}{h - \lambda(1 - g(h))}, \tag{24}$$

where $g(h)$ is the Laplace transform of service time probability density function (Peterson and Chamberlain, 1996).

Based on the queueing theory, we obtain a series of principles of energy mules ready to work at the base station. We can formalize the number of energy mules at the base station and avoid energy mules waiting in vain at the same time. These criteria are extremely helpful for saving energy and rationally allocating energy and mule resources. Moreover, they provide insightful guidance for setting the simulation parameters.

6. Simulation analysis

In this section, simulation experiments are conducted to evaluate the performance of the proposed schemes.

6.1. Simulation setup

We evaluate the performance of HOCS through simulation experiments. Since there have not been any prior art in URNs (or underwater recharging in general), we use two benchmark schemes from WRSNs, termed ERS and NRS (Yang and Wang, 2015) as comparison baselines. ERS refers to the Emergency Recharge Scheme, in which the mules firstly charge nodes with the least energy. NRS refers to the Normal Recharge Scheme, where mules firstly charge nodes with the least traveling energy cost. Next, we compare the performance among ERS, NRS, and HOCS. Related simulation parameters are listed in Table 5.

We randomly placed $N = 80$ sensors in an underwater region, which has a size 1000 m × 1000 m × 1000 m. All mules start from
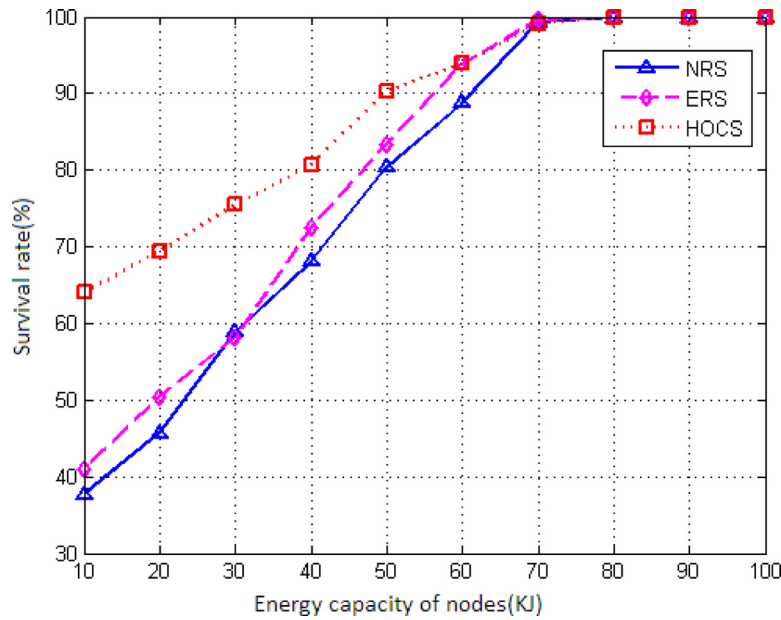
Fig. 11. Influence of node capacity.

Table 5
Simulation parameters.

Parameters	Values
Region size	1000 m × 1000 m × 1000 m
Number of nodes	80
Starting location of mules	(500, 500, 1000)
Energy consumption rate of nodes (J/s)	0–0.2
Traveling cost of mules (J/m)	8
Charging speed of mules (J/s)	2
Energy threshold	0.4
Initial energy of nodes (J)	13,669
Initial energy of mule (KJ)	190
Traveling speed of mules (m/s)	1
Charging algorithms	ERS, NRS, HOCS

location (500, 500, 1000), and they travel at a speed of 1 m/s with 8J energy consumed per meter. They consume energy about 2J/s to charge a sensor node. Initial energy of node is 13669J, and energy consumption rate of each node varies from 0 to 0.2. When a node's remaining energy falls below 40 percent of its full capacity, it will be regarded as an emergency node, and meanwhile an emergency mule will be immediately called to help.

6.2. Influence of nodes' energy capacities

First, we compare the survival rate among three charging algorithms. It is the most essential factor for representing the remaining number of nodes in the network.

In this simulation, we mainly concentrate on the influence of nodes energy capacities on the survival rate. A larger capacity of node indicates a longer working time. As shown in Fig. 11, when the energy capacity of a node is enlarged, its corresponding lifetime is prolonged, which promotes the survival rate. Because when the energy capacity is increased and the energy consumption rate is steady, nodes will have longer lifetime and lower death rates. We also observe that the survival rate of HOCS is always higher than those of NRS and ERS.

6.3. Influence of Mules' traveling speed

In this simulation, we mainly compare the effect of traveling speed on survival rate among these three algorithms, as depicted in Fig. 12. With the increment of traveling speed, the survival rate of HOCS, NRS and ERS will not fluctuate much. However, the gap between HOCS and the other two is apparent. On average, the survival rate of HOCS is approximately 67%, which is much higher than NRS and ERS.

When the energy capacity of the node is very small, the emergency node will increase. Since the HOCS preferentially serves the node with low power, it can maintain the node survival rate more than NRS and ERS. When the node capacity is getting larger and the emergency node is reduced, the difference in the impact of the three charging strategies on node mortality is reduced.

6.4. Influence of Mules' charging speed

In this simulation, we further analyze the influence of charging speed of mules on survival rate. As shown in Fig. 13, with the increase in charging speed, the survival rates of three algorithms gradually increase. Because when the charging speed is increased, nodes will take a shorter time on obtaining the same energy. Thus the other nodes will have a shorter waiting time, meaning that the survival rate of the network will increase. To some degree, HOCS possesses the greatest survival rate. Noticeably, there is no death node when the charging speed reaches to 3.5 J/s for HOCS and ERS.

Since the HOCS uses dynamic programming to charge the nodes, when a new emergency node, that is, a node with a higher priority in the task queue, can quickly respond to the corresponding location to charge the node, NRS and ERS do not have this point, so Compared with NRS and ERS, the survival rate of hocs has obvious advantages at the same speed. However, as the speed increases, the node survival rate of HOCS, NRS and ERS does not fluctuate greatly. The reason is that the mule's charging speed is limited. Therefore, in the same algorithm, the increase of driving speed will not have great impact on node survival rate
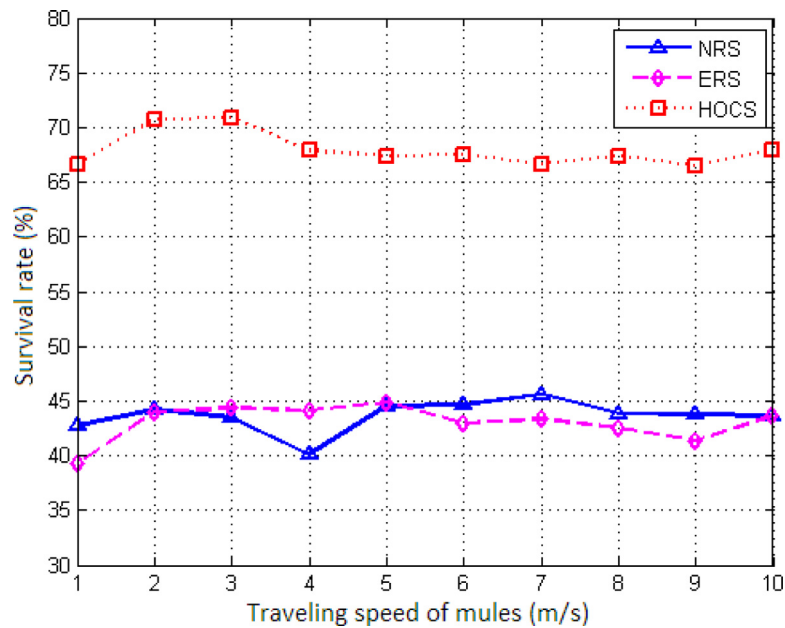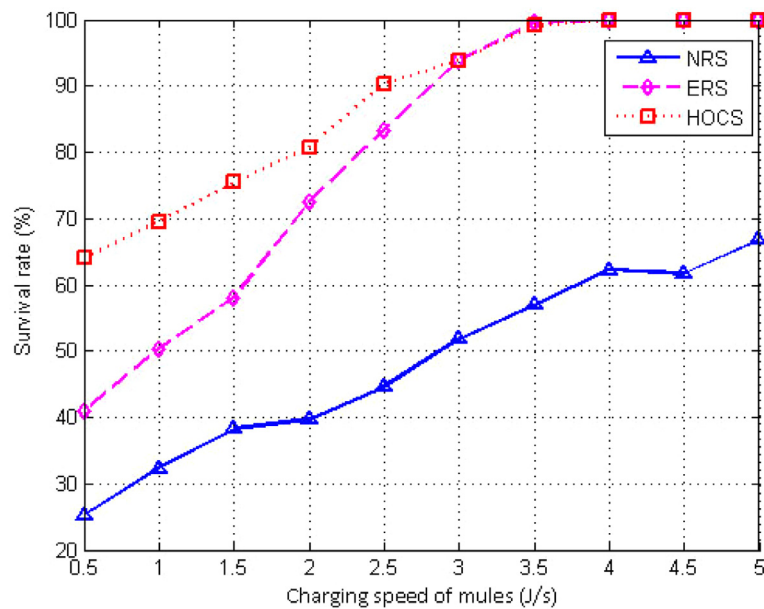
Fig. 12. Influence of travel speed.

Fig. 13. Influence of charging speed.

6.5. Throughput of charging request

Next, we compare throughput of charging requests for three schemes. Here, throughput is defined as the number of successful charges in each unit time (hour), a vital factor for keeping system stable and prolonging network lifetime. As shown in Fig. 14, HOCS serves more nodes than ERS and NRS, because two kinds of mules: common mules and emergency mules are employed. By classifying functionalities of nodes, mules can collaboratively work simultaneously, enhancing the throughput.

6.6. Influences of 30° restriction

Concerning the restriction of equipment, we conduct an experiment to find out the influence of this restriction on energy efficiency.

We calculate energy efficiency which indicates the fraction of energy eventually obtained by sensor nodes. Compared with the scheme without 30 ° restriction, the actual one averagely decreases ratio of efficient energy to 4.67 percent. Therefore, it is undoubted that physical devices with degree limitation will not damage our algorithm. The detailed comparison is shown in Fig. 15.

6.7. Other characteristics analysis

In this section, the influences of other factors are discussed in detail.

6.7.1. Ratio of dead nodes

In our simulation, 50 to 300 nodes are randomly deployed in an underwater environment. As shown in Fig. 16, we note that ratio
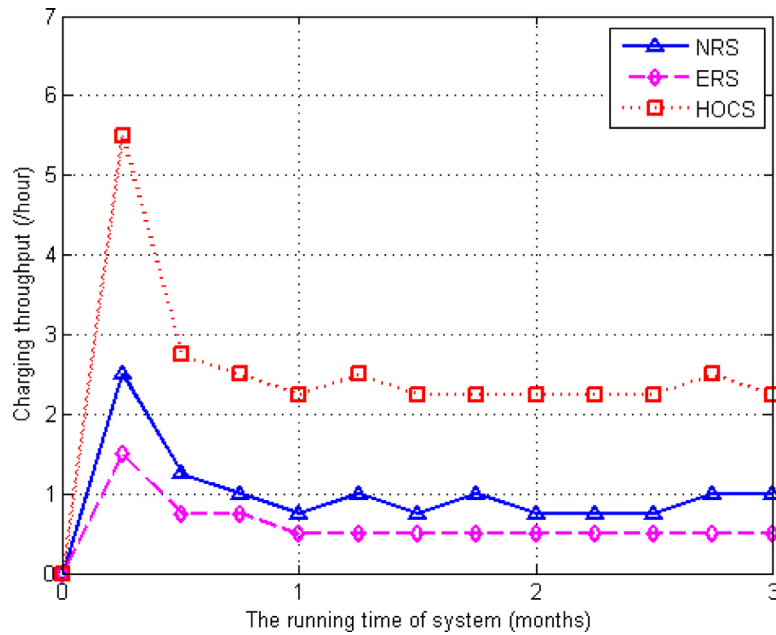
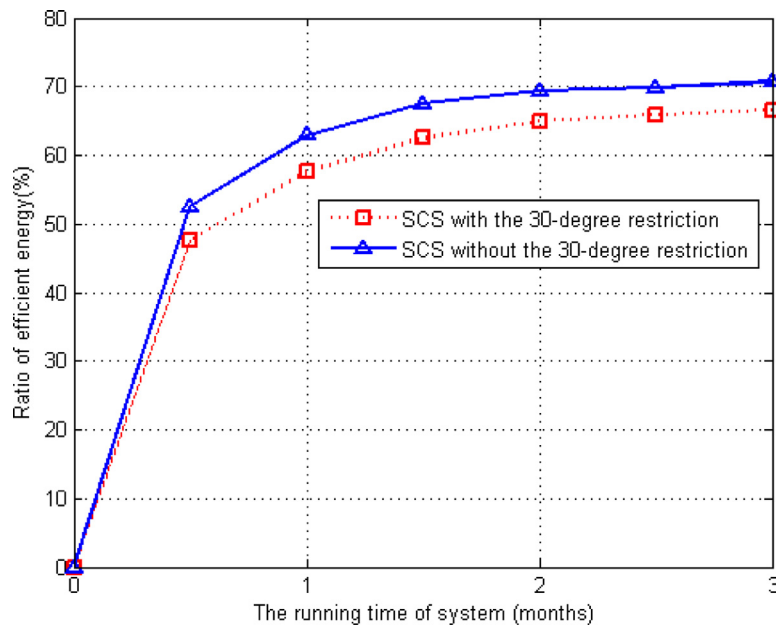**Fig. 14.** Comparison of charging throughput.

Fig. 15. Influences of the 30° restriction.

of dead nodes in HOCS is less than NRS and ERS, which reflects the superiority of HOCS.

In Fig. 16, with the increasing number of nodes, the ratio of dead nodes gradually reduces. The ratio in HOCS is 5.4 percent and 9.8 percent lower than those of ERS and NRS, respectively. The reason is that, NRS minimizes the traveling cost, and issues of emergency nodes are not taken into consideration. ERS only focuses on the nodes carrying the least energy. Whereas in HOCS, when emergency nodes appear, emergency mules are set out, hence, the emergency nodes can be rescued timely. HOCS focuses on the energy and node lifetime, which are lacked in NRS and ERS. Therefore, the corresponding ratio of dead nodes is the lowest.

6.7.2. Average waiting time

As shown in Fig. 17, we note that the average waiting time of HOCS is less than those of NRS and ERS, which indicates a higher responding speed. With the increasing number of sensor nodes, the average waiting time in NRS and ERS are 51 s and 456 s, which are longer than HOCS.

The reason is that ERS only deals with the nodes with the least energy, and the charging time is longer than other schemes, it hereby prolongs the average waiting time. In NRS, an emergency node cannot be timely responded. Therefore, the average waiting time will be longer.

According to Eq. (22), we can draw theoretical chart and experimental chart (Fig. 18). By comparison, the average waiting time in the experiment is slightly longer than the theoretical average
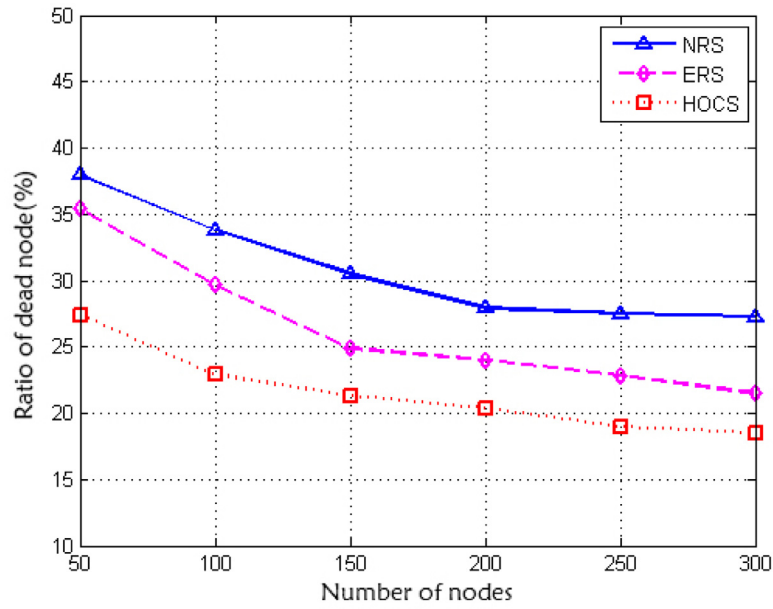
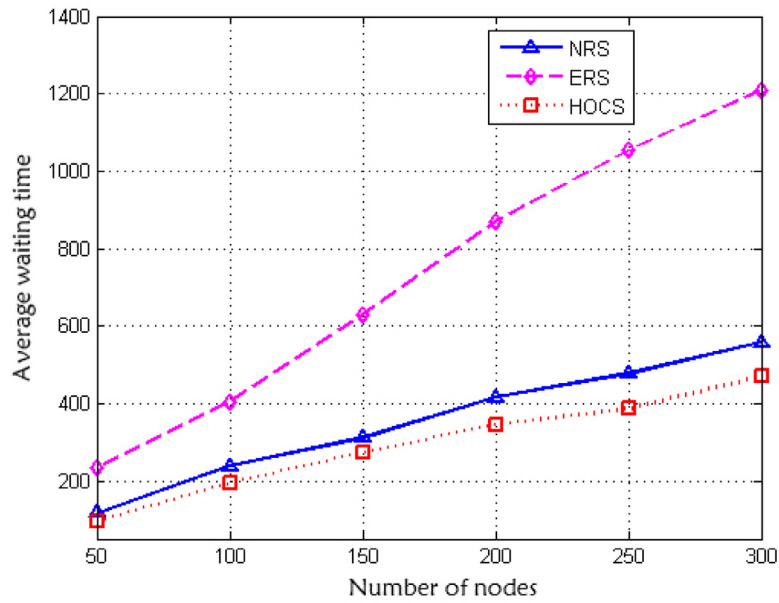**Fig. 16.** Comparison of ratio of dead nodes.

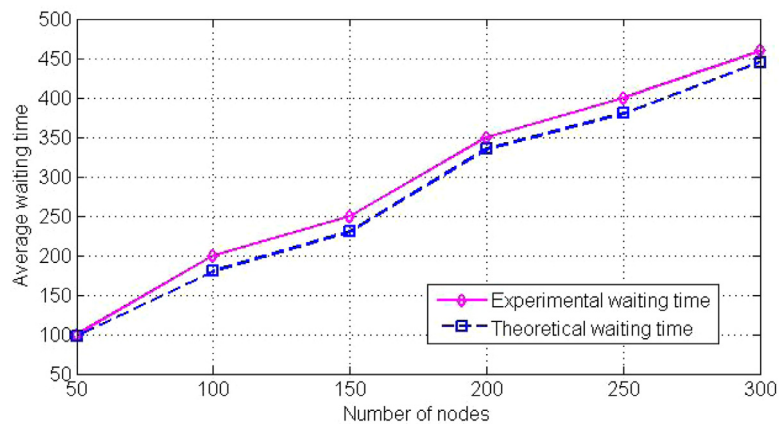**Fig. 17.** Comparison of average waiting time.

Fig. 18. Difference between simulation result and theoretical result.

waiting time due to the delay in the transmission of information among nodes, which indicates the correct of the theoretical chart.

7. Conclusions and future works

In this paper, we proposed several charging schemes for 3D underwater wireless rechargeable sensor networks. First of all, we develop a basic charging scheme SCS, which aims at minimizing the traveling cost so as to save energy in the underwater environment. Then, to deal with urgent charging requests, we develop ECS, which concentrates on timely responding to the emergency nodes. As both of them show advantages in saving ordinary and emergency nodes, after that, a charging algorithm that combines ECS and SCS, namely, HOCS is devised. HOCS both considers the remaining power of the node and the energy consumption of the route, which greatly improves the node mortality and the energy efficiency of the entire network. Then, to determine the working regions of all mules, a $K - means$ clustering algorithm is utilized, which designates every mule to work within deterministic area. At last, experimental simulations are conducted to show the outperformed merits of the proposed scheme. Simulation results show that the proposed scheme is able to enhance the throughput and prolong the network lifetime.

As part of our future work, we will focus on implementing underwater rechargeable sensor networks.

1. How to realize real time communications between energy mules.
2. How to deploy energy-efficient charging architecture for underwater wireless rechargeable sensor networks.

Acknowledgement

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