Towards Wireless Power Transfer in Mobile Social Networks

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Abstract—Wireless power transfer (WPT) is an enabling technology that energizes IoT devices as well as sensors at a distance without power plugs. In this paper, we consider WPT for mobile social networks (MSNs), where power is transferred from one to another via close proximity contacts among humans with a mobile device. In such a scenario, we introduce the problem of wireless charger allocation for MSNs, in which for the given number of wireless chargers, a subset of nodes are selected as power source nodes, and then, power is disseminated from the power sources to the other nodes via direct and/or indirect contacts. To this end, we first design the weighted connectivity metric for quantifying the importance of nodes and then propose the adaptive wireless charger allocation (AWCA) algorithm. Our AWCA consists of two phases. In the first phase, wireless chargers are allocated to a subset of nodes as power sources. In the second phase, power is efficiently transferred over an MSN. For performance evaluation, computer simulations using real human contact traces are conducted, and the simulation results demonstrate that the proposed AWCA algorithm achieves its design goals as long as the transmission efficiency is sufficiently high.

Index Terms—Wireless charger allocation, mobile social networks, MSNs, wireless power transfer, WPT.

1 Introduction

With the advancement of wireless power transfer (WPT) technologies, computing devices, including smartphones [1], sensors [2], RFID tags [3], automobiles [4], and unmanned aerial vehicles [5], can be wirelessly charged without power wiring [6]. This enables a variety of personal/business products and services including environmental monitoring using battery-free wireless rechargeable sensors [7]. The wireless charging market is growing rapidly and will reach 13.78 billion US dollars in 2020 [8].

Much effort has been devoted to theoretical, algorithmic, and application-oriented research works that exploit the WPT technologies from the computer science standpoint. Specifically, wireless charging scheduling [2], [9], [10] minimizing the charging delay, power control [11], [12] maximizes the utilities while minimizing energy cost, wireless charger placement [13], [14] optimizing the charging quality based on the distances among chargers and sensors, and trajectory planning [15]–[17] to minimize the moving cost of mobile chargers. In peer-to-peer energy sharing [18], [19] for opportunistic networks, some peers (i.e., persons with a mobile device) provide others with excessive energy to prolong a network lifetime.

To the best of our knowledge, there is no work on WPT for mobile social networks (MSNs). An MSN is one type of contact-based network constructed from a set of contact events, and a contact is defined as an event when two persons have a close proximity interaction. In general, social relations are involved in these contact events, e.g., students in the same class will have more contacts with each other than strangers. Here, persons with computing devices are abstracted as *nodes*. In an MSN, power can be wirelessly transferred from one node to another at a contact in close proximity. For example, real contact patterns among US high school community members are collected using wireless sensors in [20]. In this trace, a contact with close proximity is defined when the distance between two persons is less than three meters, which is sufficiently close for a wireless charger to transfer power to another computing device. In this paper, not only direct power transfers, but also multi-hop power transfers are considered. Figure 1 shows a snapshot of WPT in an MSN, where shaded rectangles represent computing devices. Node 1 serves as a power source node with a wireless charger, and she wirelessly transfers power to node 2 when they are in close proximity. Later on, say 60 minutes later, node 2 moves to another place and has contact with node 3. Then, node 2 may transfer power to node 3. That is, power initiated from node 1 is eventually transferred to node 3 via multi-hop contacts.

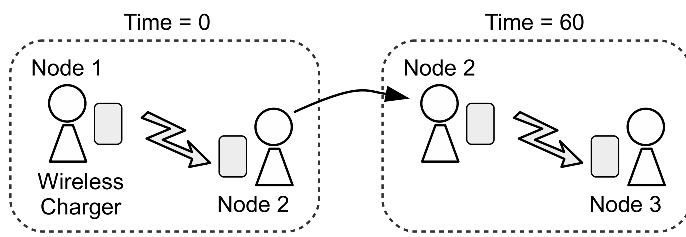

Fig. 1. An example of WPT in a MSN.

WPT for MSNs benefits many critical scenarios. For example, in disaster recovery, vehicle-based mobile wireless chargers cannot enter a controlled area due to various reasons, e.g., roads

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Manuscript received April xx, 2005; revised August xx, 2015.

are destroyed. In such areas, only humans can be the carriers of wireless chargers. Another application is energy harvesting for sensor-equipped soldiers in guerrilla missions, where neither tanks nor aerial vehicles can be deployed. By wirelessly transferring power, sensors attached to soldiers can be charged without replacing their batteries during missions. In addition, wireless crowd charging [21], [22] is a potential business application where workers with a mobile charger travel to landmarks in a city area in order to share energy with their customers or sensors with a mobile device for pay.

In this paper, we introduce a new wireless charger allocation problem in an MSN, in which wireless chargers are assigned to a subset of nodes and power is wirelessly transferred to other nodes via multi-hop contacts. The contributions of this paper are listed as follows.

- First, we introduce a new wireless charger allocation problem for MSNs, where wireless chargers are assigned to important nodes in a network and then power is wirelessly transferred to other nodes over a multi-hop contact network. The goal of this problem is to transfer a certain level of power from the power source nodes with wireless chargers to the others within a time constraint. The power transmission efficiency is assumed to be high, which is indeed a strong assumption compared with the current standard. However, our research becomes beneficial when the physical layer capability improves in the near future.
- Second, we design a new centrality metric, namely the weighted connectivity centrality, to quantify the importance of nodes. The proposed metric not only combines the contact frequencies and contact duration, but also the number of hops and power losses due to multi-hop transfers. By doing this, the nodes which are tightly connected to the other nodes via both direct and indirect contacts are selected as the power source nodes.
- Third, we propose the adaptive wireless charger allocation (AWCA) algorithm, which consists of two phases. The first phase is the adaptive wireless charger assignment, in which the nodes with the highest centrality are iteratively selected as power source nodes with wireless chargers; the second phase is the power dissemination, which efficiently transfers power from the power source nodes to the others. In the proposed algorithm, power transfer flows are directed in order to reduce power losses due to unnecessary power transfers.
- Fourth, we conduct extensive computer simulations using real human contact traces [20], in which close proximity contact events among US high school community members are recorded. The simulation results demonstrate that the proposed scheme outperforms the baseline protocol with well-known centrality metrics, e.g., degree, betweenness, and closeness, in the network science field.

The rest of this paper is organized as follows. In Section 2, related works are reviewed. In Section 3, the problem of wireless charger placement in MSNs is formulated. The baseline centrality metrics for selecting important nodes are provided in Section 4. We propose the weighted connectivity metric as well as the AWCA algorithm in Section 5. The performance of the proposed scheme is evaluated by simulations using real human contact traces in Section 6. Section 7 concludes this paper.

2 Related Works

2.1 Wireless Chargers

Much effort has been devoted to the research on wireless chargers with different design goals and different physical layer assumptions. The authors in [13] design a framework for placing wireless chargers to supply sufficient power to all devices in a given area. The work in [11] studies the static charger placement that maximizes electromagnetic radiation for a given plane. The scheduling problem is introduced in [2], where a set of static wireless sensors are selected to minimize the charging delay under the radio interference. This work is extended to accommodate practical wireless charging settings by incorporating not only the distance but also the relative angle between a sensor and a charger's orientation [10]. The placement and power allocation of static chargers are jointly optimized in [12]. In addition, electromagnetic radiation safety is incorporated into the scheduling design in [9].

In mobile wireless charger scenarios, the energy consumption of movement and budget constraint are considered and discussed in [15]. The trajectory of mobile chargers can be optimized by maximizing the number of nodes charged in a fixed time [16]. The work in [14] jointly optimizes power allocation and movement cost. The concept of bundle charging is introduced in [17], which exploits the broadcasting nature of wireless charging and allows mobile chargers to visit the anchor point of each bundle for power transfer. The charging problem with multiple mobile chargers is studied in [23], [24]. In the work [23], an on-demand charging scheme by multiple chargers is designed by applying the fuzzy logic. The charging algorithm proposed in literature [24] identifies the optimal charging tours of multiple mobile chargers that minimizes the maximal charging delay.

In some works, human mobility is exploited to wirelessly charge sensors. In [21], mobile users participate in a crowd-charging system as workers to charge sensors and/or IoT devices by reaching the close proximity of their targets. In [22], the similarity of user characteristics between online social networks and face-to-face human networks is exploited for socially aware energy sharing. The works most related to our research are peer-to-peer energy sharing protocols [18], [19] for opportunistic networks. In [18], some mobile users receive excessive energy from others in order to avoid cord-based energy charging from the electric adapter in a wall. In [19], a single and multi-hop energy balancing protocol is invented for prolonging a network lifetime. However, none of them addresses power source allocation issues.

2.2 Opportunistic Networks

Opportunistic networks are sparse ad hoc networks, where links among nodes are intermittently disconnected and no end-to-end communication link is available. Thus, data transmission is possible only when two mobile nodes are within the communication distance, which typically ranges from 10 to 250 meters. The limited transmission opportunity forces protocol designs to exploit nodal mobility, so called the store-and-carry paradigm, in data routing [25]. At present, opportunistic networks are widely applied to many critical scenarios, such as anonymous communications [26], crowdsourcing [27], disaster recovery [28], [29], and so on.

Mobile social networks (MSNs) are special kinds of opportunistic networks, where close proximity interactions among people are defined as contact events. MSNs are widely studied in many different fields. In [30], human disease propagation in

TABLE 1
Notations.

Symbol	definition
C, c	A set of contact events, contact event $c \in C$
V, E	A set of nodes and a set of links
G	A directed graph, $G = \{G, E\}$
v_i	Node v_i
$e(v_i, v_j)$	The link between v_i and v_j
$N(v_i)$	The open neighbor set of v_i
$w(v_i, v_j)$	The link weight between v_i and v_j
T	A time period
P_i	The power level of node v_i
P_{min}	The target power level
P_{max}	The maximum power level
$P_{i,j}^{(Tx)}$	The amount of power transferred from v_i to v_j
γ	The transmission efficiency
n	The number of wireless chargers
$d(v_i, v_j)$	The shortest path distance from v_i to v_j
$h(v_i, v_j)$	The number of hops from v_i to v_j
$W_x(v_i)$	The node weight of v_i with centrality x

an MSN is modeled and critical factors for preventing epidemics are identified. Targeted vaccination [31] is a network science-based solution, where a small subset of persons are selected for vaccination to prevent the spread of disease in an MSN. Malware containment [32] prevents malicious programs from infecting mobile devices, e.g., smartphones, at close proximity contacts among mobile nodes. Community discovery algorithms [33] detect and/or classify participants in an MSN in order to illuminate the social structures.

2.3 Dataset

In this paper, we use real contact traces among US high school community members recorded across three days during an influenza season in 2012 [20]. Each high school staff member and student carries a Crossbow TelosB mote, and stationary motes are deployed throughout the inside of buildings, such as classrooms, dining halls, and restrooms. The trace collection starts around 7am and ends at 4pm. Each mote broadcasts a beacon every 20 seconds. Using the signal strength of beacons, the close proximity interactions within three meters between two mobile motes (as well as between mobile and stationary motes) are recorded as contact events. If a participant is inside a building, her mote shall receive the signal from at least one of the stationary nodes. Such records indicate whether the participants stay indoors or outdoors during some time instances, and with these records, a contact between two nodes can be categorized as an indoor or outdoor contact event.

3 Problem Formulation

3.1 Network Model

The network model considered in this paper is trace driven. A human contact trace contains a set of contact events, where humans are abstracted as *nodes*. When two nodes are in close proximity, e.g., within three meters [20], these nodes are said to have a *contact*. Each contact event contains three pieces of information: two node IDs and the global timestamp at which a contact event occurs. We define a set of contact events by $C = \{c_1, c_2, c_3...\}$, and each contact c_i is defined by a tuple, $(c_i.ID_s, c_i.ID_d, c_i.gts)$. Here, $c_i.gts$ is a discrete timestamp bounded between 0 and T. The duration of contact is always one time step. When two nodes are in proximity for a period of time, distinct contact events are recorded, each of which has a subsequent timestamp.

A mobile social network (MSN) is represented by a directed graph, denoted by $G = (V, E)$, where V is a set of nodes and E is a set of edges. Let $v_i \in V$ be a node with ID i. Node v_i is in V if and only if there exists the corresponding ID in a trace, i.e., $\exists c \in C$ such that $c.ID_s = i$ or $c.ID_d = i$. Let $e(v_i, v_j)$ be the link from v_i to v_j. Then, $e(v_i, v_j) \in E$ if and only if $\exists c \in C$ such that $c.ID_s = i$ and $c.ID_d = j$. We define an open neighbor set of v_i by $N(v_i)$. We can say that $v_j \in N(v_i)$ if and only if $e(v_i, v_j) \in E$. That is, nodes v_i and v_j are connected in G if they have at least one contact. Note that a graph constructed from a given trace is directed due to the coarse granularity. A contact event is detected by individual nodes. Even if node v_i detects a contact with v_j at some time step, v_j might not detect a contact with v_i at the same time step.

We define the time period, denoted by T, within which contact events occur. Thus, for all contact events c, $0 \leq c.gts \leq T$ holds. The link weight of $e(v_i, v_j)$, denoted by $w(v_i, v_j)$, is quantified based on the number of contact events between them and given time period T. We can formulate $w(v_i, v_j)$ as Equation 1.

$$w(v_i, v_j) = \frac{1}{T} \sum_{t=0}^{T} r(v_i, v_j, t) \tag{1}$$

Here, $r(v_i, v_j, t)$ equals to 1 if and only if they have a contact at t, i.e., $\exists c \in C$ such that $c.ID_s = i$, $c.ID_d = j$, and $c.gts = t$. Otherwise, $r(v_i, v_j, t)$ is set to be 0. Therefore, the link weight increases as the contact frequency and contact duration between two nodes increase.

We define $d(v_i, v_j)$ as the shortest path distance between v_i and v_j. A path consists of a set of links. Let $[v_i, ..., v_k, ..., v_j]$ be an η-hop path from v_i to v_j, where v_k is the k-th intermediate relay node ($0 \leq k \leq \eta$). By definition, $e(v_k, v_{k+1}) \in E$ must hold. Then, $d(v_i, v_j)$ is defined by Equation 2.

$$d(v_i, v_j) = \sum_{k=0}^{\eta-1} \frac{1}{w(v_k, v_{k+1})} \tag{2}$$

Because $d(v_i, v_j)$ has the non-decreasing property, well-known algorithms, such as Dijkstra, can be directly applied to computing the shortest path distance.

The notations used in this paper are listed in Table 1.

3.2 Wireless Charge Model

Each node v_i has its power level, denoted by P_i. We define the target power level by P_{min}, as the minimum power level to be charged after wireless power transfer over an MSN. When power is wirelessly transferred from node v_i to v_j at a contact, power loss occurs. That is, the amount of power received by v_j is smaller than the one transmitted by v_i. Such a ratio is called the *transmission efficiency*, denoted by $\gamma \in [0, 1]$. Let $P_{i,j}^{(Tx)}$ be the amount of power transmitted by v_i within single time step, then the amount of power to be charged at v_j will be $\gamma \cdot P_{i,j}^{(Tx)}$.

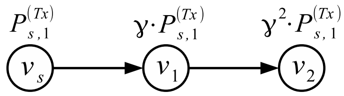

Fig. 2. The received power.

The current state-of-the-art [34] achieves $0.7 \leq \gamma \leq 0.9$ with a near field WPT using inductive coupling, where the distance between two devices is less than 0.5 meter. In addition, we will have $0.5 \leq \gamma \leq 0.75$ with the magnetic resonant coupling when the distance is shorter than three meters. As we will show later, the proposed scheme requires γ to be at least 0.8, which assumption might be slightly strong with the current WPT standard. However, our research on WPT for DTNs is still beneficial, when the transmission efficiency becomes sufficiently high in the future.

3.3 Problem of Wireless Charger Allocation

The wireless charger allocation problem for an MSN consists of two stages. In the first stage, given the number of wireless chargers, denoted by n, a subset of nodes are selected to allocate wireless chargers. Such a subset of nodes is denoted by $V_s \in V$, and the nodes in V_s are called *power source nodes* since they serve as power sources with wireless chargers. The examples of power source nodes include the mobile users with mobile wireless chargers who are willing to supply power with the others and automobile which are dedicated to supply power with the uses in an MSN. The second stage is power dissemination, in which power is wirelessly transferred from the power source nodes in V_s to the others. Note that not only direct power transfer from $v_i \in V_s$ to $v_j \in \{V \setminus V_s\}$, but also multi-hop power transfer is considered, e.g. power transfer from $v_i \in V_s$ to $v_j \in V$ and then to $v_k \in \{V \setminus V_s\}$, where $\setminus$ denotes the set minus operation.

A node is said to be *energized* if its power level is greater than or equal to P_{min} after power dissemination. The goal of wireless charger allocation is to maximize the number of nodes that are energized by power source nodes via direct and/or indirect contacts. To this end, we introduce the notion of the energized rate as follows.

Definition 1 (Energized Rate) *Let $\tilde{V} \subseteq V$ be a set of nodes such that $\forall v_i \in \tilde{V}, P_i \geq P_{min}$. Then, the energized rate is defined by* $\dfrac{|\tilde{V}|}{|V| - |V_s|}$.

The problem of wireless charger allocation can be formally defined by Definition 2.

Definition 2 (Wireless Charger Allocation Problem) *For the given number of wireless chargers n and time constraint T, the wireless charger allocation problem is to maximize the energized rate.*

3.4 The Optimal Wireless Charger Allocation

The definition of the optimal solution is essential in designing efficient wireless charger allocation algorithms in MSNs. To this end, several assumptions are made. The power source nodes have an infinite amount of power, intermediate nodes can store an unlimited amount of power in their battery, and there is no power loss due to multi-hop power transfers. Then, the problem of selecting the optimal wireless power sources can be reduced to constructing multi-source spanning trees, which is known to be NP-hard.

Let $v_i^{(src)}$ be the closest power source node in V_s from node v_i. The shortest path from node v_i to $v_i^{(src)}$ is the one with the smallest distance, i.e., $d(v_i, v_i^{(src)})$. Then, the optimal wireless charger allocation is defined by Definition 3.

Definition 3 (Optimal Wireless Charger Allocation) *The optimal set of power source nodes, denoted by OPT, is defined by the subset of nodes obtained by Equation 3.*

$$OPT = \underset{V_s}{\operatorname{argmin}} \left\{ \sum_{v_i \in V} d(v_i, v_i^{(src)}) \right\} \tag{3}$$

The problem is essentially the same as finding the minimum number of multi-source spanning trees. In Section 5, we will design greedy-based algorithms to approximate OPT under the aforementioned wireless charge model.

3.5 Research Challenges

Different design issues of the wireless charger allocation problem for MSNs impose the following research challenges.

- **Challenge 1:** The first challenge is how to model the centrality of nodes. The importance of nodes should be quantified based on the amount of power which can be disseminated via both direct and indirect contacts among nodes. In addition, the amount of power transferred from one node to another depends on the contact frequency and contact duration. Furthermore, transmission efficiency plays a critical role for multi-hop power transfers. For example, Figure 2 illustrates the WPT from node v_s to v_2 via v_1, where circles represent nodes and arrows represent power transfer from one node to another. The amount of power that v_2 can charge decreases according to the number of hops and the transmission efficiency, γ. Therefore, the aforementioned considerations must be incorporated in the centrality design.
- **Challenge 2:** The second challenge is how to select the best node as a power source. When a wireless charger is assigned to one node in an MSN, the importance of the other nodes will change. This is because some nodes will be charged by their closest power source node. To be specific, assume that node $v_2 \in V_s$ in Figure 3 is one of the power source nodes. In this figure, solid lines represent links between two nodes. The neighbors of v_2, i.e., v_1, v_3, and v_4, are most likely to be energized by v_2. Thus, selecting either v_1, v_3, or v_4 as another power source node may not contribute much to the overall energized rate. Thus, a set of power source nodes should be iteratively selected to maximize the energized rate for all nodes.
- **Challenge 3:** The third challenge is how to efficiently transfer power from the power source nodes to the others. Since there is power loss when power is wirelessly transferred from one node to another, all the loops must be eliminated. Otherwise, transferred power decreases unnecessarily. Removing loops does not mean that power transfer flows must be a spanning tree. In fact, a spanning tree will reduce the opportunities of power transfers. Therefore, power transfer flows starting from a set of power source nodes must be carefully constructed.

4 Baseline Metrics

As the baseline of the node weight, centrality-based metrics are considered, including *degree*, *betweenness*, and *closeness*, which are widely used in network science [35]. In general, the nodes with higher weight are considered to be important nodes.

4.1 Degree Centrality

The degree centrality prioritizes the nodes tightly connected to their neighbors. Recall that $w(v_i, v_j)$ is the link weight from node v_i to v_j. The degree centrality of node v_i, denoted by $W_{deg}(v_i)$, is defined by Equation 4.

$$W_{deg}(v_i) = \sum_{v_j \in N(v_i)} w(v_i, v_j) \tag{4}$$

Since node weights are locally computed in the degree centrality, indirect relationships among nodes are not considered.

4.2 Betweenness Centrality

The betweenness centrality quantifies how often a node is involved in the shortest path of two other nodes. Note that the shortest path is defined as the path with the smallest distance formulated in Equation 2. Let $\sigma_{s,t}$ be the total number of shortest paths from node v_s to v_t and $\sigma_{s,t}(v_i)$ be the number of shortest paths in which node v_i is an intermediate node. The betweenness centrality of node v_i, denoted by $W_{btwn}(v_i)$, is defined by Equation 5.

$$W_{btwn}(v_i) = \sum_{s \neq t \neq i, s,t \in V} \frac{\sigma_{s,t}(v_i)}{\sigma_{s,t}} \tag{5}$$

While the betweenness centrality considers the indirect relationship among nodes, computing the betweenness of all the nodes takes a long time, i.e., $O(|V|^3)$ [35].

4.3 Closeness Centrality

The closeness centrality defines how close a node is to the other nodes in terms of the shortest path distance. The closeness centrality of node v_i, denoted by $W_{close}(v_i)$, is obtained as follows.

$$W_{close}(v_i) = \frac{|V| - 1}{\sum_{v_j \in \{V \setminus v_i\}} d(v_i, v_j)} \tag{6}$$

When two nodes, v_i and v_j, are disconnected, $d(v_i, v_j)$ is ignored. The closeness centrality considers the indirect relationship among nodes, and its computation is relatively faster than that of betweenness. This metric, however, does not work well when a graph is not strongly connected, which is typically the case of MNNs.

In addition, the effect of multi-hop power transfer is not considered in any of the aforementioned centrality models.

Example 1 An example of each centrality is presented using Figure 3. The real value at each solid line indicates the link weight between two nodes. For simplicity, the graph is undirected, i.e., the links are bidirectional. When $n = 2$, the degree centrality will return nodes 2 and 3 as power source nodes, since $W_{deg}(v_3)$ is the highest and $W_{deg}(v_2)$ is the second highest among $W_{deg}(v_i)$ for all $1 \leq i \leq 10$. The issue is that nodes 2 and 3 are neighbors

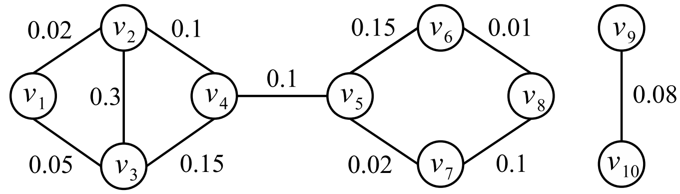

Fig. 3. A graph of an MSN.

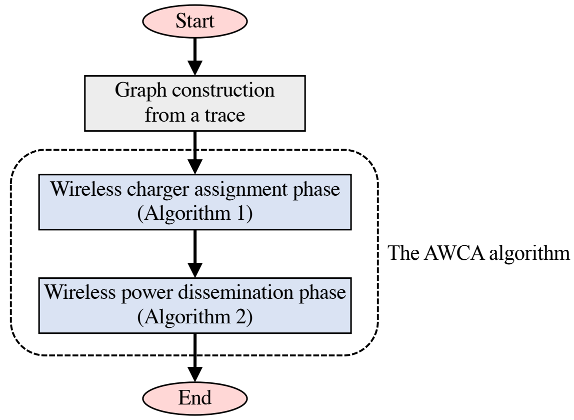

Fig. 4. The flowchart of the AWCA algorithm.

to each other, and the nodes at the right side of the corresponding component may not receive sufficient power from them.

The betweenness centrality will select nodes 4 and 5, since these two nodes are involved in many of the shortest paths between each pair of nodes. The number of shortest paths is $\sigma_{s,t} = 58$ for all $1 \leq s \leq 10$ and $1 \leq t \leq 10$ with $s \neq t$. We will have $\sigma_{s,t}(v_4) = \sigma_{s,t}(v_5) = 32$, which is much larger than those of the other nodes. Nodes 4 and 5, however, are neighbors to each other. In addition, $w(v_5, v_6)$ and $w(v_6, v_8)$ are small, and as a result, node v_5 may not be able to charge nodes v_6, v_7, and v_8.

The closeness centrality will have nodes 9 and 10 as power source nodes, which is apparently a bad selection. As shown in Figure 3, nodes 9 and 10 are isolated, which makes the denominator of Equation 6 small. Therefore, the closeness centrality does not work out well when a graph is not strongly connected.

5 Adaptive Wireless Charger Allocation

5.1 Overview

In this paper, we first design the weighted connectivity centrality that quantifies the extent to which each node can directly and indirectly transfer power to the other nodes. In the proposed metric, not only the distance among nodes, but also the number of hops and expected power flow are incorporated. Hence, the connectivity is weighted. Then, we propose the adaptive wireless charger allocation (AWCA) algorithm, which consists of two phases: the wireless charger assignment phase and the wireless power dissemination phase. In the wireless charger assignment phase, a set of n nodes are selected as power source nodes. After selecting one power source node, the importance of the other nodes is most likely to be changed, since the nodes close to power source nodes become less important. Thus, the power source nodes are iteratively selected using the weighted connectivity metric. In the wireless power dissemination phase, power is wirelessly transferred over an MSN. To avoid unnecessary power transfers, the directed flow rooted at a set of power source nodes is constructed based on the shortest path distances, and then, power is wirelessly disseminated from the power source nodes to the others via contacts.

The flowchart of the proposed AWCA is presented in Figure 4. First, a graph is constructed form a mobility trace. The wireless charger assignment phase uses the weighted connectivity centrality as a building block. Then, the power dissemination phase is performed. Each component of our AWCA algorithm addresses the challenges listed in Section 3.5.

5.2 Weighted Connectivity

The proposed weighted connectivity centrality quantifies how much power nodes can transfer to other nodes, and the connectivity is weighted by two factors, i.e., the number hops and the expected power flow level.

The first consideration is the effect of the number of hops. The amount of power which can be transferred from v_i to v_j at a distance exponentially decreases as the number of hops between them increases. Let v_k be the k-th intermediate node in the shortest path from v_i to v_j, where the bases are $v_0 = v_i$ and $v_{h(v_i,v_j)} = v_j$. For simplicity, let $P_{min} = 0$ and $P_{max} = \infty$. At the first hop, the amount of power transferred from v_0 to v_1 is bounded by $\gamma \cdot P^{(Tx)}_{0,1} \cdot w(v_0, v_1) \cdot T$. For the second hop, we will have $\min\{\gamma^2 \cdot P^{(Tx)}_{0,1} \cdot w(v_0, v_1) \cdot T, \gamma \cdot P^{(Tx)}_{1,2} \cdot w(v_1, v_2) \cdot T\}$. This implies that the amount of power transferred from v_i to v_j is dominated by the one at the first hop. Let $\tilde{P}^{(Recv)}_{i,j}$ be the expected amount of power transferred from v_i to v_j. Then, we may derive the upperbound of $\tilde{P}^{(Recv)}_{i,j}$ by Equation 7.

$$\begin{aligned}\tilde{P}^{(Recv)}_{i,j} &= \min_{0\le k\le h(v_i,v_j)-1}\{\gamma^{h(v_i,v_j)-k} \cdot P^{(Tx)}_{k,k+1} \cdot w(v_i, v_j) \cdot T\} \\ &\le \gamma^{h(v_i,v_j)} \cdot P^{(Tx)}_{i,j} \cdot w(v_i, v_j) \cdot T \end{aligned} \tag{7}$$

The above equation indicates that $\gamma^{h(v_i,v_j)}$ can be the weighting factor for the number of hops. Therefore, the shortest path distance between v_i and v_j can be weighted by $\frac{\gamma^{h(v_i,v_j)}}{d(v_i,v_j)}$. That is, the shorter distance leads to higher connectivity, but the larger number of hops reduces the connectivity. Note that if v_i and v_j are disconnected in a graph, $d(v_i, v_j)$ will be infinite, and thus, the connectivity from v_i to v_j does not increase the centrality of v_i.

The second consideration is the expected power flow. Consider the connectivity from v_i to v_j. When v_j is a neighbor of a power source node, i.e., $\exists v_s \in V_s$ such that $v_j \in N(v_s)$, node v_j should not increase the centrality of node v_i, since selecting v_i as a power source node most likely does not contribute to charging v_j. Thus, the connectivity from v_i to v_j should be deprioritized by a given weight based on the expected power flow of v_j. We define $\tilde{P}_j$ as the expected power flow of v_j with $P_{min} = a$ for some non-negative constant a and $P_{max} = \infty$, which can be computed as follows. Let v_s be the closest power source node to v_j, i.e., $v_s := \operatorname{argmin}_{v_k\in V_s}\{d(v_k, v_j)\}$, and v_k be the k-th intermediate node in the shortest path from v_s to v_j. Then, $\tilde{P}_j$ is approximated by Equation 8.

$$\tilde{P}_j = \max\{(w_{min} \cdot T - (h(v_j, v_s) - 1) \cdot P_{min}) \cdot \gamma^{h(v_j,v_s)}, 0\} \tag{8}$$

Algorithm 1 Assignment($G = (V, E)$, n, P_{min}, γ)

1: Initialize an empty set, $V_s \leftarrow \emptyset$
2: Initialize a set, $V' \leftarrow V$
3: **for** from $k = 1$ to n **do**
4:   For each $v_i \in V'$, node v_i computes $W_{wc}(v_i)$
5:   $v_s \leftarrow \operatorname{argmax}_{\forall v_i\in V'}\{W_{wc}(v_i)\}$.
6:   Add v_s to V_s
7:   Remove v_s from V'
8:   **for** each node v_i in V **do**
9:     v_i computes $\tilde{P}_i$
10:     v_i computes $d_{min}(v_i) \leftarrow \min_{\forall v\in\{V_s\cup v_s\}}\{d(v_i, v)\}$
11: Return V_s

Here, w_{min} is the weight of the bottleneck link defined by $w_{min} := \min_{0\le k<h(v_j,v_s)}\{w(v_k, v_{k+1})\}$. Note that P_{min} is deducted at each hop. This is because an intermediate node can transfer power to another only when its power level is greater than P_{min}.

Since the amount of power transferred from v_s to v_j is dominated by the bottleneck link, the link with the minimum weight is computed in the above formula.

Let $\beta_{i,j}$ be the weighting factor regarding the expected power flow of v_j. We may formulate $\beta_{i,j}$ with Equation 9.

$$\beta_{i,j} = \begin{cases} \left(\dfrac{P_{min}}{\tilde{P}_j}\right)^{\alpha} & \text{if } \tilde{P}_j \ge P_{min} \\ 1 & \text{otherwise.} \end{cases} \tag{9}$$

Here, α is a constant, which is set by simulations. For instance, the connectivity from v_i to v_j quadratically decreases, when $\alpha = 2$.

We define $W_{wc}(v_i)$ as the centrality of node v_i. By combining the aforementioned observations, $W_{wc}(v_i)$ is formulated by Equation 10.

$$W_{wc}(v_i) = \sum_{v_j\in\{V\setminus\{V_s\cup v_i\}\}} \frac{\beta_{i,j} \cdot \gamma^{h(v_i,v_j)}}{d(v_i, v_j)} \tag{10}$$

Remark The proposed weighted connectivity centrality in Equation 10 will approximate the optimal solution in Equation 3. First, the two factors, $\beta_{i,j}$ and $\gamma^{h(v_i,v_j)}$, can be removed from Equation 10 if the amount of power stored in relay nodes is unlimited and there is no power transmission loss. The distance from a power source to the other nodes is the inverse of the centrality. Therefore, the set of n nodes with the highest W_{wc} will approximate the set of n nodes in OPT.

5.3 Wireless Charger Assignment Phase

Before the wireless charger allocation, the link weights among nodes are computed from given graph $G = (V, E)$. Note that a certain amount of information about the contact graph is assumed to be available to each node when it comes to MSNs. This is because everyday social interactions shall generate similar contact patterns among the nodes in an MSN, e.g., a contact graph from Monday to Friday in a high school.

As defined in Section 3.1, the link weight $w(v_i, v_j)$ between v_i and v_j can be obtained by Equation 1 for each pair of nodes in V. In addition, the shortest path distance defined by Equation 2 as well as the number of hops from one node to all the other nodes can be easily computed from $G = (V, E)$ by any graph algorithm, such as Dijkstra.

For a given number of wireless chargers n, a subset of n nodes in V are selected as power source nodes as presented in Algorithm 1. Let V_s and V' be sets, which are initialized by an empty set $\emptyset$ and by V, respectively. From lines 3 to 10, a set of nodes are repeatedly added to V_s. To this end, each node except the ones in V_s computes its centrality, i.e., the node centrality, as shown in line 4. Recall that $W_{wc}(v_i)$ is computed by Equation 10. At line 5, the node with the highest centrality is selected, which is denoted by v_s. Then, v_s is included into V_s and removed from V' as shown in lines 6 and 7. In order to update the influence of the newly selected power source node, all the nodes in V' update their expected power flow $\tilde{P}_i$ by Equation 8 at line 9. In addition, each node v_i computes the shortest path distance to the closest power source node by computing $d_{min}(v_i) \leftarrow \min_{\forall v \in \{V_s \cup v_s\}} \{d(v_i, v)\}$, which is used to construct directed power transfer flows in the power dissemination phase.

At the end of this process, n nodes are selected and wireless chargers are assigned to them.

Example 2 An example of how AWCA selects two power source nodes in Figure 3 is presented. Assume that $\gamma = 0.8$, $P_{min} = 50$, $P_{max} = 100$, $P_{i,j}^{(Tx)} = 3$ for $1 \leq i, j \leq 10$, and the time period is $T = 1000$. At the beginning, the expected power flow of all the nodes is 0, and thus, the connectivity is not weighted by $\beta_{i,j}$. Thus, node 3 is selected as the power source node, as $W_{wc}(v_3)$ has the highest value among all the nodes. After node 3 is selected, the expected power flows from node 3 are computed, as shown in Figure 5, where shaded circles represent the power source nodes. Nodes 1, 3, 4, 5, and 6 are expected to be fully charged by node 2. However, the expected power flows of nodes 7 and 8 remain 0. In the second iteration, the connectivity from each node to any of nodes 1, 2, 4, 5, and 6 will be less weighted, since $\beta_{i,j}$ is very small for $1 \leq i \leq 10$ and $j \in \{1, 2, 4, 5, 6\}$. As a result, node 7 will be selected as another power source node. At the end of this process, wireless chargers are assigned to nodes 3 and 7, and the expected power flows are shown in Figure 6. Except nodes 9 and 10, which are isolated from the other nodes, all the nodes will be charged with sufficient power from nodes 3 and 7.

We derive the complexity of the proposed AWCA by Theorem 1.

Theorem 1 *The complexity of AWCA is* $O(|V|^3)$.

Proof: The complexity of AWCA can be derived as follows. First, the shortest path hops and the shortest path distances must be computed, which takes $O(|V| \log |V| + |E|)$ by the Dijkstra algorithm. Here, $|E|$ is the number of edges, which is bounded by $O(|V|^2)$. These computations are repeated up to $|V|$ times. Thus, identifying the node with the highest weighted connectivity centrality requires $|V|^3$. In addition, after one power source is selected, the expected power flow is computed for each node. Since the shortest path from one node to the other nodes is already computed, each node needs $O(|V|)$ to estimate the amount of power that it will receive from the closest power source node. Thus, computing expected power flow for all the nodes takes $O(|V|^2)$. The power source selection repeats n times. Here, n is a constant and selecting multiple power source nodes does not increase the complexity. The outgoing neighbor set at each node can be computed in $O(|V|)$, as only local information is used.

Therefore, the complexity of AWCA is $O(|V|^3)$. ∎

Algorithm 2 Dissemination($G = (V, E)$, C)

1: /* Initialization. */
2: Each node v_i computes $N_{out}(v_i)$
3: /* Contact event handling */
4: **for** each c in C **do**
5: $\quad v_i \leftarrow c.ID_1$ and $v_j \leftarrow c.ID_2$
6: $\quad$ **if** $P_i \geq P_{min} + P_{i,j}^{(Tx)}$ and $P_j < P_{max}$ **then**
7: $\quad\quad P_i \leftarrow P_i - P_{i,j}^{Tx}$
8: $\quad\quad P_j \leftarrow \min\{P_j + \gamma \cdot P_{i,j}^{(Tx)}, P_{max}\}$
9: $\quad\quad$ Call a subroutine, Notify(v_j)
10: /* Node v_i does the following. */
11: Notify(v_i):
12: **if** $P_i \geq P_{min}$ and $N_{out}(v_i) = \emptyset$ **then**
13: $\quad$ **for** each v_j in $N(v_i)$ **do**
14: $\quad\quad$ **if** $v_i \in N_{out}(v_j)$ **then**
15: $\quad\quad\quad$ Remove v_i from $N_{out}(v_j)$

5.4 Wireless Power Distribution Phase

Before wireless power distribution, the outgoing neighbor set at each node is initialized in order to remove loops from $G = (V, E)$. Let $N_{out}(v_i)$ be the outgoing neighbor set of node v_i, which is a subset of its open neighbor set, i.e., $N_{out}(v_i) \subseteq N(v_i)$. Node $v_j \in N(v_i)$ is included in $N_{out}(v_i)$ if and only if $d_{min}(v_i) < d_{min}(v_j)$ for $v_j \in N(v_i)$, and the tie can be broken by their node IDs. That is, v_i is closer to some source node than v_j, and thus, v_i transfers power to v_j with a high probability. Each node v_i can locally compute $N_{out}(v_i)$. By doing this, the power transfer flows from the power source nodes in V_s remove all the loops.

For a given set of nodes V and contact events $C = \{c_1, c_2, c_3, ...\}$, wireless power transfer over an MSN is conducted as demonstrated in Algorithm 2. Here, all the events in C are kept in a priority queue with the priority being global timestamps. That is, each contact c is executed in the increasing order of $c.gts$, and the tie can be broken by the IDs of two nodes, $c.ID_1$ and $c.ID_2$.

Lines 4 to 9 outline how each event is processed. When node v_i detects a contact with v_j, node v_i will determine whether or not it transfers power to v_j based on two conditions. One is whether v_i will still have a sufficient power level after v_i transfers power to v_j; the other is that v_j's power level is smaller than the maximal capacity, i.e., $P_i \geq P_{min} + P_{i,j}^{(Tx)}$ and $P_j < P_{max}$. Note that node v_j may transfer power to another node, unless it is located at the edge. Hence, v_j should be charged from v_i even if v_j's power level exceeds P_{min}. If both conditions are met, then v_i's power level is decremented and v_j's power level is incremented by $P_{i,j}^{(Tx)}$ as shown in lines 7 and 8. Note that the graph is directed, and thus, only node v_i transfers power to v_j in this contact event. If the contact is bidirectional, then v_j also detects another contact event with v_i at the same timestamp. At line 9, a subroutine, i.e., Notify(v_i), is called to avoid unnecessary power transfers.

From lines 11 to 15, the Notify(.) subroutine is defined. Node v_i checks whether or not it has already received sufficient power and there is no outgoing neighbor, i.e., $P_i \geq P_{min}$ and $N_{out}(v_i) = \emptyset$. If $N_{out}(v_i)$ is empty, v_i has no neighbor to transfer power. Thus, once v_i accumulates sufficient power, there

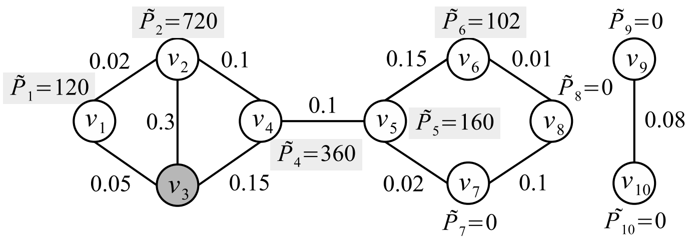

Fig. 5. The state at after the first iteration of AWCA.

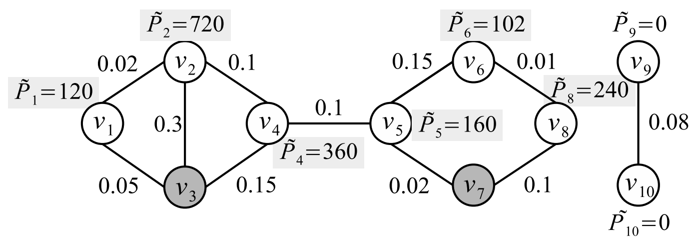

Fig. 6. The state at after the second iteration of AWCA.

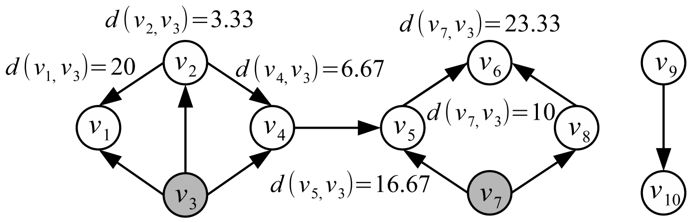

Fig. 7. The power transfer flows of AWCA.

is no need for v_i to be charged from the nodes close to the power sources. When these conditions are met, node v_i notifies $v_j \in N(v_i)$ to remove itself from its outgoing neighbor set $N_{out}(v_j)$.

Example 3 Figure 7 illustrates the shortest distance of each node to the closest power source node, after the power source selection algorithm described in Example 2 is completed. Since nodes 3 and 7 are the power source nodes, power transfer flows are rooted at either node 3 or 7. Note that the power transfer flow structure is not a tree, and some nodes can be charged from more than one node.

6 Performance Evaluation

In this subsection, the proposed AWCA scheme is implemented along with the baseline centrality metrics, and computer simulations using real contact traces are conducted.

6.1 Simulation Configuration

In the day-1 contact trace of [20], contacts among 444 high school staff and students with a sensor mote are recorded throughout a day, approximately 7.8 hours, or 1400 time steps. A subset of nodes ranging from 200 to 400 is randomly selected out of 444 nodes in the trace, and a contact graph is generated. The link weight of each pair of two nodes is computed by Equation 1 using the contact events recorded in the trace with the period of time being $T = 1400$. Note that due to the coarse granularity of the trace, the link between two nodes is directed. Even if the link from node v_i to v_j exists, the one from v_j to v_i might not exist. However, it does not affect our algorithms. The percentage of wireless chargers (i.e., the power source nodes) with respect to the number of nodes ranges from 2% to 10% with the default value being 5%. Unless specified, the transmission efficiency γ is set to be 0.8.

According to [15], the amount of power that a mobile wireless charger consumes to energize a sensor is approximately $0.9J$ per 60 seconds, where J indicates Joule. Since one time step in the trace corresponds to 20 seconds, the amount of power transferred from one node to another in one time step is set to be $0.3J$, i.e., $P_{i,j}^{(Tx)} = 0.3$ for all $v_i, v_j \in V$. The target power level is set to be $P_{min} = 5J$, and the maximal amount of power that each intermediate node can store is set to be $P_{max} = 2 \cdot P_{min}$. Note that it is known that $2J$ is sufficient for a sensor to operate for a reasonable period of time [2]. In addition, a sensor can be charged in 155 seconds [7], which corresponds to 7.75 time steps in the trace. Thus, the simulation parameters regarding wireless charging are reasonable. The power source nodes are assumed to have an unbounded amount of power.

The value of α, which is a protocol specific parameter of AWCA, is set to be 2. The simulation is conducted 1000 times by selecting different subsets of nodes in the trace.

6.2 Evaluation Metrics

In the simulations, four evaluation metrics, the energized rate, average power level, charging delay, and the number of multi-hop power transfers are considered. The energized rate is the most important metric in this paper as provided in Definition 1. The average power level of non-power source nodes is obtained by $\frac{\sum_{\forall v_i \in \{V \setminus V_s\}} P_i}{|V|-n}$. The charging delay is defined as the required time (minutes) that v_i's power level reaches the target power level, P_{min}. The number of multi-hop power transfers is defined as the number of power transfers between two nodes, v_i and v_j in $\{V \setminus V_s\}$. This metric indicates the extent to which the power is wirelessly transferred to nodes at more than two hops away from the power source nodes.

6.3 Simulation Results

Figure 8 shows the energized rate of different algorithms with respect to the number of nodes, where $n = 5\%$ and $\gamma = 0.8$. As shown in the figure, the energized rates of all the algorithms increase as the number of nodes increases. This is because there are more contact events when there exists a larger number of nodes in an MSN. The proposed AWCA algorithm achieves a higher energized rate than the others by up to 20%. The betweenness centrality results in a slightly higher energized rate than the degree centrality does. The closeness centrality has a lower energized rate among the others, especially when the number of nodes is low. The primary reason for this is that a contact graph is not strongly connected when the number of nodes is low, and as a result, the node weight does not work well. The difference of the energized rate becomes small when the number of nodes equals to 400. This is because most of the nodes are eventually energized when the number of contact events is sufficiently large.

Figure 9 illustrates the energized rate of different algorithms with respect to the percentage of power source nodes, where $|V| = 300$ and $\gamma = 0.8$. Our AWCA presents the highest energized rate compared to all by up to 30%. The difference of the

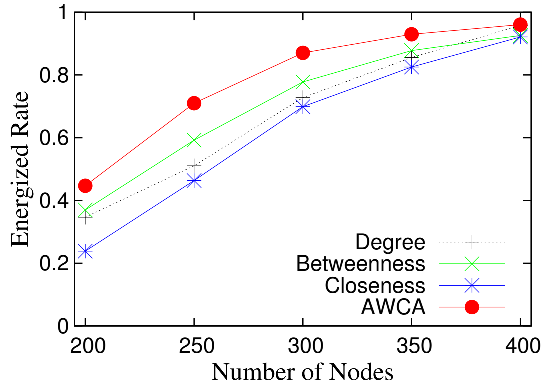

Fig. 8. The energized rate vs. the number of nodes.

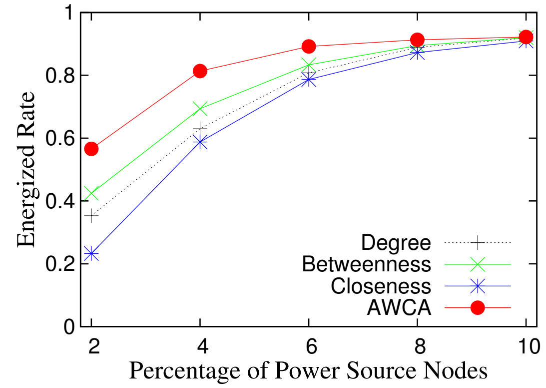

Fig. 9. The energized rate vs. the percentage of power source nodes.

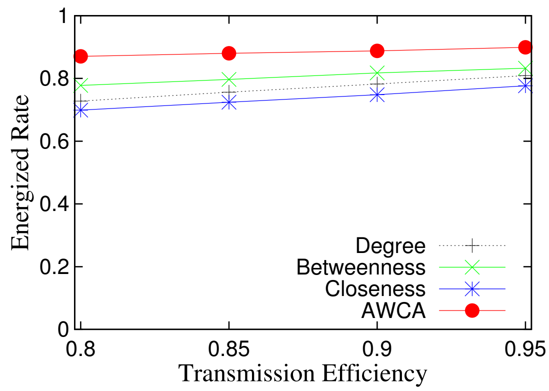

Fig. 10. The energized rate vs. the transmission efficiency.

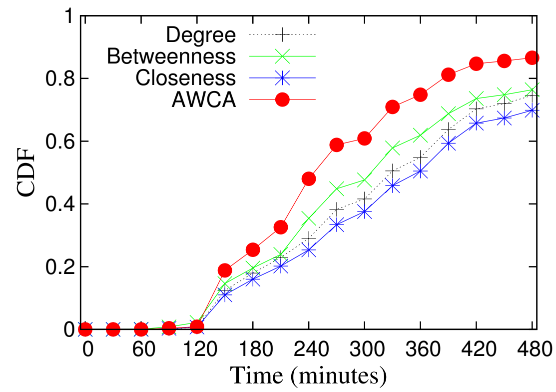

Fig. 11. The CDF of the energized rate.

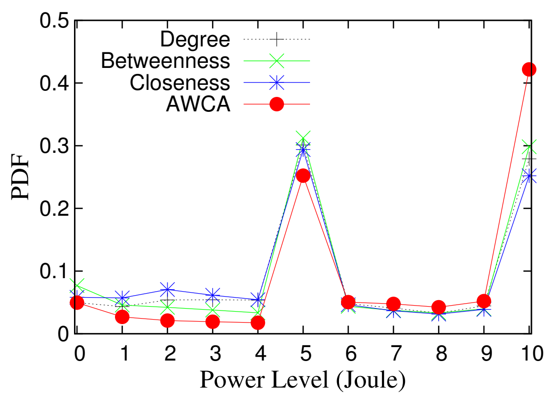

Fig. 12. The PDF of the power level.

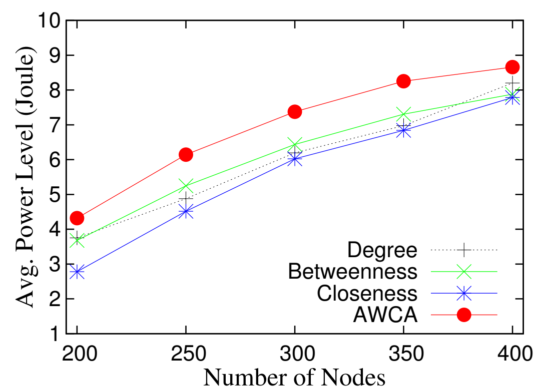

Fig. 13. The average power level vs. the number of nodes.

resulting energized rate becomes smaller when the percentage of power source nodes reaches 10%, i.e., 30 nodes among 300 nodes. This is because the role of multi-hop power transfer becomes less important when more nodes serve as power sources.

Figure 10 demonstrates the energized rate of different algorithms with respect to the percentage of transmission efficiency, where $|V| = 300$ and $n = 5\%$. The energized rate of all the algorithms slightly increases when the transmission efficiency increases. This implies that the effect of a power loss does not impact much compared to contact opportunities and the percentage of power source nodes as long as $\gamma \geq 0.8$. The energized rate of the AWCA algorithm always results in the highest among all the algorithms by approximately 10%. The degree, betweenness, and closeness centrality metrics yield a similar energized rate, since none of them consider the power loss for multi-hop power transfer.

Figure 11 presents the cumulative distribution function (CDF) of the energized rate of different algorithms with respect to the time (minutes), where $|V| = 300$, $n = 5\%$, and $\gamma = 0.8$. The figure indicates the percentage of the energized nodes out of all the nodes except power source nodes at given time steps. As can be seen in the figure, the CDF of all the algorithms increases at 120 minutes after the simulation starts. In other words, most of the nodes are not energized within 120 minutes due to few contact opportunities. The energized rate of the proposed AWCA increases quicker than that of the others, which implies that AWCA efficiently transfers power. Note that the energized rate cannot reach 100%, since the number of contact events is limited within $T = 1400$ (approximately 7.8 hours) and some nodes are isolated, i.e., some nodes never come in contact with others. Figures 8 to 11 demonstrate that our AWCA successfully achieves wireless power transfer over an MSN.

Figure 12 gives the probability distribution function (PDF) of

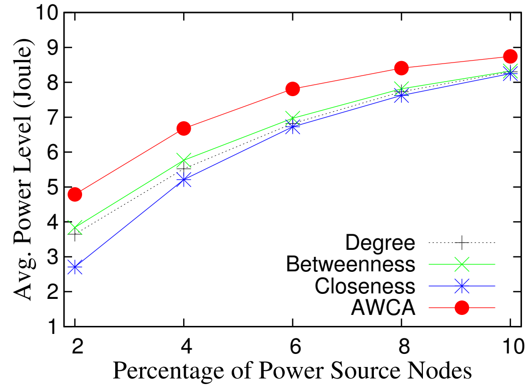

Fig. 14. The average power level vs. the percentage of power source nodes.

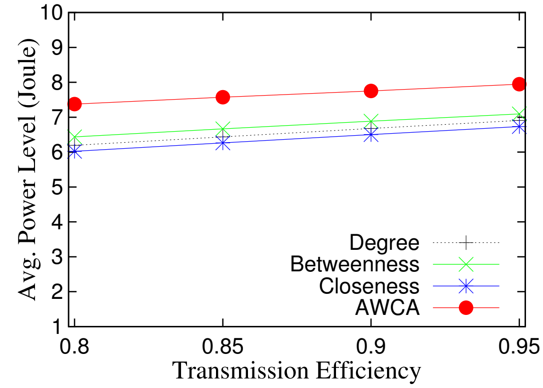

Fig. 15. The average power level vs. the transmission efficiency.

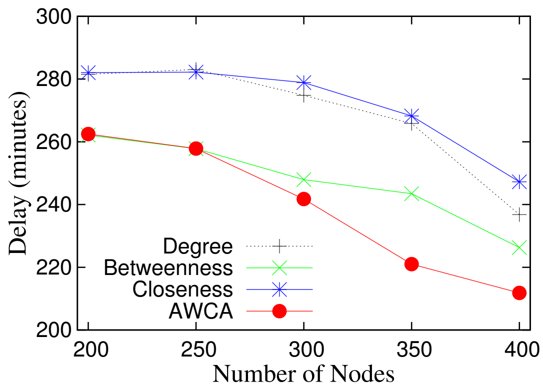

Fig. 16. The delay vs. the number of nodes.

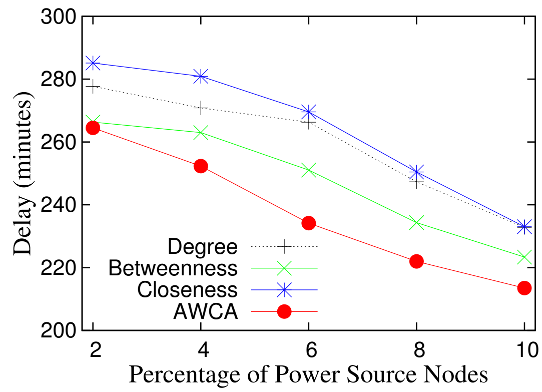

Fig. 17. The delay vs. the percentage of power source nodes.

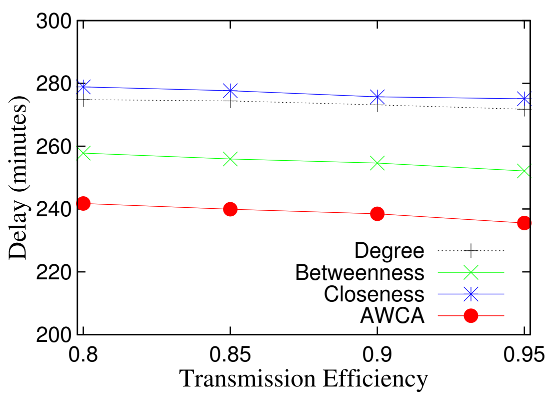

Fig. 18. The delay vs. the transmission efficiency.

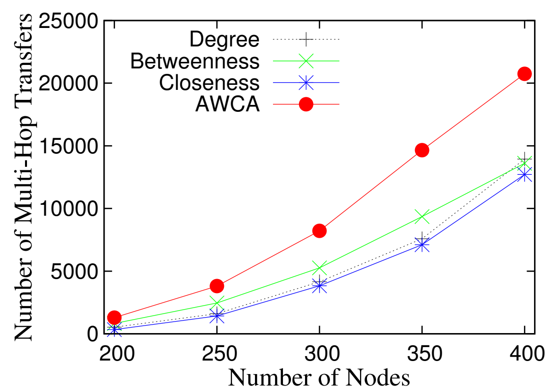

Fig. 19. The number of multi-hop transfers vs. the number of nodes.

different algorithms with respect to the power level at each node in $\{V \setminus V_s\}$, where $|V| = 300$, $n = 5\%$, and $\gamma = 0.8$. As can be seen in the figure, the probability density is high at power levels 5 and 10. According to the power dissemination phase, a set of power transfer flows rooted at power source nodes are constructed. Thus, the nodes at the edge stop receiving power when their power levels exceed the target power level, i.e., $P_i \geq P_{min} = 5J$. On the other hand, the nodes close to any of the power source nodes will receive as much power as possible to transfer power to others, and as a result, their power level reaches the maximum capacity, i.e., $P_{max} = 10J$. This is why the probability densities at 5 and 10 are high compared to the other power levels.

Figure 13 depicts the average power level of different algorithms with respect to the number of nodes, where $n = 5\%$ and $\gamma = 0.8$. While the target power level P_{min} is set to be $5J$, relay nodes must store a larger amount of power than P_{min} to transfer power to other nodes. A trend similar to that in Figure 8 is observed, i.e., for all the schemes, the average power level increases as the number of nodes increases. Again, our AWCA always achieves the highest average power level among all the algorithms.

Figure 14 shows the average power level of different algorithms with respect to the percentage of power source nodes, where $|V| = 300$ and $\gamma = 0.8$. It is intuitive that having more power source nodes lead to more opportunities for power transfers. As a result, the average power level increases when the percentage of power source nodes increases. The proposed AWCA always results in a higher average power level than the others.

Figure 15 illustrates the average power level of different algorithms with respect to the transmission efficiency, where

$|V| = 300$ and $n = 5\%$. For all of the algorithms, the average power level slightly increases when the transmission efficiency increases. Unlike the other factors, the impact of the transmission efficiency is not significant. As shown in the figure, AWCA always presents a higher average power level than the other algorithms by at least $1.5J$.

Figure 16 illuminates the charging delay of different algorithms with respect to the number of nodes, where $n = 5\%$ and $\gamma = 0.8$. It is intuitive that the charging delay decreases as the number of nodes increases. Our AWCA incurs the smallest charging delay when the number of nodes is greater than or equal to 300. AWCA and the betweenness result in a similar delay when the number of nodes is smaller than 300. This indicates that AWCA efficiently exploits multi-hop power transfers even when the number of contact events is low. On the other hand, the degree and closeness centralities incur a longer charging delay than AWCA does.

Figure 17 presents the charging delay of different algorithms with respect to the percentage of power source nodes, where $|V| = 300$ and $\gamma = 0.8$. The delays of AWCA and the betweenness centrality are very close to each other when the percentage of power source nodes equals to 2%. When $n \geq 4\%$, AWCA achieves faster charging than the betweenness by 10%. In addition, AWCA incurs much smaller charging delay than the degree and closeness do.

Figure 18 demonstrates the charging delay of different algorithms with respect to the transmission efficiency, where $|V| = 300$ and $n = 5\%$. The figure implies that a higher transmission efficiency reduces the charging delay. The delay of our AWCA is always the shortest among all of the algorithms. To be specific, AWCA achieves approximately 8% faster charging than the betweenness and 15% faster charging than the degree and closeness.

Figure 19 gives the number of multi-hop power transfers of different algorithms with respect to the number of nodes, where $n = 5\%$ and $\gamma = 0.8$. As can be seen in the figure, the number of multi-hop power transfers increases as the number of nodes increases. Among all the algorithms, the proposed scheme results in the largest number of multi-hop power transfers. This indicates that our AWCA algorithm effectively utilizes a multi-hop MSN.

7 Conclusion

In this paper, we first introduce a new research problem, namely wireless charger allocation in mobile social networks (MSNs), in which wireless chargers are allocated to a set of important nodes in a network, and then power is wirelessly transferred to other nodes via a multi-hop contact network. To this end, the weighted connectivity centrality is designed to quantify the extent to which each node can directly and indirectly transfer power to the others. The proposed metric combines not only the shortest path distance, but also the number of hops with the consideration of transmission power loss and the expected power flow. Then, we propose the adaptive wireless charger allocation (AWCA) algorithm that adaptively selects the nodes with the highest centrality as power source nodes and effectively transfers power from the power source nodes to the others in an MSN. To evaluate the performance of the proposed algorithm, extensive simulations using real human contact traces are conducted. The simulation results demonstrate that the proposed AWCA outperforms the baseline algorithms with common centrality metrics in terms of the energized rate, average power level, and charging delay. Our research on WPT in DTNs will be more effectively exploited, when the physical layer capability in terms of the transmission efficiency improves in the near future.

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ACKNOWLEDGEMENT

This research has been funded in part by the JSPS KAKENHI Grant Number 20K19786 and the U.S. National Science Foundation grants IIS-1618669 (III) and ACI-1642133 (CICI).

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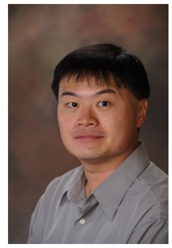

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