RESEARCH ARTICLE

Achieving energy-neutral data transmission by adjusting transmission power for energy-harvesting wireless sensor networks
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ABSTRACT

Recently, benefiting from rapid development of energy harvesting technologies, the research trend of wireless sensor networks has shifted from the battery-powered network to the one that can harvest energy from ambient environments. In such networks, a proper use of harvested energy poses plenty of challenges caused by numerous influence factors and complex application environments. Although numerous works have been based on the energy status of sensor nodes, no work refers to the issue of minimizing the overall data transmission cost by adjusting transmission power of nodes in energy-harvesting wireless sensor networks. In this paper, we consider the optimization problem of deriving the energy-neutral minimum cost paths between the source nodes and the sink node. By introducing the concept of energy-neutral operation, we first propose a polynomial-time optimal algorithm for finding the optimal path from a single source to the sink by adjusting the transmission powers. Based on the work earlier, another polynomial-time algorithm is further proposed for finding the approximated optimal paths from multiple sources to the sink node. Also, we analyze the network capacity and present a near-optimal algorithm based on the Ford–Fulkerson algorithm for approaching the maximum flow in the given network. We have validated our algorithms by various numerical results in terms of path capacity, least energy of nodes, energy ratio, and path cost. Simulation results show that the proposed algorithms achieve significant performance enhancements over existing schemes. Copyright © 2016 John Wiley & Sons, Ltd.

KEYWORDS
energy harvesting; energy-neutral path; energy-neutral operation algorithm; network capacity

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1. INTRODUCTION

Recently, energy harvesting technologies have received a lot of concerns from researchers and practitioners who aim to relieve energy limitations residing in development of wireless sensor networks. Numerous research works have been carried out on developing the critical techniques on harvesting the ambient environmental energy, such as solar [1], wind [2,3], light and thermal [4], and tree movement [5,6]. The wireless sensor network equipped with an energy harvesting device is called an energy-harvesting wireless sensor networks (EHWSNs). In EHWSNs, restricted by the size limitations of sensor nodes, the harvested energy is limited. Therefore, proper use of the harvested energy has become one of the most critical issues that affect the overall network performance of the EHWSNs. Furthermore, this greatly affects the wide deployment of wireless sensor network-based applications.

Consider an energy-harvesting wireless sensor network as shown in Figure 1(a). For purposes of illustration, the numbers shown in the rectangles are assumed to be the harvested energy from the environment, represented by the number of data packets that can be delivered with the current transmission power. Labels imposed on the links between two network nodes are the cost associated with them. Given 500 packets for transmission, it is easy to figure out that the optimal path is \( \pi_1 : S \rightarrow B \rightarrow D \) by using the Dijkstra’s Shortest Path (DSP) algorithm [7], where \( S \), \( B \), and \( D \) are the source node, the relay node, and the sink node, respectively. But if 1000 packets are
planned for transmitting at the source node $S$, obviously path $\pi_1$ cannot support the data transmission caused by the harvested-energy “bottleneck” of node $B$. Figure 1(b) shows a case that the network can support 1000-packet transmission when the transmission range is changed from the big dashed blue circle to the small one by adjusting the transmission power of node $B$. In the right figure, the optimal path is $S \rightarrow B \rightarrow A \rightarrow D$ and node $B$ doubles the data amount with the lower transmission power, where $A$ is designated as a relay node. In this example, it easily concludes that (1) an efficient method is required for finding the optimal path from single source node to the sink node; (2) when there are multiple source nodes, how to use relay nodes such that the harvested energy of each relay node is sufficient for supporting data transmission by properly adjusting its transmission power; and (3) how to determine the capability of the network in terms of data transmission, that is, the maximum data amount that can be transmitted by the network.

Increasing efforts can be found in literatures that focus on improving the usage of the harvested energy. As for harvested energy awareness for the ambient environment, Zeng et al. [8] proposed two energy aware geographic routing protocols that make routing decision in a localized manner by jointly taking into account channel condition, distance information, residual battery energy, and harvested energy. Eu et al. [9] evaluated the performance of three different geographic routing algorithms and two relay node placement schemes, which emphasize on the optimal combination of routing algorithms and relay node placement schemes with the objective to maximize the required performance metric. Lin et al. [10] explored how to maximize the workload under given environmental constraints. The main idea is to make the nodes with higher harvesting rates more preferable when routing data packets. Meng et al. [11] proposed an adaptive energy harvesting aware clustering routing protocol, which adjusts the cluster head considering the remaining energy and energy harvesting rate for sensor nodes rather than that only considers the remaining energy in the traditional way. Chen et al. [12] investigated the utility maximization problem for sensor networks with energy replenishment, in which they addressed the joint problem of energy allocation and routing to maximize the total system utility, without prior knowledge of the replenishment profile. Nabil et al. [13] proposed a secure efficient routing protocol based on cross-layer design and energy-harvesting mechanism. The parameters residing in different layers are exchanged to ensure efficient use of energy. Some research works also have been carried out on opportunistic routing in EHWSNs in [14,15]. Aiming at achieving high throughput for the EHWSNs, Eu and Tan [14] presented an adaptive opportunistic routing protocol that takes the network conditions and energy availability into account. Beheshhtiha et al. [15] came up with an opportunistic routing algorithm with adaptive harvesting-aware duty cycling. Jakobsen et al. [16] put forward a new adaptive and distributed routing algorithm for finding energy optimized routes in an EHWSN. The concept of energy distance is proposed as a distance that uses the distance penalty to compensate for node with lower energy availability. The distance penalty is a monotonically decreasing function of the energy of each node, which is used for transforming the energy availability to the distance penalty. In all, the majority of these research works are based on the energy states of nodes, and the path is determined according to the network characteristics, such as the physical location and real-time energy status of each node. However, no work refers to the issue of minimizing the overall data transmission cost on the basis of the limited harvested energy by adjusting transmission power for nodes in EHWSNs.

In this paper, we consider the optimization problem of deriving the energy-neutral minimum cost paths (ENMCPs) between the source nodes and the sink node. The main contributions of this paper are as follows: (1) on the basis of energy-neutral operation [1], we present three important concepts for EHWSNs, energy-neutral node, energy-neutral path, and energy-neutral minimum cost path, especially the energy-neutral minimum cost path is first proposed; (2) we propose a polynomial-time algorithm for deriving the energy-neutral minimum cost path between single source node and single sink node and prove that this algorithm achieves the optimal
solution; (3) another polynomial-time algorithm is proposed for finding the approximated optimal paths from multiple source nodes to the sink node; (4) we analyze the network capacity under the energy-neutral constraint and present a near-optimal algorithm to approach the maximum flow through a single-source single-sink network; and (5) extensive experiments are carried out, and the numerical results in terms of path capacity, least energy of nodes, energy ratio, path cost, and so on have been presented to show that the proposed algorithms achieve significant performance enhancements over existing schemes.

The rest of this paper is organized as follows. In Section 2, we state system models and mathematically formulate the optimization problem between the source nodes and the sink node. Then, in Section 3, the polynomial-time algorithms are proposed for deriving the solutions. In Section 4, we analyze the network capacity and propose a near-optimal algorithm for deriving the network capacity. Section 5 conducts the experiments and evaluates the performance of our proposed algorithms. Finally, we conclude the paper in Section 6.

2. PROBLEM STATEMENT

2.1. System models

In the EHWSN, each node has a finite energy buffer that is a battery or an ultracapacitor to store energy. Actually, the energy storage mechanism is not ideal because of the following factors: (1) the energy buffer is limited; (2) the charging efficiency \( \beta \) is strictly less than 1; and (3) the energy buffer is suffered from leakage [1]. Suppose, for node \( v \), the harvesting power from the energy source is \( P_s(v,t) \), and the consuming power at that time is \( P_c(v,t) \) at time \( t \). First, define a rectifier function \([x]^+\) and \([x]^-\) as follows:

\[
[x]^+ = \begin{cases} 
    x, & x > 0 \\
    0, & x < 0
\end{cases} \quad \text{and} \quad [x]^- = \begin{cases} 
    0, & x > 0 \\
    -x, & x < 0
\end{cases} \quad (1)
\]

Then, the energy conservation of node \( v \) on the time interval \([0,T]\) \((T \in [0, \infty))\) can be calculated as

\[
\mathcal{E}(v,0 \leq t \leq T) = \mathcal{E}_0(v,t = 0) + \beta \int_0^T [h(v,t)]^+ dt - \int_0^T [h(v,t)]^- dt - \int_0^T P_{\text{leak}}(v,t) dt \quad (2)
\]

where \( h(v,t) = P_s(v,t) - P_c(v,t) \), \( \mathcal{E}_0(v,t = 0) \) is the initial energy stored in the energy buffer and \( P_{\text{leak}}(v,t) \) is the leakage power for the energy buffer. Note that \( T \) here can be 1 h, 1 day, or any other time period. Then, the harvested energy on the time interval \([0,T]\) can be written as

\[
\mathcal{E}_h(v,0 \leq t \leq T) = \begin{cases} 
    \int_0^T P_s(v,t) dt, & \text{if } h(v,t) \leq 0; \\
    \int_0^T P_s(v,t) dt + \beta \int_0^T h(v,t) dt, & \text{if } h(v,t) > 0
\end{cases} \quad (3)
\]

The harvesting power from the energy source \( P_s(v,t) \) is less than the consuming power \( P_c(v,t) \), while \( h(v,t) \leq 0 \), that is, \( P_s(v,t) \leq P_c(v,t) \). Thus, the harvested energy on the time interval \([0,T]\) is \( \int_0^T P_s(v,t) dt \), which is entirely consumed. On the other hand, if \( h(v,t) > 0 \), that is, \( P_s(v,t) > P_c(v,t) \), then the harvesting power from the energy source \( P_s(v,t) \) is more than the consuming power \( P_c(v,t) \). Thus, one part of the harvested energy has been consumed \( \left( \int_0^T P_c(v,t) dt \right) \), and the other has been stored \( \left( \beta \int_0^T h(v,t) dt \right) \), where \( \beta \) is the charging efficiency. Specifically, as the harvested energy may exceed the buffer capacity, the excess energy has been depreciated. Thus, we do not involve the “overflow” energy in the derivation of the harvested energy for Equation (3).

As for energy consumption, we adopt the free space propagation model in the wireless sensor network [17]. The path loss \( L_{fs} \) between two nodes can be expressed as

\[
[L_{fs}] (dB) = 32.44 + 20 \log d (km) + 20 \log f (MHz) \quad (4)
\]

where \( L_{fs} \) is the transmission loss, \( d \) is transmission distance, and \( f \) is the carrier frequency. The signal strength attenuates as a function of distance from the transceiver to the receiver, which is calculated quantitatively according to Equation (4). The received signal can be detected and decoded correctly under the condition that the signal strength received by the receiver is above the receiving sensitivity threshold \( R_s \), which is described as the following formula [18]:

\[
P_c(v,t) - L_{fs} \geq R_s \quad (5)
\]

Then, the consumed energy \( \mathcal{E}_c(v,0 \leq t \leq T) \) of node \( v \) running with power \( P_c(v,t) \) during time interval \([0,T]\) can be calculated as

\[
\mathcal{E}_c(v,0 \leq t \leq T) = \int_0^T P_c(v,t) dt + \int_0^T P_{\text{leak}}(v,t) dt \quad (6)
\]

Here, during time interval \([0,T]\), power \( P_c(v,t) \) may experience the duration of sleep, listening, transmission, or receiving mode.

Further, an EHWSN can be modeled as a directed graph \( G(V,E(t)) \) at time \( t \) with node set \( V \) and link set \( E(t) \), where \( u \in V \) represents a node within the network, and a link \((u,v) \in E(t)\) means the fact that node \( v \) is within the communication radius of node \( u \) and can hear from \( u \) directly at time \( t \). \( S = \{ S_i \}_{i=1} \) are all the source nodes that collect the information of interest and send back to...
the sink node $D$, where $r$ is the number of source nodes. We define power profile $P_i(t)$ and $P_{r}(t)$ as the vector of all the nodes’ harvesting powers and transmission powers at time $t$, respectively. As for data delivery, for each node, it has $l$ transmission power levels, $E = \{e_{i}\}_{i=1}^{l}$, with $e_{1} < e_{2} < \ldots < e_{l}$. For each node $u \in V$, let $P_{r}(u,t) = e_{r}$, and we derive a network with maximum number of links, denoted by $G(V,E_{\text{max}})$. The graph induced by power profile $P_{r}(t)$ is a subgraph of $G(V,E_{\text{max}})$, denoted by $G(V,E(t))$.

### 2.2. Problem formulation

Before going further, we first introduce an important concept of energy-neutral operation, which describes a node that uses the harvested energy at an appropriate rate such that the system continues to operate perennially, proposed by Kansal et al. in [1]. On the basis of this concept, we present the following definition.

**Definition 1** (Energy-neutral node). During time interval $[0,T]$, node $v$ achieves the energy-neutral operation if its harvested energy $E_{h}(v,0 \leq t \leq T)$ and consumed energy $E_{c}(v,0 \leq t \leq T)$ satisfy

$$E_{h}(v,0 \leq t \leq T) \geq E_{c}(v,0 \leq t \leq T) \quad (7)$$

where $E_{h}(v,0 \leq t \leq T)$ and $E_{c}(v,0 \leq t \leq T)$ are calculated with Equations (3) and (6), respectively. Node $v$ is the so-called energy-neutral node.

Further, energy-neutral path is defined as follows.

**Definition 2** (Energy-neutral path). Let $\pi_{i}$ be a path in $G(V,E(t))$. Path $\pi_{i}$ is called an energy-neutral operation path if each node on this path achieves energy-neutral operation, that is,

$$E_{h}(v,0 \leq t \leq T) \geq E_{c}(v,0 \leq t \leq T) \quad \text{for each } v \in \pi_{i} \quad (8)$$

Denote by $c_{i}(u,v)$, the cost of link $(u,v)$ at time $t$ and then the path cost of $\pi_{i}$ can be calculated as

$$c(\pi_{i},t) = \sum_{(u,v) \in \pi_{i}} c_{i}(u,v) \quad (9)$$

Each node has $l$ transmission power levels, each of which determines the number of neighboring nodes of the node. The node usually has more neighboring nodes when it chooses higher transmission power level. Let $P_{r}(S_{i} \leftrightarrow D)$ denote the set of all available paths between source node $S_{i}$ and sink node $D$ in $G(V,E(t))$. Path $\pi_{i}$ is called the ENMC if, given transmission tasks and energy harvesting rates of nodes, $\pi_{i}$ achieves the minimum cost among all energy-neutral paths. Now, we consider the optimization problem of how to find the energy-neutral paths from all source nodes $S = \{S_{i}\}_{i=1}^{r}$ to the sink node $D$ such that the overall transmission cost for delivering all packets generated by those source nodes is minimized. Let $G_{i}$ be the data amount that would be imposed on path $\pi_{i} \in P_{r}(S_{i} \leftrightarrow D)$ on time interval $[0,T]$. Then, the optimization problem earlier can be described mathematically as

**Main Problem**

$$\min_{\pi_{i}} \sum_{i=1}^{r} c(\pi_{i},t) \cdot G_{i}$$

s.t.: $\{ \pi_{i} \in P_{r}(S_{i} \leftrightarrow D), \quad E_{h}(v,0 \leq t \leq T) \geq E_{c}(v,0 \leq t \leq T) \}$

for each $v \in V$ \quad (10)

where $E_{h}(v,0 \leq t \leq T)$ denotes the consumed energy of node $v$ on path $\pi_{i}$ ($i = 1,2,\ldots, r$). It is worthy to be mentioned that power profile $P_{r}(t)$ has $l^{|V|}(l > 2)$ states, that is, graph $G(V,E_{\text{max}})$ has $l^{|V|}$ subgraphs. This results in intractable computational complexity for enumerating all subgraphs. Therefore, developing an efficient algorithm for finding the optimal paths among subgraphs is necessary.

### 3. SOLUTION METHOD

In this section, we first consider the special case, in which collected data are delivered from the single source to the sink, of Main Problem (10) and present an optimal algorithm for it. Then, considering that Main Problem (10) can be reduced to a Subgraph Isomorphism problem [19], which is non-deterministic polynomial-time hard (i.e., NP-hard), we develop an algorithm for deriving the near optimal solution based on the aforementioned algorithm, where the definition of NP-hard is restated as follows.

**Definition 3** (NP-hard [20]). A problem H is NP-hard if and only if there is an NP-complete problem L that is polynomial time Turing-reducible to H (i.e., L $\leq_T$ H).

In other words, L can be solved in polynomial time by an oracle machine with an oracle for H.

#### 3.1. Data transmitting from single source

We consider the special case of the main problem of minimizing data transmission cost between the single source and the sink by properly adjusting transmission power level of each node such that every node achieves the energy-neutral operation, that is, we consider the optimization problem for deriving the ENMC between source node $S_{i}$ and sink node $D$, which can be simplified from Equation (10) as

$$\min_{\pi_{i}} c(\pi_{i},t) \cdot G_{i}$$

s.t.: $\{ \pi_{i} \in P_{r}(S_{i} \leftrightarrow D), \quad E_{h}(v,0 \leq t \leq T) \geq E_{c}(v,0 \leq t \leq T) \}$

for each $v \in V$ \quad (11)
First, we obtain $G(V, E_{\text{max}})$ by setting $P_c(v, t) = \tau_i$ for each $v \in V$. Then, the minimum cost path $\pi_i$ between source node $S_i$ and sink node $D$ is derived by using DSP algorithm. Initialize $N \leftarrow \emptyset$. Check the expected harvested energy $\hat{E}_h(v, 0 \leq t \leq T)$ and the expected consumed energy $\hat{E}_c(v, 0 \leq t \leq T)$ for each $v \in \pi_i$. If $\hat{E}_h(v, 0 \leq t \leq T) \geq \hat{E}_c(v, 0 \leq t \leq T)$ for any $v \in \pi_i$, then the derived path $\pi_i$ is the ENMCP. Otherwise, put the node that satisfies $\hat{E}_h(v, 0 \leq t \leq T) < \hat{E}_c(v, 0 \leq t \leq T)$ on path $\pi_i$ into set $N$. Denote by $P_c(v, t) = \tau_i$ the current power level of node $v$ at time $t$. Then, for each $v \in N$, remove node $v$ from $G(V, E(t))$ if $P_c(v, t) = \tau_i$; otherwise $P_c(v, t) = \tau_{i-1}$, where $\tau_{i-1}$ implies that the power is reduced to a lower level of $\tau_i$. Here, a subgraph of $G(V, E_{\text{max}})$ is obtained by using the new power profile $P_i^t(t)$. Then, the aforementioned procedures are repeated until the ENMCP is derived. The pseudo-code of aforementioned procedure is presented in Algorithm 1.

### Algorithm 1 Deriving the ENMCP between $S_i$ and $D$.

**Require:** $G(V, E_{\text{max}})$, harvesting and transmission power profile $P_i^t(t)$ and $P_i(t)$, given data amount $G_i$ of $S_i$.

1: while at least one path exists between $S_i$ and $D$ do
2: Find the minimum cost path $\pi_i$ by using DSP algorithm.
3: $N = \emptyset$
4: for each $v \in \pi_i$ do
5: Calculate $\hat{E}_h(v, 0 \leq t \leq T)$ and $\hat{E}_c(v, 0 \leq t \leq T)$
6: if $\hat{E}_h(v, 0 \leq t \leq T) < \hat{E}_c(v, 0 \leq t \leq T)$ then
7: $N = N \cup \{v\}$
8: end if
9: end for
10: if $N = \emptyset$ then
11: Break
12: else
13: for each $v \in N$ do
14: Remove $v$ from $G(V, E(t))$ if $P_c(v, t) = \tau_i$; otherwise $P_c(v, t) \leftarrow \tau_{i-1}$
15: end for
16: end if
17: end while
18: return $\pi_i$

As for computational complexity of Algorithm 1, running the DSP algorithm takes $O(\|V\|^2)$ time. After the minimum cost path $\pi_i$ is found, we implement the procedure of removing the nodes from $V$ at most $|V|$ times and adjusting transmission power at most $l \times |V|$ times. Therefore, the overall computational complexity of Algorithm 1 is $O(l \times |V|^3) = O(l|V|^3)$.

### Proposition 1.

Algorithm 1 achieves the optimal path.

**Proof.** We will prove this proposition in the Appendix for a better flow of the paper.

### 3.2. Data transmitting from multiple sources

Considering the NP-hardness of the main problem Equation (10), here we aim to develop an efficient algorithm for deriving an approximate solution based on Algorithm 1. The main idea of this approximate algorithm is described as follows. Initialize $\Pi = \emptyset$. Without loss of generality, assume that the source nodes $\{S_i\}_{i=1}^r$ are sorted in descending order of $G_i$ as $G_1 > G_2 > \cdots > G_r$. Let the available harvested energy $\hat{E}_{\text{ava}}(v, 0 \leq t \leq T) = \hat{E}_h(v, 0 \leq t \leq T)$ for each node $v$. For a given source node $S_j$, node set $N'$ and $N''$ are initialized as $\emptyset$. The minimum cost path $\pi_j$ is derived by running the DSP algorithm. If $\pi_j$ achieves energy-neutral operation, that is, $\hat{E}_{\text{ava}}(v, 0 \leq t \leq T) \geq \hat{E}_c(v, 0 \leq t \leq T)$ for each $v \in \pi_j$, add $\pi_j$ into path set $\Pi$. For each node $v \in \pi_j$, update their available harvested energy as

$$\hat{E}_{\text{ava}}(v, 0 \leq t \leq T) = \hat{E}_{\text{ava}}(v, 0 \leq t \leq T) - \hat{E}_c(v, 0 \leq t \leq T)$$

Otherwise, check the nodes that cannot achieve energy-neutral operation. If $v \in \Pi$ or $P_c(v, t) = \tau_i$, $N' \leftarrow N' \cup \{v\}$; else, $N'' \leftarrow N'' \cup \{v\}$. Next, let $P_c(v, t) = \tau_{i-1}$ for each $v \in N''$. Repeat earlier procedures until $\pi_j$ achieves the energy-neutral operation. The energy-neutral paths for other source nodes are derived following the same steps. The details of the pseudo-code for this procedure are shown in Algorithm 2.

For computational complexity, running the DSP algorithm takes $O(|V|^2)$ time, and we run the DSP algorithm $r \times l \times |V|$ times. Therefore, the overall computational complexity of Algorithm 2 is $O(r \times l \times |V|^3) = O(r|V|^3)$.

### 4. DISCUSSIONS ON NETWORK CAPACITY

In the last section, we develop two efficient algorithms for deriving the approximate solutions from one or multiple source nodes to the sink node. Considering the limited capability on energy collecting and energy storing, it is critical to determine the network capacity that is defined as the maximum data amount that can be transmitted by the harvested energy of sensor nodes with properly adjusting the transmission power levels of sensor nodes.

#### 4.1. Analysis of network capacity

Before going into the technical details, we first explain that the case of data transmitting from multiple sources can be transformed into the case of data transmitting from single source. Considering a multi-source single-sink network, we transform it into a single-source single-sink network by adding a consolidated source connecting to each source in $\{S_i\}_{i=1}^r$ [21]. The transformation process is shown in...
Algorithm 2 Deriving the ENMCPs between $S$ and $D$.

Require: network $G(V, E(t))$, harvesting and transmission power profile $P_h(t)$ and $P_e(t)$, given data amount \( \{G_i\}_{i=1}^r \) of source nodes

1: \( \Pi \leftarrow \emptyset \)
2: For each \( v \in V \), calculate \( E_h(v, 0 \leq t \leq T) \) and \( E_{aux}(v, 0 \leq t \leq T) \leftarrow E_h(v, 0 \leq t \leq T) \)
3: for \( j = 1 \) to \( r \) do
4: \( V' \leftarrow \emptyset \)
5: while the ENMCP for node \( S_j \) is not found do
6: \( V'' \leftarrow \emptyset \)
7: Derive the minimum cost path \( \pi_j \) for \( S_j \) in \( G(V', E(t)) \) by using the DSP algorithm
8: if \( E_{aux}(v, 0 \leq t \leq T) \geq E_h(v, 0 \leq t \leq T) \) for each \( v \in \pi_j \) then
9: \( \Pi = \Pi \cup \{\pi_j\} \)
10: Update \( E_{aux}(v, 0 \leq t \leq T) \) with Eq. (12) for each \( v \in \pi_j \)
11: Break
12: else
13: for \( v \in \pi_j \) do
14: Calculate \( E_e(v, 0 \leq t \leq T) \)
15: if node \( v \) satisfies \( E_{aux}(v, 0 \leq t \leq T) < E_e(v, 0 \leq t \leq T) \) then
16: \( V' \leftarrow V' \cup \{v\} \) if \( v \in V \) or \( P_e(v, i) = \tau_j \)
17: \( V'' \leftarrow V'' \cup \{v\} \) if \( v \notin \Pi \) and \( P_e(v, i) \neq \tau_j \)
18: \( P_e(v, i) \leftarrow \tau_{j-1} \) for each \( v \in V'' \)
19: end if
20: end for
21: end if
22: end while
23: end for
24: return \( \Pi \)

Figure 2, where \( S \) is the consolidated source, and the link connecting \( S \) and \( S_i \) is represented as \((S, S_i)\), \( i = 1, 2, \ldots, r \). Therefore, in the following, we just consider the case of data transmission from the single source.

Let \( \mathcal{V}(P_e(t)) \) denote the flow originating from the source under the power profile \( P_e(t) \), \( P_e(t) \) represent the power profile set, that is, \( P_e(t) = \{P_e(t_1), P_e(t_2), \ldots, P_e(t_n)\} \) and \( P_e(v_i, v_j) \) be the constraint of link \((v_i, v_j)\) under the power profile \( P_e(t) \). Then, the problem of finding the maximum capacity of the network can be described mathematically as

\[
\max_{P_e(t) \in \mathcal{V}(t)} \{\max_{v \in V} \mathcal{V}(P_e(t))\}
\]

s.t.: \[
\sum_{(v_i, v_j)} f_{ij} - \sum_{(v_i, v_j)} f_{ji} = \begin{cases} \mathcal{V}(P_e(t)), & \text{if } v_i = S \\ 0, & \text{if } v_i \neq S, D \\ -\mathcal{V}(P_e(t)), & \text{if } v_i = D \end{cases}
\]
\( 0 \leq f_{ij} \leq r_{ij}(P_e(t)) \)

(13)

Because each node has \( l \) power levels, we totally have \( l^r \) combinations of the power levels of \( n \) sensor nodes, that is, the original network has \( l^r \) subgraphs in total. Because enumerating all subgraphs is NP-hard [19], we propose an algorithm based on the Ford-Fulkerson algorithm for deriving the approximate capacity of the network.

4.2. Deriving the approximate network capacity

In this subsection, we will develop an approach for finding the approximate network capacity. We first initialize the network by assigning the transmitting power level for each node as \( \tau_j \), that is, \( P_e(v, i) = \tau_j \) for each \( v \in V \). Because each node has \( l \) transmission power levels and only one node’s transmission power level is adjusted each time, we traverse \((l-1) \times n \) subgraphs in total. Set \( \mathcal{P} \) is utilized to store the nodes whose power level has achieved \( \tau_j \). \( \mathcal{F} \) denotes the max flow of these subgraphs.

To achieve energy-neutral operation, let the harvested energy of nodes be the constraint. Before going further, the directed network is required to be converted into another graph for applying the Ford-Fulkerson algorithm. Here, we restate to the procedures proposed in [22] for facilitating the usage of the Ford-Fulkerson algorithm. In \( G(V, E(t)) \), for each node \( u \in V \), we split node \( u \) into two nodes: \( u_{in} \) and \( u_{out} \), where \( u_{in} \) is the incoming node while \( u_{out} \) is the outgoing node. Then we add arc \((u_{in}, u_{out})\) to connect \( u_{in} \) and \( u_{out} \), which can be simply represented as \( (u_{in}, u_{out}) \).

The link constraint of \((u_{in}, u_{out})\) is the data amount that can be transmitted by the harvested energy of node \( u \), while the constraint for the other arcs in \( E \) is set up to \( M \) (\( M \) is usually large enough without restricting the flow of the network data). Also, the arc cost of \((u_{in}, u_{out})\) is set to 0, and the other arcs have the same cost to their original link in \( E(t) \). Then, denote as \( G(N, \mathcal{F}(t)) \) the new network after preprocessing with earlier procedures.

Here, we give a simple example for illustrating the preprocessing procedures as shown in Figure 3. In Figure 3(a), it shows the initial directed network graph. The number labeled on each link denotes the cost, while the number located in each rectangle represents the data amount in
terms of the number of packets that can be delivered with the harvested energy. For node \( a \), it has been split into \( a_{in} \) and \( a_{out} \). The link constraint of \((a_{in}, a_{out})\) is 200, and the link cost of \((a_{in}, a_{out})\) is 1. The link constraint \( M \) on the other links is set up to 900. Then, the new network converting from Figure 3(a) is shown in Figure 3(b).

With the converted graph \( G(N, A(t)) \) earlier, the Ford-Fulkerson algorithm is adopted to find the max flow \( M \) of \( G(N, A(t)) \). On the one hand, if we achieve \( M = 0 \) on the current graph \( G(N, A(t)) \), it implies no flow exists from source node \( S \) to sink node \( T \). Thus, \( v_k \leftarrow \arg \max_{v \in \mathcal{V} \setminus \mathcal{P}} y(v, t) \) is chosen and let the transmission power level \( \tau_z \) of node \( v_k \) be \( P_c(v_k, t) = \tau_z+1 \). Here, we define \( y(v, t) \) as the functional time that node \( v \) could survive until it runs out of its harvested energy, that is,

\[
y(v, t) = \frac{E_h(v, 0 \leq t \leq T)}{P_c(v, t)}
\]  

(14)

where \( E_h(v, 0 \leq t \leq T) \) can be calculated with Equation (3). On the other hand, if we obtain \( M > 0 \), put the nodes of flow \( M \) into set \( \mathcal{L} \). Then we choose node \( v_k \leftarrow \arg \max_{v \in \mathcal{L} \setminus \mathcal{P}} y(v, t) \) and let \( P_c(v_k, t) = \tau_z+1 \). If \( v_k \) satisfies \( P_c(v_k, t) = \tau_z \), we add node \( v \) into set \( \mathcal{P} \) considering that its transmission power cannot be improved. Now, we compare \( \mathcal{F} \) and \( M \), let \( \mathcal{F} = M \) if \( M > \mathcal{F} \). Repeat the aforementioned procedures until we traverse all of the \( l \times (n-1) \) subgraphs. The pseudo-code of this algorithm is presented in Algorithm 3.

Algorithm 3 Deriving the approximate capacity of the network.

Require: network \( G(V, E(t)) \), harvesting and transmission power profile \( P_h(t) \) and \( P_c(t) \)
1: Set \( P_c(v, t) = \tau_z \) for each \( v \in \mathcal{V}, \mathcal{P} \leftarrow \emptyset \) and \( \mathcal{F} = 0, j = (l - 1) \times n \\
2: for i = 1 to j do \\
3: \( G(V, E(t)) \rightarrow G(N, A(t)) \) \\
4: Find the max flow \( M \) for \( G(N, A(t)) \) with the Ford-Fulkerson algorithm \\
5: if \( M = 0 \) then \\
6: \( v_k \leftarrow \arg \max_{v \in \mathcal{V} \setminus \mathcal{P}} y(v, t) \) \\
7: else \\
8: \( L \leftarrow \emptyset \) \\
9: Put the nodes which flow \( M \) passes through into set \( L \) \\
10: \( v_k \leftarrow \arg \max_{v \in \mathcal{V} \setminus \mathcal{P}} y(v, t) \) \\
11: end if \\
12: \( P_c(v_k, t) = \tau_z+1 \) \\
13: if \( P_c(v_k, t) = \tau_z \) then \\
14: \( \mathcal{P} \leftarrow \mathcal{P} \cup \{v_k\} \) \\
15: end if \\
16: if \( M \geq \mathcal{F} \) then \\
17: \( \mathcal{F} = M \) \\
18: end if \\
19: end for \\
20: return \( \mathcal{F} \)

For the computational complexity, as the Ford-Fulkerson algorithm takes \( O(|\mathcal{V}| \times |\mathcal{E}|^2) \) and we run Ford-Fulkerson algorithm at most \( l \times |\mathcal{V}| \) times. So the computational complexity of Algorithm 3 is \( O(l \times |\mathcal{V}| \times |\mathcal{V}| \times |\mathcal{E}|^2) = O(|\mathcal{V}|^3|\mathcal{E}|^2) \). Meanwhile, the computational complexity of enumerating method to achieve the maximum network capacity is \( O(|\mathcal{V}| \times |\mathcal{V}| \times |\mathcal{E}|^2) \). We can see that it is not practical for its exponentially growing characteristic.

4.3. Relations of the proposed algorithms

We develop Algorithms 1 and 2 to search the energy-neutral minimal cost paths for the single-source single-sink and multi-source single-sink networks, respectively. Algorithm 1 is proposed to search a single path for the network, and Algorithm 2 is an extension for multiple source nodes in the network. As for multiple paths, if any pair of paths does not share the same node, Algorithm 1 can be used repeatedly instead of running Algorithm 2. Otherwise, only Algorithm 2 can be adopted to search the multiple energy-neutral paths.

As for Algorithm 3, it aims to derive network capacity by adding the amount of data packets on the paths step by step [23]. According to the max flow min cut theorem [1], if we impose a given amount of data gradually and adopt Algorithm 1 to search the energy-neutral path,
the network capacity is equivalent to finding the corresponding amount of transmitted data until the energy-neutral path cannot be found. Algorithm 1 searches energy-neutral path from the local perspective, while Algorithm 3 focuses on the combined use of paths from the global view. Moreover, Algorithm 3 finds an upper bound for the network in the theoretical.

It is worthy to mention that our proposed algorithms work in a centralized fashion that is also adopted by some other works [24,25]. Because our algorithms are data-driven, that is, once the amount of transmission data and the harvesting profile have been determined, the routing paths can be figured out with an offline way. As for large-scale networks, it can be divided into many small networks by some existing approaches, for example, LEACH (low-energy adaptive clustering hierarchy) [26]. Then, for each small network, our proposed centralized algorithms can be applied effectively.

5. PERFORMANCE EVALUATION

During the simulations, we randomly distribute sensor nodes over a square field. Each node is equipped with an energy buffer with initial energy of 2000 J and the buffer size of 7700 J [1]. The time period $T$ is set as 1 day. Each time source node $S_i$ generates 200 KB (kilo-byte) packets of the collected data and transmits them to the sink node $D$ via the chosen multi-hop path. According to [18], each node is supposed to have eight transmission power levels as 0.001, 0.0316, 0.1, 0.3162, 1, 3.1623, and 5.0119 mW, the receiving sensitivity is set up to $-100$ dBm, and the carrier frequency is 433 MHz. We adopt the idea of Sensor-MAC [27], a request to send/clear to send protocol using duty cycle to control the listening and sleeping period. In our simulations, the Distributed Energy Harvesting Aware Routing (DEHAR) algorithm [16] and DSP algorithm (Dijkstra) are selected for comparison with our proposed energy-neutral operation scheme (Neutral). The DEHAR algorithm [16] derives the energy optimized route from the source node to the sink node with energy distance, which takes the available energy of each node and physical distance into account. The DSP algorithm is used to find the shortest path to the sink from the source node without considering node energy.

We assume that each node is able to gather its local information including the position of the node via the special hardware (for example, GPS module) or localization service provided by the network [28,29]. Then it sends a signaling message including local information to the sink node. Here, sink node or some other node may act as a control node for deriving the optimal path with collected global information of sensor nodes. Usually, compared with data transmission, the exchange of local information consumes a rather small part of energy. And the route discovery is usually executed with a long-time cycle. Hence, we do not consider the energy consumption for information exchange in this paper. Also, we suppose that the sink node is equipped with enough energy and will not run out of energy, which is the same as that used in other studies [30,31].

5.1. Data transmission from single source

The experiments are carried out on the network with 200, 250, 300, 350, 400, and 450 nodes randomly distributed over a $400 \times 400$ m$^2$ field. The source and sink nodes are located at the opposite side of the field.

To illustrate the found paths, we present the routing paths derived from the Dijkstra, DEHAR, and Neutral schemes, respectively, in Figure 4. This instance shows a network with 250 nodes randomly scattered over a $400 \times 400$ m$^2$ field, where harvested energy of each node is normalized and displayed from low (blue) to high (red). It is observable that Dijkstra algorithm concludes the minimum cost path because of its shortest path characteristic. The DEHAR algorithm selects its routing path according to the energy distance that is collaboratively determined by the harvested energy and location information of each node. Our proposed algorithm makes a tradeoff between the path length and harvested energy of each node, in order to achieve the energy-neutral operation.

We collect the results of the capacity of the derived paths by using three schemes. It can be observed that in Figure 5(a), our proposed scheme outperforms the other two schemes in terms of path capacity, where path capacity is defined as the number of packets per minute that path can transmit. This illustrates that the path derived from our proposed scheme can transmit more data than the other two schemes. It is also observed that our energy-neutral scheme outperforms two reference schemes over average 393.19% and 128.18% enhancements, respectively, compared with the Dijkstra and DEHAR schemes. We also compare the least energy of nodes on the selected paths at the data

![Figure 4. Routing paths derived from the Dijkstra, DEHAR, and Neutral schemes, where the network is scattered randomly with 250 nodes over a $400 \times 400$ m$^2$ field where the harvested energy is not uniformly distributed.](image-url)
packet rate of 140 packets per minute. Figure 5(b) shows the results of the least energy of nodes in four days, where the black dashed line is the baseline for the initial energy of 2000 J in the energy buffer. The harvested energy of each node is randomly generated each day considering the environment variation. It is observable that only our proposed scheme can always stay above the baseline. Although the DEHAR scheme achieves the energy-neutral operation in the third day, it cannot guarantee the energy-neutral operation all the time. That is because this scheme heavily depends on the harvested energy of each node. Considering that the nodes on the routing path derived by our neutral scheme should satisfy energy-neutral operation according to Algorithm 1. Thus, the least energy of nodes on the selected path is determined by the node whose energy is closest to the baseline.

To validate the performance of our proposed method in statistics, we exploit the student’s t test for deriving the confidence intervals for the path capacity. Suppose we have the optimal values of \(x_1, x_2, \ldots, x_n\) with the mean \((\mu)\) after running \(n\) tests. The standard deviation of the parameter distribution (standard error) is \(\sigma\). According to literature [32], we can compute the \((1-\epsilon)\) confidence interval of the optimal value \(x\) as

\[
\mu - \frac{B\sigma}{\sqrt{n}} \leq x \leq \mu + \frac{B\sigma}{\sqrt{n}}
\]  

where \(B\) is the critical value with significance level \(\epsilon\), which can be found from the appendix B “The t Distribution” in [32].

We have carried out 100 tests for the scenario of data transmitting from single source (Section 5.1) and presented the results in terms of path capacity in Figure 6. In this figure, it can be observed that our proposed Neutral scheme achieves average 312.98% and 50.43% enhancements, compared with the Dijkstra and DEHAR schemes.
Achieving energy-neutral data transmission for EHWSNs

Figure 6. The results of path capacity for 100 tests derived by Dijkstra, DEHAR, and Neutral schemes, respectively.

<table>
<thead>
<tr>
<th>Confidence levels</th>
<th>Dijkstra</th>
<th>DEHAR</th>
<th>Neutral</th>
</tr>
</thead>
<tbody>
<tr>
<td>99%</td>
<td>(19.390, 26.688)</td>
<td>(53.609, 72.888)</td>
<td>(89.821, 100.470)</td>
</tr>
<tr>
<td>95%</td>
<td>(20.282, 25.796)</td>
<td>(55.966, 70.531)</td>
<td>(91.123, 99.168)</td>
</tr>
<tr>
<td>90%</td>
<td>(20.732, 25.346)</td>
<td>(57.154, 69.342)</td>
<td>(91.780, 98.511)</td>
</tr>
</tbody>
</table>

Figure 7. Comparison of the consumed energy and harvested energy of the nodes on the selected path derived from our proposed scheme.

Also, according to Equation (15), we have derived the 90%, 95%, and 99% confidence levels of path capacity under different schemes and show the results in Table I. From Table I, it can be observed that our neutral scheme performs better than the other two schemes from 90%, 95%, and 99% confidence levels. Therefore, the results in statistics sufficiently illustrate the effectiveness of our proposed method.

5.2. Data transmission from multiple sources

This set of experiments aims at evaluating the performance of our proposed scheme between multi-source nodes and single sink node and has been carried out on a 200-node network randomly distributed over a 1000 × 1000 m² field. In this network, 10 nodes are randomly selected as the...
source nodes. Then, we collect the results of the consumed energy and harvested energy of the network nodes. Figure 7 shows the harvested energy and consumed energy of the nodes on the selected paths derived from our proposed scheme. It is remarkably observed that the harvested energy is more than the consumed energy, that is, our proposed scheme successfully achieves the energy-neutral operation. Next, we evaluate the performance by comparing the results with the other two schemes. Here, a new definition is proposed for performance comparison.

**Definition 4 (Energy ratio).** For each node $v$, the energy ratio ($\eta$) of node $v$ is the ratio of the consumed energy to the harvested energy on the time interval $[0, T]$, that is,

$$\eta = \frac{\xi_c(v, 0 \leq t \leq T)}{\xi_h(v, 0 \leq t \leq T)} \quad (16)$$

Obviously, the scheme achieves-energy neutral operation if $\eta \leq 1$; otherwise, the scheme does not achieve energy-neutral operation. Figure 8 shows the comparison of energy ratio versus the number of nodes on the selected paths derived from the Neutral, Dijkstra, and DEHAR schemes. It can be observed that only our proposed scheme can guarantee the energy-neutral operation for all the nodes on the selected paths, while the other two schemes fail. In other words, only the nodes on the routing path derived by our proposed (Neutral) scheme keep $\eta \leq 1$ compared with the other two schemes. This is because 27 nodes (except the source node and the sink node) are adopted.
as the relay nodes to share the data transmission task of our Neutral scheme, while Dijkstra and DEHAR schemes only use seven and eight nodes to relay the data packets, respectively. As more nodes are used to share the transmission task, each node avoids being depleted excessively and achieves energy-neutral operation.

We also compare the cost of paths derived by different algorithms. The path distance from the source to the sink is chosen as the cost to illustrate our algorithm’s approximated optimality. This is because the distance is closely related to some significant parameters, such as delay, packet loss ratio [33,34]. The result is shown in Figure 9. It records the cost of 10 paths for the 10 source nodes. Obviously, the Dijkstra algorithm performs the best for its shortest path characteristic. And our Neutral scheme behaves a little worse than the Dijkstra as it should first preserve the path neutral property. Compared with DEHAR, it behaves average 7.33% performance enhancements. This is because the routing path derived by the DEHAR scheme is based on energy distance rather than physical distance.

5.3. Network capacity

To verify our approximate algorithm’s effectiveness, we downsize the network scale and nodes’ adjustable power levels to complete the simulations. We obtain the exact maximum network capacity by the enumerating method. The experiment is carried out on a 100 × 100 m² field where 10 nodes are randomly scattered. Each node has four adjustable power levels. The source and sink nodes are located at the opposite side of the field, which is the same as in the previous experiment of Section 5.1.

![Network capacity under different algorithms.](image1)

![Running time under different algorithms.](image2)

Figure 10. Performance evaluation on the network capacity and running time derived by our proposed scheme and the enumerating scheme.
Figure 10 reports the results of 20 experiments. As indicated in Figure 10(a), our approximate network capacity behaves almost the same trend as the maximum capacity, while our algorithm decreases the computational complexity greatly, which was illustrated in Figure 10(b). We can derive that our approximate algorithm can reach 83.76% of network capacity in average at a pretty low cost. In another words, our algorithm sacrifice little accuracy to achieve the polynomial-time computability. It was in line with our front computational complexity analysis.

6. CONCLUSION

In this paper, we have considered the optimization problem of deriving the energy-neutral minimum cost paths between the source nodes and the sink node. The concepts of the energy-neutral node, energy-neutral path, and energy-neutral minimum cost path are defined. By adjusting the transmission power of nodes, two polynomial-time algorithms have been proposed for finding the energy-neutral minimum cost path aiming at single-source single-sink and multi-source single-sink scenarios, respectively. We have proved that the algorithm achieves the optimal solution in the single-source single-sink scene. Also, another approximate algorithm has also been proposed for deriving the maximum flow through a single-source single-sink network that is subject to neutral operation. The simulation results have shown that the proposed algorithms have achieved significant performance enhancements over the existing schemes.

APPENDIX A: PROOF OF PROPOSITION 1

Suppose \( \pi_i \) is the minimum cost path found by running the Dijkstra’s shortest path algorithm. If node \( v \in \pi_i \) satisfies the energy-neutral operation, that is, for given data amount \( G_n \), node \( v \) satisfies \( E_{op}(v, 0 \leq t \leq T) \geq E_{op}(v, 0 \leq t \leq T) \), and then its transmission power level will not be adjusted. For node \( u \in \pi_i \) which does not satisfy the energy-neutral operation, removing it from the network while its transmission power level \( \tau_u = \tau_i \). Otherwise, adjusting its transmission power level from \( \tau_u \) to \( \tau_{u-1} \). Here, notice that the transmission power is decreased by one step (from \( \tau_u \) to \( \tau_{u-1} \)) instead of one step further (from \( \tau_u \) to \( \tau_{u-2} \)). Because the network graph derived by setting \( P_c(u, t) = \tau_{u-1} \) may have more links than that derived by setting \( P_c(u, t) = \tau_{u-2} \), under the condition that the other nodes’ power keeps a constant. The node with bigger transmission power covers a larger area, leading to more path selection. In other words, the graph derived by setting \( P_c(u, t) = \tau_{u-2} \) is a subgraph of that derived by setting \( P_c(u, t) = \tau_{u-1} \). Thus, if the transmission power is decreased by one step further (from \( \tau_u \) to \( \tau_{u-2} \)), the optimal path might be missed. Then, \( \pi_i \) is updated by running the Dijkstra’s shortest path algorithm. This procedure is repeated until all the nodes of path \( \pi_i \) achieve the energy-neutral operation. Assume \( \pi_j \) is another energy-neutral operation path with a cost smaller than \( \pi_i \) in the network. And this contradicts with our former analysis because \( \pi_i \) is selected by running the Dijkstra’s shortest path algorithm. Therefore, the proposition holds.

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