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Research on Hybrid Cooperative Charging Scheduling Schemes in Underwater Sensor Networks

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ABSTRACT The lifetime of underwater sensor networks (USNs) can be prolonged significantly thanks to wireless power transfer technology. In this paper, we first proposed a Shortest Path Partial Charging based on Charging Curve Scheme (SPBS) to increase the survival rate of nodes in 3D underwater networks, and then we proposed a concept of secondary charging stations for mobile charging ships to reduce the traveling cost and improve charging efficiency. We first use k-means clustering algorithm to divide our network with k clusters, and then we place our secondary stations at k clustering centers, in this way, mobile charging ships can be charged at secondary stations quickly. Based on secondary stations, we proposed Hamilton Charging Scheme (HCS) using the Hamilton ring, and then we proposed a temporal and spatial collaborative charging algorithm (mCS-TS) for USNs with multiple mobile charging ships and secondary charging stations, which also takes the cluster factor and deadline time into consideration. Simulation results show the effectiveness of our proposed algorithms.

INDEX TERMS Underwater sensor networks, survival rate, SPBS, secondary charging stations, mobile charging ships, cluster factor.

I. INTRODUCTION

With the development of emerging information and communication technologies, such as intelligent Internet of things, 5G, cloud computing, artificial intelligence and machine learning, great changes have taken place in people's lifestyles. In traditional networks, sensor nodes are powered by batteries with limited capacity, which limits the working hours of sensor nodes. Battery exhaustion means the end of the sensor node lifetime. Therefore, the battery capacity becomes a main factor that restricts the lifetime of the whole sensor network. Fortunately, the advancement of wireless communication and microelectronic technology furthermore contributed to the emergence of wireless sensor networks and bring a new choice for extending batteries lifetime.

Wireless Sensor Networks (WSNs) are composed of a large number of sensors that are deployed in the monitoring area in a self-organizing and multi-hop manner. Characterized by low cost, low power consumption and multiple functions [1]. WSNs are widely used in important fields such as environmental detection, military, smart home and telemedicine [2], [3]. In remote areas or areas where human intervention is not suitable, replacing the battery for the sensor nodes are troublesome and costly. Therefore, it is necessary to extend the lifetime of WSNs, and the energy consumption of sensor nodes in the area must be equalized and then study the energy supply technology of sensor nodes.

Fortunately, recent breakthrough in wireless power transfer (WPT) provides a new alternative for extending devices' life. Yang and Wang [4] had applied this transfer technology in health care for energy replenishment. Moreover, researchers has done many efforts to extend the lifetime of WSNs by applying this technology. Xie *et al.* [5] proposed the concept of a rechargeable wireless sensor networks (WRSNs). In a rechargeable wireless sensor network, one or more Mobile chargers (MCs) equipped with wireless power transmission equipment periodically provide charging services to sensor nodes in the network. Many algorithm,

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such as Pushwait, PSB, $^{\eta}$Pushwait, clustercharging(β), H$^{\eta}$clustercharging(β), DMC, C-MCC, MsMsEBP and so on. are proposed by researchers to improve the performance of the network and prolong the life of the WRSNs [6], [7].

Nowadays, Marine economy accounts for an increasing proportion of the economy of all countries. Underwater sensor networks (USNs) have become a research hotpot in many countries. USNs [8] are a new type of sensor networks applied to water environment. These are widely used in activities such as sea information collection [9], [10] and underwater resource exploration [11], [12]. Unlike WRSNs, the USNs [13] are more complex, which are composed of underwater sensor nodes with short communication ranges, surface buoy nodes and two-way underwater acoustic links between nodes. The capabilities of these nodes include information perception data processing and classification. The USNs can be used to relay information back to ship-based relay stations through the underwater nodes [14], and reach the ground base stations (BSs) through satellites or the Internet.

Similar to WRSNs, sensor nodes used in traditional USNs [15] are powered by batteries, and the lifetime of a USN is seriously limited by the battery life of sensor nodes. In addition, battery replacement is not only difficult but also results in high maintenance costs especially underwater. The emergence of wireless power transmission (WPT) technology has enabled supplying power wirelessly to underwater communication systems [16]. Batteries for wireless communication equipment can be supplemented remotely using microwave WPT devices.

After taking full investigation, we found that energy charging in USN is facing multiple challenges:

1. Underwater channel is characterized by high latency, multipath effect, severe drooler dispersion, low bandwidth and dynamical channel conditions.
2. Underwater sensor nodes have high mobility due to water flotage, wind and other factors. In addition, it is difficult and costly to replace the energy batteries for sensors, so it is wisely to charging them by WPT.
3. Proposed algorithms, charging models, charging schemes based on WRSNs are not suitable for underwater sensor networks. Therefore, new charging scheduling schemes are imminent.

Therefore, it is important to study the charging and lifetime extension of the USNs, improve survival rates, and improve network throughput as well as reduce network operation and maintenance costs. In this paper, we focus on extend the lifetime of USNs by effective charging schemes with effective usage of energy and low dead rate of nodes. We proposed a shortest path partial charging based on charging curve scheme (SPBS) to reduce the dead nodes, and then we proposed a concept of secondary charging stations for mobile charging ships to reduce the traveling cost and improve charging efficiency. We also use k-means clustering algorithm to divide our network with k clusters place our secondary stations at k clustering centers, in this way, MSs can be charged at secondary stations quickly.

The main contributions of this study are as follows:

First, we partially charge nodes with charging curve, which reduce the dead rate of nodes and improve the network's life.

Second, our design decreases the distance that the MSs need to travel with secondary charging stations, which reduce any extra energy consumption in the USN.

Third, by considering the cluster factor and deadline time, we hope that the cluster with shorter distance, lower energy will have higher charging priority.

The rest of this paper is organized as follows: Section II gives a brief overview of related works on underwater sensor networks. Section III describes the USN charging model and the concept of secondary charging stations. Section IV details the proposed algorithms. Section V describes the simulation environment and numerical evaluation. In Section VI, we conclude the paper and present directions for future research.

II. RELATED WORKS

In many recent works, significant efforts have been devoted to enhancing the performance of USNs through optimal routing protocols, or pay attention to the characteristics of water devices or proposed new architectures. Optimal protocols mainly based on divide the sensors into several clusters to balance sensor node energy consumption and promote USN energy consumption efficiency [17]–[19]. Clustering can be carried out using the k-means algorithm, which can efficiently process large data sets, and has close to linear time complexity. However, the final clustering result is greatly affected by the selection of initial nodes. The algorithm is also very sensitive to data with large deviations [20]. Another well-known self-organizing, adaptive clustering and scheduling algorithm known as low energy-adaptive clustering hierarchy (LEACH), uses randomization to evenly distribute the energy load among the network's sensor nodes. Alhazmi *et al.* [21] proposed a novel solution named underwater modified LEACH (UMOD_LEACH) to minimize energy consumption. Li *et al.* [22] proposed the LEACH-L, which consists of two phases: an initialization phase and an update phase. The former phase is similar to that in the LEACH protocol. In the latter phase, unlike the LEACH protocol, only a few nodes are updated locally rather than the entire network's nodes. This local update helps in minimizing the energy consumption. Mansouri and Loualalen [23] proposed the LEACH algorithm for routing in Underwater Wireless Sensor Networks (UWSNs). They used an adaptive approach for the LEACH protocol in which the residual energy of clustering head (CH) is considered. Hou *et al.* [24] proposed a new clustering model that considers the required transmission power of sensor nodes, and CH residual energy and loads to improve upon the poor stability and unsatisfactory clustering results of the existing USN clustering algorithms.

Wireless charging scheduling approaches have been widely applied in WRSNs to prolong its lifetime [25], [26]. In general, the charging scheduling approaches used in

WSRNs fall into two categosries: single mobile (SM) charger and multiple mobile (MM) chargers. Research on the former charging category aims to solve cycling task scheduling problem and improve charge service throughput in the WRSNs [27]. Zhang *et al.* [28] proposed a novel charging mode: cooperative mobile charging. In this mode, mobile chargers (MCs) not only charge the nodes in the network, but also charge one another. The multi-MCs collaborative charging strategy c-mcc proposed in [30] considers the remaining electric charge in each node and the distance between nodes and MCs to make charging decisions, and then arranges charging paths to improve charging efficiency. Lin *et al.* [31] proposed a new real-time charging scheduling scheme. This scheme is based on a joint metric of spatial and temporal requirements from charging requests that takes advantage of the availability of multiple MCs and allows them to make optimal decisions.

With the respect to the wireless charging in USN, Lin *et al.* [32] first proposed underwater wireless sensor network model, then they focused on how to effectively schedule mules (underwater WCVs) by proposed SCS (Shortest-path Charging Scheme) and HOCS (Hybrid optimal Charging Scheme). Although few art of wireless charging underwater environment, issues of researching charging schemes for USNs are still deserved to be mentioned.

Most of the methods reviewed in the previous paragraphs use routing protocols to prolong the network lifetime and reduce the network energy consumption. However, these methods do not consider the charging scheduling method [32]–[34]. Inspired by the charging scheduling of MCs applied in the WRSN networks and underwater charging model and charging schemes proposed in [32], we first proposed an efficient algorithm based on charging curve named SPBS for USNs and then proposed the concept of secondary charging stations applied to USNs. We then proposed Hamilton Charging Scheme (HCS) using the Hamilton ring and a new algorithm that uses temporal and spatial collaborative charging for underwater sensor networks with multiple mobile charging ships (MSs) and secondary charging stations (mCS-TS). The algorithms make full use of collaborative charging characteristics and takes time/distance and cluster density factor into consideration.

III. PROBLEM STATEMENT

A. NETWORK MODEL FOR THE USN

Underwater sensor networks mainly include underwater sensor nodes, satellite, BSs, surface anchor nodes, water BS and ship-based relays. Fig. 1 shows our USN charging model.

The main features of this model are as follows:

1) There are N underwater sensor nodes randomly dropped by aircraft, denoted by $S = \{s_1,s_2,s_3,\ldots\ldots,s_N\}$, and then the anchors are used to determine the initial position of the equipment after they are dropped, so that the sensor equipment will not leave the monitoring area due to fluctuations in the sea water. Both surface anchor nodes and ship-based relays of underwater sensor nodes have

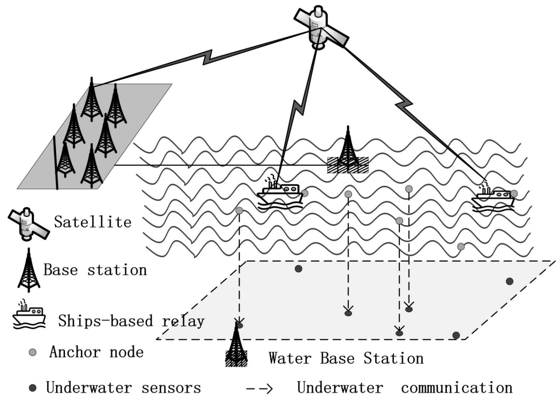


FIGURE 1. USN network model.

GPS mode or positioning algorithm, and have limited energy supply. The underwater sensor nodes relay the information back to the ship-based relays and then to the ground BS by satellites or the Internet.

2) The BS is mainly responsible for information collection and fusion and is the location of energy concentration.

3) The water base station (WBS), connected to the ground BS by cables is a water energy station. There are K mobile charging ship-based relays (MSs) on the surface, denoted by $MS=\{MS_1, MS_2,\ldots\ldots MS_K\}$. The MSs start from the WBS regularly and charge sensor nodes. They can accurately locate a node and its information, and charge it when needed. The WBS is connected to the BSs and its energy is considered to be infinite.

B. ENERGY COUNSUMPTION MODEL

We model the distribution of underwater sensor nodes as $G(S, E)$. $S = \{s_1,s_2,s_3,\ldots,s_N\}$ donates sensors' labels and locations and E denotes the set of edges. We donate X_{ij} as the distance between node i and j. Then the energy consumption in the USN includes energy consumption of the nodes forwarding and receiving data E_{node}, the total energy of MSs E_{MS}, energy consumption of the MSs for traveling E_{move} and the energy that the MSs transfer to the sensor nodes E_{charge}.

With the complex of USN, we used traveling cost formula in [32], the traveling cost C_{ij} from node i to node j is computed as (1), where α is the constant for total energy and distance, γ *is* the constant for total energy and force, satisfying $\alpha/\gamma = 10$, β is a proportional constant value for energy and distance in USN, X_{ij} is the distance between i and j, Q_{ij} is the relevant energy cost of total force in the vertical direction.

$$C_{ij} = \alpha^* \beta^* X_{ij} + \gamma^* Q_{ij} \tag{1}$$

Before the MSs charging the nodes, we should make sure that MSs have sufficient energy return to the water station. We define the battery capacity of a sensor node and MS as ea and P, respectively. The energy consumption rate and the speed of a MS, and the energy consumption rate of node s_i, are denoted as c_s, v_s, and re_i respectively. We define the remaining energy of a node as e_r and the remaining energy of a MS as P_r, C_{jw} is the energy cost from node j to water base station, then we have the following equation:

$$P_r - C_{ij} - C_{jw} - (P_j - e_r) \geq 0 \tag{2}$$

C. THE CONCEPT OF SECONDARY-CHARGING STATION

In WRSN,once the energy of MCs go below a certain threshold, they directly return to BS to recharge themselves. and the energy usage effectiveness (EUE) metric is defined as: $\eta = E_{node}/(E_{charge} + E_{move} + E_{MC})$.

In USNs, a sensor usually has two states: alive and dead. We define $S(i)$ as the state of node i.

$$S(i) = \begin{cases} 1, & alive \\ 0, & dead \end{cases} \tag{3}$$

We aim to minimize the number of dead nodes N_d to improve nodes survival rate.

$$\text{Min } \mathrm{N}_d = \sum_{i=0}^{N} S(i) \tag{4}$$

We also aim to charge more nodes to prolong the lifetime of network with high energy usage, thus we need to maximize this metric in the USNs,

$$\text{Max EUE} = \frac{E_{node}}{E_{node} + E_{MS}} \tag{5}$$

Subject to:

$$\mathrm{t}_j = t_i + X_{ij}/v\_s \tag{6}$$

$$T(j)_{deadline} = e_r/re \tag{7}$$

$$T(j)_{deadline} > t_j \tag{8}$$

where E_{node} and E_{MS} are the total energy of MSs used for charging nodes and the energy used by MSs for traveling, respectively, t_i is the arrival time at node i and j is i's next node.

To reduce the energy consumption of MSs caused by returning frequently to the WBS for charging, we introduce a secondary charging station in the USNs. First, according to the number of MSs, we use the k-means algorithm to cluster the USN into $K-1$ clusters. The set of these cluster is denoted by $C = \{C_1, C_2, \ldots\ldots, C_{K-1}\}$. The cluster centers of the $K-1$ clusters are used as the secondary charging stations in USN. These cluster centers are represented by $CS = \{CS_1, CS_2, \ldots\ldots, CS_{K-1}\}$ and we set secondary charging stations at CS for MS_i energy replenishing, so that MS_i only charges the nodes of C_i, and only need be charged by special MS_K at CS_i, where i ranges from 1 to $K-1$.

Theorem 1: Given the WBS, $CS = \{CS_1, CS_2, \ldots\ldots, CS_{K-1}\}$, and $MS = \{MS_1, MS_2, \ldots\ldots MS_{K-1}\}$. The total distance traveled by MSs from CS_i to WBS is denoted as d_D. In the USNs, we know that the MS_i can be charged by the MS_K at CS_i, where $1 \leq i \leq K-1$. The total distance travelled by the MS_K for charging is denoted as d_{cs}. Therefore, we have the theorem: $d_D > d_{cs}$.

Proof: Take $K = 5$ for example. As shown in Fig. 2, we define the distance between the WBS and MS_i as

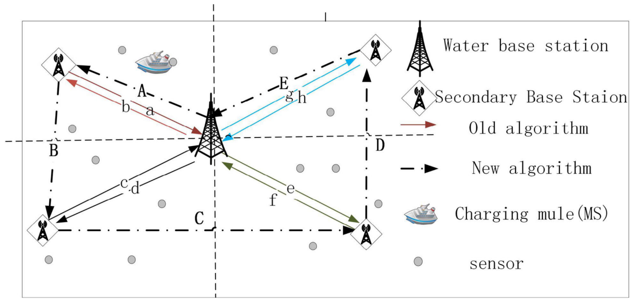


FIGURE 2. Travel path.

d(WBS,MS_1) = a = b = A, d(MS_1,MS_2) = B, d(WBS,MS_2) = c = d, d(MS_2,MS_3) = C, d(WBS,MS_3) = e = f, d(WBS,MS_4) = g = h = E, and d(MS_3,MS_4) = D.

So d_D = a+b+c+d+f+e+h+g, and d_{cs} = A+B+C+D+E.

Fig. 2 reveals that

$$\begin{aligned} b + c &> B, \\ d + f &> C, \\ e + h &> D, \\ a &= A, \\ g &= E \end{aligned} \tag{9}$$

Since b+c+d+f+e+h+a+g>B+C+D+A+E, $d_D > d_{cs}$.

Inference: We can prove $d_D > d_{cs}$ irrespective of the location of the WBS and the value of K.

IV. PROPOSED SCHEME

In this paper, we aim to increase the survival rate of nodes in 3D underwater networks and reduce the traveling cost and improve charging efficiency, and three charging schemes namely SPBS, HCS and mCS-TS are proposed.

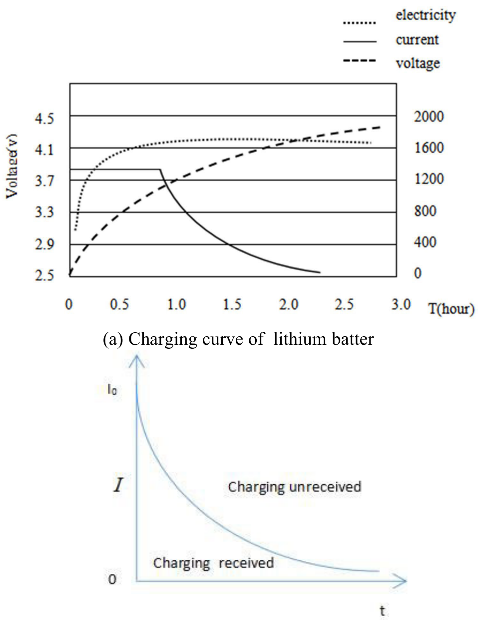
A. SHORTEST PATH PARTICAL CHARGING BASED ON CHARGING CURVE SCHEME (SPBS)

At present, most studies on battery charging are mainly based on the optimal charging curve. Constant current and constant voltage charging mode is usually adopted to charge lithium batteries. In 1972, American scientist J.A. Mas [33] proposed that the battery has the best charging curve during the charging process,

$$I = I_0 e^{\alpha t} \tag{10}$$

where I_0 is the initial charging current of the battery, α is charging acceptance rate; t is the charging time.

The charging process starts with the constant current charging mode, in which the battery voltage is low and the charging current is stable. With the charging process, the voltage gradually rises to 4.5V, and the charger immediately switches to the constant voltage mode. The voltage fluctuation is limited to be less than 1%, and the charging current gradually decreases. When the current drops to certain range and goes into the trickle charging phase, the charger continues



(a) Charging curve of lithium batter

(b) Optimum charging curve

FIGURE 3. **Charging curve.**

to charge the battery at a certain charging rate until the battery is fully charged. Fig. 3(a) shows the charging curve of lithium battery [34], [35].

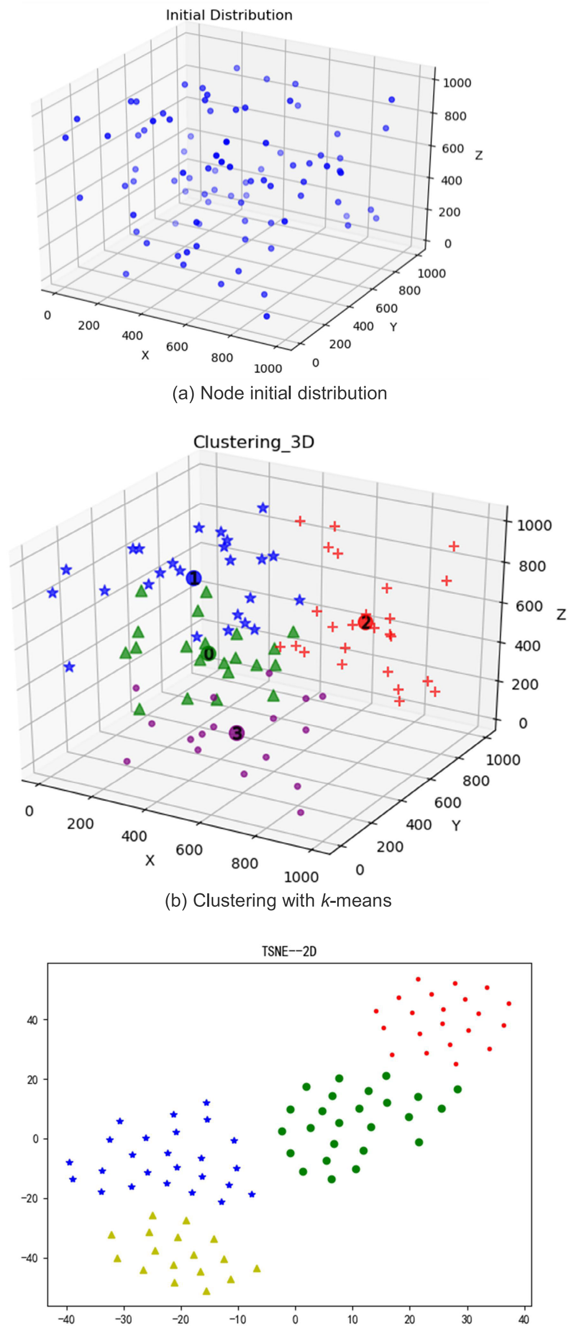
Moreover, some studies have found that a full battery charge at one time or a charge after battery exhaustion could speed up the scrapping of the battery. Fig. 3(b) shows charging characteristic of a lithium battery. If the charging current exceeds this optimal charging curve, the gas outflow of the battery increases, instead of the charging rate. When the charging current is less than this optimal charging curve, it will not harm the battery but the charge time is long and the charging rate is low [29].

Therefore, we improved the shortest-path schemes in [32] and proposed our Shortest Path Partial Charging based on charging curve scheme (SPBS). In SPBS, we set the charging curve threshold is 0.8 which means MSs always charge node to 80%, and then turn to charge next nodes.

Firstly, as the large-scale of underwater environment [35] and limited energy capacity of MS, it is unwise to arrange only one MS to charge nodes, which with lead to high death rate. Thus, we use the k-means algorithm first to cluster the USN into $K-1$ clusters, the set of these cluster is denoted by $C = \{C_1, C_2, \ldots\ldots, C_{K-1}\}$, where we have K MSs in our network, then MS_i only need to charge nodes in C_i.

As shown in Fig. 4, Fig. 4(a) shows the initial placement of about eighty-eight nodes in UANS, then we use k-means algorithm [32] to group our nodes with 4 categories, results are shown in Fig. 4(b). In addition, in order to better display the clustering result, TSNE was used for data dimension reduction (see Fig .4(c)).

The we use our SPBS scheme to charge nodes, the SPBS can be describe as Algorithm1. Originally, we have charging candidate list L, null charging list Q and null dead list D. We define the latest charging node as p, WBS as w, SPBS always choose the node with minimum C_{pj} in L as the next charging node j, when a MS satisfies (2), MS will go to charge node j. After charging finished, we need to update the nodes not in Q and D first, if there are some nodes' energy below 0J, we need to change their state to dead ($S = 0$), then we need to update the remaining energy of MS. Repeat these processes until L is none and we export our charging list Q and dead list D.



(a) Node initial distribution

(b) Clustering with k-means

(c) Data dimension reduction with TSNE

FIGURE 4. **USN sensor nodes.**

Algorithm 1 Shortest Path Partial Charging Based on Charging Curve Scheme (SPBS)

```
Input: Charging candidate list L
Initial: p ← w
Outpu t: Charging list Q, Dead list D,
For all i ← {0 ,. . . . . . ,n}
Find a node j with minimum C_pj in L do
If Eq. (2) and Eq. (5) are satisfied then
    Q ← Q U {j}, charge nodes with charging curve
    L ← L \ {j}
    Update all non-charging nodes ks_k not in Q and D
    If s_k's energy <0 then
        S(k) = 0, D ← D+{k}
    Update MS remaining energy
else:
    Find the next node with minimum C_Pj in L
end if
end for
Return Q, D
```

TABLE 1. Information of charging nodes.

nodes_Id	Latest Charging Time(s)	T_S(s)	R_energy(J)
0	0	4000	0
10	0	4000	0
13	4164.41	6564.41	640
18	0	4000	0
25	0	4000	0
31	0	4000	0
32	0	4000	0
40	2851.85	6051.85	377.48
45	0	4000	0
46	0	4000	0
49	3852.69	6252.69	577.65
63	0	4000	0
66	3243.40	5643.40	455.79
68	3594.26	5994.26	525.96
79	3080.63	5480.63	423.24
85	0	4000	0

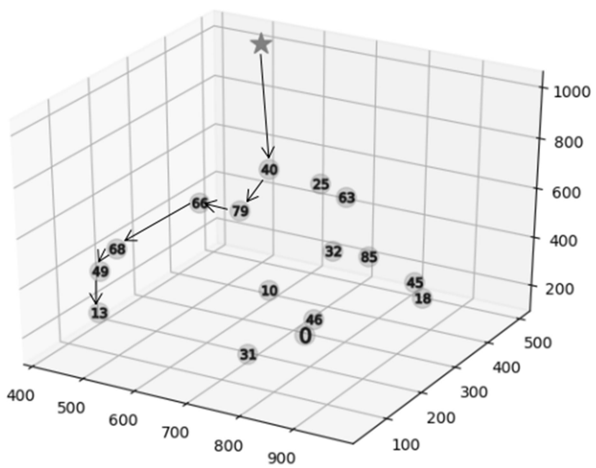


FIGURE 5. USN Charging process of SPBS.

To better understand of our SPBS, we present an example for illustrating the charging process in Fig. 5.

There are 16 nodes are given in a USN. Initially, MS stays at (500, 500, 1000) and we always choose the node j with minimum C_{pj} as the next object. Obviously, $C_{P,40}$ is the smallest through computing. Hence, node 40 will be charged first, then we will choose the next node with minimum cost. Repeat process above, we have the charging list: [13], [40], [49], [66], [68], [79], and the table 1 lists the nodes' latest charging time, dead Time T_S and remaining_energy after charged.

B. THE PROPOSED SCHEMES BASED ON SECONDARY CHARGING STATIONS

In this section, we will address how to decide to recharge a MS_i through the MS_K based on the secondary charging stations. We define the total initial energy of the cluster $C_i \ldots$ as E_{CSi}. At time t, the energy consumed by C_i is denoted as $E_{COCS}(i,t)$. The expressions for these energies are given as follows:

$$E_{CSi} = N^*_{CSi}ea \tag{11}$$

$$E_{COCS}(i,t) = \sum_{k=1}^{Ncsi} re^{i}_{id(k)}{}^{*}t \tag{12}$$

where N_{CSi} stands for the number of the sensors in C_i. The energy consumption rate of a node whose id is $id(k)$ in cluster C_i is given by $re^{i}_{id(k)}$, where $id(k)$ is used to get the index of the k_{th} node.

The residual energy and the time needed for charging of C_i at time t, which are denoted as $E_{rCS}(i,t)$ and $T_{rCS}(i,t)$, respectively, can be calculated as follows:

$$E_{rCS}(i,t) = E_{CSi} - E_{COCS}(i,t) \tag{13}$$

$$T_{rCS}(i,t) = E_{COCS}(i,t)/q\_s \tag{14}$$

The energy consumed in the network also includes the energy consumed by the movement of the MSs, which is denoted as E_{MS}. The distance of MSs traveling is d, therefore, we obtain

$$\mathrm{E}_{MS} = d^{*}c\_s \tag{15}$$

Based on (9) - (12), we have

$$\text{Max } EUE = \frac{E_{node}}{E_{node} + E_{MS}} = \frac{\sum_{i=1}^{K-1} E_{COCS}(i,t)}{\sum_{i=1}^{K-1} E_{COCS}(i,t) + E_{MS}} \tag{16}$$

Algorithm 2 Directly Charging Scheme (DCS)

Input: Cluster set C, Cluster center set CS, Mobile charging ships set MS,
Initial t: the time of applying for charging

Output: The energy achieved by nodes E_{node}, Total consumed time T_total, EUE

1. Calculate D_i, the distance between CSi and WBS,.
2. Sort D_i and put the index to list $Minj$ from $\min(D_i) \rightarrow \max(D_i)$.
3. Calculate the time of first coming MS_i, $t\_arrival = D(Minj[0]) / v\_s + t$, $t\_total = t + t\_arrival$.
4. $E_{node} = ECOCS(i, t\_total)$
5. Calculate the charging time for the first coming MSi, t_charging $= T_{rCS}(i, t\_arrival)$ using (14).
6. Update the current total time: $t\_total = t\_arrival + t\_charging$.
7. **for** number in range(1,len[Minj]):
8. Recalculate the arriving time of the next MS_{next}, update $t\_arrival$
9. **if** ($t\_arrival <= t\_total$):
10. $E_{node1} = E_{COCS}(i, t\_total)$
11. **else**:
12. $E_{node1} = E_{COCS}(i, t\_arrival)$
13. Update $t\_charging1$, t_total, $E_{node} += E_{node1}$
14. Calculate the return time of the last charging cluster, update t_total, and $T\_total = t\_total$
15. Calculate the energy used by MS_i: total energy is E_{MS1}
16. Calculate the energy usage effectiveness using (16)

and we should make sure not all nodes are dying after time t, then we have $E_{CSi} - E_{COCS}(i, t) \geq 0$.

In many proposed algorithms [31], [37], MS_i only charges the nodes of C_i, and stays at CS_i initially, MS_i goes to WBS to recharge when charging tasks are finished, we rename this charging scheme as directly charging scheme (DCS). In DCS, we first need to calculate the distance between CS_i and WBS by euclidean distance algorithm, and the first coming MS_i is chose to be the first charging object. The distance and the charging time are used to update the total using time (*t_total*). Then, we compare the time *t_arrival* needed by the next MS (MS_{next}) traveling from the next nearest cluster center CS_{next}, to the WBS with the *t_total* calculated earlier. If the time to arrive at WBS is less than *t_total*, MS_{next} needs to wait at WBS ... until the previous task is finished; otherwise, we need to wait the coming MS_{next} and *t_total* is updated to *t_arrival*. Afterwards, we calculate the charging energy needed by MS_{next} based on $E_{cocs}(i,t\_total)$ defined in (12). After all the *MSs* are charged, the MS_i goes back. The pseudo-code of this algorithm is shown below.

1) THE PROPOSED HAMILTON CHARGING SCHEME (HCS)

Hamilton path refers to a path that passes through each node just once in a graph G. Finding a Hamilton path has been proved to be a typical NP-complete problem [38]. Based on the idea of the shortest Hamiltonian ring, we propose an Hamilton charging scheme (HCS) for USN.

In our HCS, the MS_i can only be charged by the MS_K at CS_i, $(1 \leq i \leq K-1)$. MS_K starts from WBS, we choose the nearest cluster C_i's MS_i as the first charging object, and the next nearest cluster $C_{nearest}$'s $MS_{nearest}$ which is the nearest to the current cluster as the next object. After all the MSs are charged at CS_i, the MS_K returns to the WBS for recharging. The pseudo-code of this algorithm is shown as follows:

Algorithm 3 Hamilton Charging Scheme (HCS)

Input: Cluster set C, Cluster center set CS, Mobile charging ships set MS, Initial t: the time of applying for charging

Output: The energy achieved by nodes E_{node2}, Total consumed time T_total2, $EUE2$

1. Calculate D_i, the distance between CS_i and WBS.
2. Choose the nearest cluster $C_{nearest}$'s $MS_{nearest}$ as the first charging object.
3. Calculate the time needed by the $\mathrm{MS_K}$ to arrive at CSnearest, $t\_arrival2 = d\ (MS_k, CS_{nearest}) / v\_s + t$
4. $E_{node2} = E_{COCS}(i, t\_arrival2)$
5. Calculate $t\_charging2$: the charging time needed by the current $\mathrm{C_i}$, using (14) with $T_{rCS}(i, t\_arrival)$
6. Then the current total time is updated as t_total2, $t\_total2 = t\_arrival2 +$ t_charging2.
7. **for** i in range(1,K):
8. Choose the nearest cluster $C_{nearest}$'s $MS_{nearest}$ to the current cluster as the next object:
9. Calculate $t\_arrival2 = d(CScurrent, CSnearest)/v\_s$
10. Calculate the energy needed for the next cluster: $E_{node2} = E_{COCS}(i,t\_arrival2 + t\_total2)$
11. Recalculate $t\_charging2$ using (14)
12. Update t_total2, E_{node2}
13. Calculate the travel time of the MS_K from the last charging cluster to the WBS, update t_total2, and $T\_total2 = t\_total2$
14. Calculate the energy used by MS_K: total energy is E_{MS2}
15. Calculate the energy usage effectiveness using (16)

2) THE PROPOSED MCS-TS SCHEME (MCS-TS)

To improve the charging efficiency and extend the life cycle of the USNs, we also propose a temporal and spatial collaborative charging algorithm. This algorithm uses temporal and spatial collaborative charging for underwater sensor networks with MSs. We call it the mCS-TS scheme and it is based on the HCS. It takes the cluster factor and deadline time into consideration to improve the energy usage effectiveness. We define the cluster factor as C_i^f

$$C_i^f = \frac{N_{CSi}}{|N|} \tag{17}$$

where $|N|$ is the total nodes number of USN and N_{CSi} represents the number of sensor nodes in the cluster C_i. A higher C_i^f means more energy is needed for charging. We define the charging deadline and the travel time to the next object as $t\_deadline$ and $t\_arrival3$, respectively. We also define urgent charging factor t_cf, where $t_1 = t\_total3 + t\_arrival3$, t_total3 is the total time needed to finish the current task. In (18), $d_{current,next}$ represents the distance between the current charging and next charging objects.

$$t\_arrival3 = d_{current,next}/v\_s \tag{18}$$

$$t\_deadline = \frac{E_{CSi} - E_{COCS}(ik, t\_total3)}{q\_s} \tag{19}$$

$$t\_cf = \frac{C_i^f/t_1}{t\_deadline} \tag{20}$$

We aim to charge the cluster having the maximum t_cf, as a lower value of t_1^* $t\_deadline$ means that the cluster has nearly run out of energy and has a lower $t\_arrival3$.

Algorithm 4 The Proposed mCS-TS Scheme

Input: Cluster set C, Mobile charging ships set MS, Time t

Output: The energy achieved by nodes E_{node3}, Total consumed time T_total3, $EUE3$, variable k.

1. Calculate D_i., the distance between CS_i and WBS.
2. Initialize lists $\times 3$ and yy_select, $E_{node3} = 0$, $t\_total3 = t$, t_min_l, tt_min_l, $k = K - 1$.
3. **for** mm in range k:
4. $max = 0$
5. **for** ik in range(k):
6. t_min_l is the index of the location of the previous task
7. **if** the next MS_i have not been charged:
8. Calculate C_i^f, $t\_arrival3$, $t\_deadline$, t, and t_cf using (17)-(20)
   if $t\_cf > max$:
   $tt\_min\_l = ik$
   $Max = t\_cf$
9. $E_{node3} = E_{COCS}(i, t)$
10. Put tt_min_l into yy_select; Put the index of this cluster into $x3$.
11. Calculate $E_{node3} += E_{node3}$
12. Update $t\_charging3$, t_total3
13. Calculate the return time of the last charging cluster, update t_total, $T\_total3 = t\_total3$
14. Calculate the energy used by MS_K: E_{MS3}
15. Calculate the energy usage effectiveness using (16)

Similar to the HCS, the MS_i can only be charged by the MS_K at CS_i, ($1 \leq i \leq K - 1$). In our method, MS_K starts from the WBS, we choose the MS having the maximum t_cf as the next charging object, and the MS_K returns to the WBS to recharge after all MS_i are charged. The proposed algorithm is given as follows:

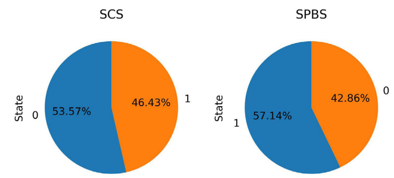


FIGURE 6. Survival rate of SPBS and SCS.

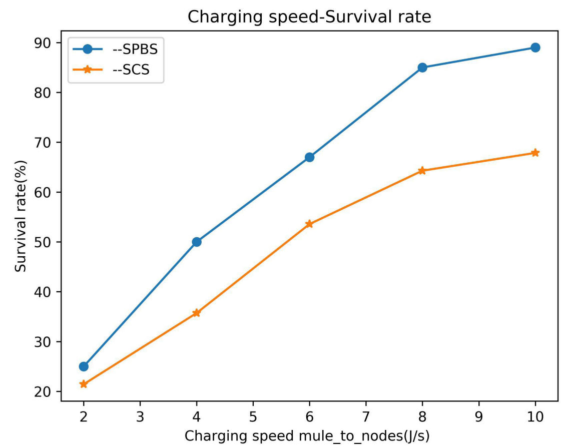


FIGURE 7. Influence of charging speed.

V. PERFORMANCE EVALUATION

To verify the performance of the proposed SPBS, HCS, mCS-TS algorithms, simulation experiments are conducted.

A. SIMULATION SETUP

The target USN has 120 nodes, which are uniformly randomly deployed in a 1km×1km×1km field. The WBS is located at a horizontal and vertical location of (500m, 500m,1000m) from the origin. We follow the settings as in [29], [32] and [39], and assume that the low energy threshold is 0.4, the battery capacity (ea) of each node is 13669J. The battery capacity of a MS is 2000 kJ, and the battery energy of the special MS_K is about 2×10^5 kJ. The speed of each MS (v_s) is 5 m/s and the energy consumption of MS traveling (c_s) is 8 J/m. The wireless charging efficiency (q_s) is by default 2 %.

B. RESULTS

In the following experiments, we vary only one parameter at a time, keeping most of the settings unchanged.

1) SURVIVAL RATE OF NODES

As shown in Fig. 6, we note that the survival rates of SPBS is 10.71 percent larger than those of SCS. The reason is that with the charging curve, we can charge the nodes to 80% energy fast and then charge more nodes.

In Fig. 7, with the increasing number of nodes, the ratio of survival nodes are increasing. The reason with that with the charging speed getting larger, we charge a node with lower time and then we will quickly move to another nodes and charge them in time. In Fig. 8 with the increasing of our

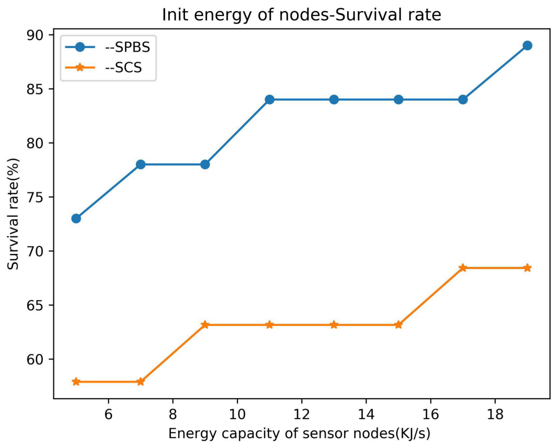
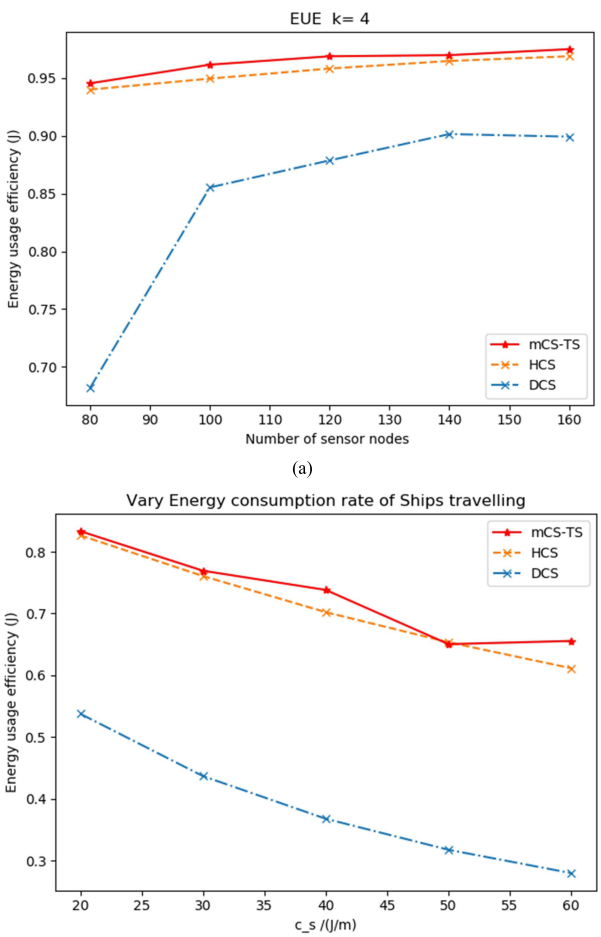


FIGURE 8. **Influence of energy capacity of sensor nodes.**



(a)

(b)

FIGURE 9. **Maximum EUE with diving network into k=4 clusters.(a) vs. numbers of sensor nodes (b) vs. energy consumption of traveling MS.**

nodes' initial energy, our nodes' survival rates will be longer, which gives more times for our MSs charging, and our SPBS algorithm only need to charge nodes to 80% which will save more nodes with low energy in time.

Obviously, our SPBS has greater performance than SCS in the aspect of improving the survival rate of nodes.

2) ENERGY USAGE OF EFFICIENCY

In USNs, we also aim to maximum energy usage of effective. The corresponding results of maximum EUE are shown in Fig. 9. There are five MSs in the network. First, we vary the numbers of sensors from 80 to 160 where we divide our network into 4 ($k = 4$) clusters, and the resulting EUE versus the varying number of sensor nodes is shown in Fig. 9(a). We also vary the c_s and display the resulting EUE versus the varying c_s in Fig. 9(b).

From Fig. 9, we can conclude that our proposed mCS-TS algorithm has better performance than the DCS in terms of EUE. Fig. 9(a) shows that our mCS-TS and HCS have similar EUE and both of them perform better than DCS when nodes become larger. Fig. 9(b) shows that the EUE decreases when the c_s increases, as the traveling cost is higher.

VI. CONCLUSION

In this paper, we focus on extending the lifetime of USNs by effective charging schemes with effective usage of energy and low dead rate of nodes. After study the basic charging algorithm SCS in [32] and the characteristic of charging curve on lithium battery, we first proposed a shortest path partial charging based on charging curve scheme (SPBS) to reduce the dead nodes.

Then we proposed a concept of secondary charging stations for mobile charging ships to reduce the traveling cost and improve charging efficiency. Before charging, we use k-means clustering algorithm first to divide our network with k clusters, and then we place our secondary stations at k clustering centers, in this way, MSs can be charged at secondary stations quickly.

We proposed HCS and a new temporal and spatial collaborative charging algorithm for underwater sensor networks with multiple mobile charging ships and charging stations (mCS-TS) for USNs under considering of the cluster factor and deadline time. Extensive simulations have been performed to evaluate the mCS-TS and HCS and SPBS compare with the existing DCS and SCS. The simulations showed that the our algorithms have higher survival rates and higher energy usage effectiveness. In future, we will merge SPBS and mCS-TS, and then focus on the sleep mechanism of the nodes in the clusters based on secondary charging stations, focus on the computational complexity as well as how to charging nodes more with remaining energy when MSs back.

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