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Utility-Based Stable Matching For Large Scale EH Relay Networks With Finite-Alphabet Inputs

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ABSTRACT The computational complexity of utility optimization for a large scale energy harvesting (EH) relay network is extremely high, especially when inputting finite-alphabet signals. This paper investigates the utility optimization for large scale EH relay networks with finite-alphabet inputs by the stable matching scheme. First, we divide the nodes, which may act as a user or a relay, into multiple clusters, and perform optimization strategy within the clusters. Second, the optimal power bought from the relay node to maximize the utility of the user is derived. Then, the mutual preference matrices between the users and relays by the maximum utility criterion are established. Base on the mutual preference matrices, an improved Gale-Shapley (GS) algorithm is proposed to get a sub-optimal result. The simulation results demonstrate that the proposed algorithm can bring significant performance improvements and achieve higher energy efficiency compared with the conventional algorithms. In contrast to the exhausted Search (ES) method, it costs much less time and accomplishes an approximative utility output. Moreover, the proposed scheme incurs low signaling overhead which makes it practical to be implemented.

INDEX TERMS Large scale relay networks, utility optimization, stable matching, finite-alphabet inputs, energy harvesting.

I. INTRODUCTION

Nowadays, we have entered the era of Internet of Things (IoT), countless sensors and other devices are deployed worldwide to fulfill the information acquisition, fusing and transmission [1]. However, due to limited battery capacity and inconvenient for battery replacement, how to achieve self-sustainability for a large scale wireless sensor network (WSN) under IoT framework becomes a challenge [2]. A promising solution to supply the energy of the nodes in WSNs is by collecting energy from the environment, that is so-called energy harvesting (EH) technology [3], [4]. With EH technology, the density of the nodes for WSNs may reach up to one hundred nodes per square meter. To improve coverage and energy efficiency, the nodes in WSNs may act as a relay of other nodes, thus a large scale EH relay network can be formed to perform maintenance-free applications such as environment monitoring [5]. In an EH relay network, how to choose the optimal relay selection and power allocation scheme has become a critical issue [6], [7]. Among all the schemes, opportunistic relaying achieves the same diversity of the multi-relay scheme, but requires less computational costs and communication overhead [8], [9]. Usually a utility function is defined to measure the effectiveness of the relay selection and power allocation scheme. For example, in [10], a slotted energy relaying model is proposed to maximize the utility of radio-frequency energy harvesting relays. In order to optimize the utility of the system, a two-hop coordinated scheduling algorithm is proposed in [11].

Most of the existing literatures on utility optimization are with the assumption of Gaussian signals input, the objective functions of which are defined based on the achieved channel

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capacity [12]–[14]. In [12], two distributed contention-based medium access control algorithms for solving the network utility maximization problem in wireless ad hoc networks are proposed. Authors in [13] propose a generalized gradient scheduling that easily finds a solution to the generalized network utility maximization problem by simplifying its objective function. In [14], the authors consider the problem of simultaneous user-scheduling, power-allocation, and rate-selection in an orthogonal frequency division multiple access (OFDMA) downlink, with the goal of maximizing expected sum-utility under sum-power constraint. However, the practical systems always utilize finite-alphabet constellations, such as pulse amplitude modulation (PAM), phase shift keying (PSK) modulation, or quadrature amplitude modulation (QAM) [15]–[21]. The explicit expression of the achieved maximal mutual information in a practical system with finite-alphabet inputs is lacked and can only be estimated by Monte Carlo method, which is computationally expensive [15]. To reduce the calculation complexity, the accurate approximation of the mutual information with finite-alphabet inputs is obtained in [16]. As the mutual information can not reach the channel capacity especially in moderate-to-high signal-to-noise ratio (SNR), this deviation makes it essential to adjust the objective function of the utility optimization problem.

Due to massive number of nodes in a large scale EH relay network, the interference becomes a more serious issue. Dividing nodes into clusters is an efficient way to mitigate the interference. Authors in [22] proposed a graph-based clustering resource allocation scheme, which divides all base stations into independent clusters based on a coloring algorithm. In [23], a semi-distributed interference management scheme is presented, which is based on joint clustering and resource allocation for femtocells. In addition to the interference problem, the optimal solution for utility optimization of the whole network becomes a NP-hard problem especially when the inputs are finite-alphabet signals. Distributed strategies such as game theory methods can be adopted to get a sub-optimal solution, which model each node in the network as a rational and selfish agent. But game theory methods are not suitable for large scale EH relay networks because of the slow convergence speed [24]. In contrast, the suitability of matching theory has been corroborated by a number of recent works such as [25], [26]. In particular, [25] presented one of the first works in this area. In this work, a one-to-one matching problem is formulated between a number of users and a number of channels. The channels are assumed to be orthogonal; hence, the game is a canonical matching game. The preferences of both users and channels are based on the same utility function, which are defined according to the rate of transmission. This work was extended in [26] to analysis the energy efficiency. Moreover, the stable matching algorithm can be utilized to get a sub-optimal solution more quickly, which has been applied in resource allocation in wireless networks [27]–[32]. In order to achieve a high access ratio and a short access latency, a content replication scheme using stable matching is proposed in [28]. In [29], a stable matching approach is applied to allocate radio resources in D2D communication under channel uncertainties. In [30], a one-to-one stable matching is considered for channel assignment in cognitive radio settings. In [32], the matching-game based scheme promises an efficient tradeoff in multi-user and multi-relay networks. To the best of our knowledge, the utility function of previous works is based on channel capacity, which leads to inaccurate utility optimization, and the stable matching for utility optimization of large scale EH relay networks with finite-alphabet inputs has never been investigated before. This prompts us to solve the problem.

In this paper, we propose a utility optimization strategy for large scale EH relay networks with finite-alphabet inputs. We divide the nodes into multiple clusters, and perform optimization strategy within the clusters. First, optimal power is obtained to maximize the utility of the users when choosing a relay as their candidate. Second, the mutual preference matrices between the users and the relays are established based on the principle of utility maximization. Third, an improved stable matching algorithm for large scale relay networks is proposed by exploiting Gale-Shapley (GS) algorithm with lower complexity. The simulation results verify that the proposed algorithm achieves better performance compared to the conventional algorithms.

The main contributions of this paper are summarized as follows:

1) We investigate the utility optimization problem in a large scale EH relay network using decode-and-forward (DF) relaying strategy with finite-alphabet inputs. Specifically, the power optimization problem to maximize the utility of a user is convex under the constraint of stored energy. The stable matching problem to maximize the utility of matching pairs is a non-deterministic polynomial NP) problem under the constraint of one-to-one matching.
2) In order to get the tradeoff between the resource utilization efficiency and the reduction of the interference, we apply the clustering scheme, where the users and relays are divided into groups. Resource are orthogonal within a cluster and are reused between the clusters. We perform optimization strategy within a cluster.
3) Efficient algorithm is proposed to optimally solve the utility optimization problem. First, we obtain the optimal power bought from a relay node by an iterative optimization method. Then, the users' and the relays' preference matrices are obtained according to their utilities based on the optimal power. Finally, with the established mutual preference matrices, we propose an improved GS algorithm to solve the stable matching problem. We also discuss the implementation, convergence, complexity, and traffic overhead of the GS algorithm.
4) Valuable insights are provided via simulations. The proposed algorithm is compared with four conventional algorithms from the aspect of the system's ergodic utility

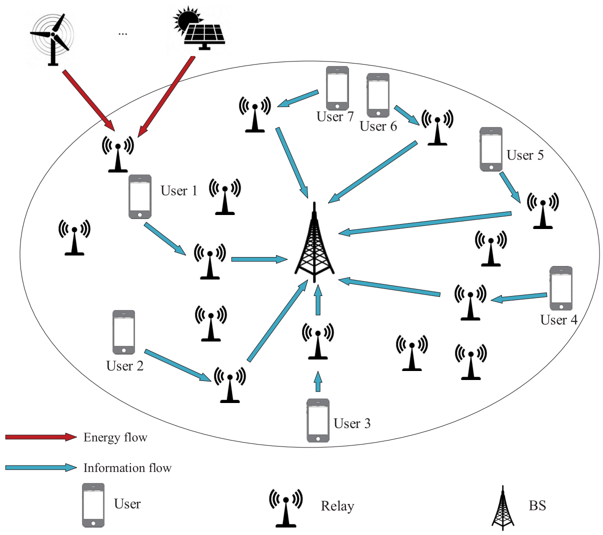

FIGURE 1. **System model of large scale relay networks.**

of the matching pairs. Simulation results demonstrate that the proposed algorithm can bring significant performance improvements and achieve higher energy efficiency compared with the other algorithms and performs close to the optimal one in practical systems.

The rest of this paper is organized as follows. Section II describes the system model for a large scale EH relay network with finite-alphabet inputs. Section III presents the proposed algorithm for the power purchase and the stable matching to maximize the utility of matching pairs. Section IV analyzes the implementation, convergence, complexity, and traffic overhead of the proposed algorithm. Section V provides simulation results and performance evaluations. Section VI concludes this paper.

Notation: Boldface uppercase (lowercase) letters denote matrices (column vectors) and italics denote denote scalars. The $[\mathbf{A}]_{i,j}$ and $[\mathbf{A}]_{-i,j}$ denote the (i,j)-th element and the elements of j-th column except (i,j)-th element of matrix $\mathbf{A}$, respectively.

II. SYSTEM MODEL

We consider a multiuser large scale EH relay network as shown in Fig. 1, in which there are in total S users, N relays and one BS d. In this paper, the users and the BS are also referred to as the source and the destination, respectively. We assume that the relay nodes rely on the harvested energy to transmit signals, while the destination node have continuous energy supplies.

We consider quasi-static fading environment and the channel can be thought as constant over an observed transmission block. The S users in the network can be denoted by the set $\mu = \{1, 2, \cdots, S\}$. Opportunistic relaying are adopted, i.e., each user $i \in \mu$ will select one optimal relay from ν for communication in a transmission slot, where $\nu = \{1, 2, \cdots, N\}$ denotes the candidate set of relays. All nodes are equipped with a single antenna and operate it in half-duplex mode. The relay nodes adopt the DF strategy.

In each slot, the relaying process can be divided into two phases [24]. Without loss of generality, the slot of transmission block can be denoted by $\tau = 1$. In phase 1, which is called the broadcast phase, the user node i broadcasts the symbols to both destination node d and the relay nodes in ν with the transmit power p_i simultaneously. Let $h_{i,j}$ denotes the complex fading coefficient of the link between the node i and node j, which is modeled as quasi-static fading Rayleigh channel $h_{i,j} \sim \mathcal{CN}(0, d_{i,j}^{-\alpha})$, where $d_{i,j}$ is the distance between i and j, and α is the path-loss exponent. The received signal at destination node d and relay k can be expressed as

$$y_{i,d} = \sqrt{p_i} h_{i,d} x_i + n_{i,d}, \tag{1}$$

and

$$y_{i,k} = \sqrt{p_i} h_{i,k} x_i + n_{i,k}, \tag{2}$$

where $h_{i,d}$ and $h_{i,k}$ represent the channel gains from node i to destination node d and relay node k, respectively. Let $n_{i,d}$ and $n_{i,k}$ represent the additive white Gaussian noises, respectively. Without loss of generality, the noise power for all the links is set to the same value and can be denoted as σ^2.

In phase 2, the relay $k \in \nu$ selected by the user i regenerates the received signals and forwards the estimated symbol x_k to the destination node d with transmitted power $p_{i,k}$. The received signal at destination node d can be expressed as

$$y_{k,d} = \sqrt{p_{i,k}} h_{k,d} x_k + n_{k,d}, \tag{3}$$

where $h_{k,d}$ is the channel gain from relay node k to the destination node d and $n_{k,d}$ denotes the received noise.

The relay nodes harvest energy from the environment and the arriving energy is stored. The energy harvesting process is modeled as a Poisson process with EH rate λ_k [33]. We assume the relays are equipped with a finite-sized battery, the size of which E_k^{tot} satisfies $0 < E_k^{tot} < \infty$. Because of the finite-sized battery, the energy harvested must meet the constraint without energy-overflow. We can get the constraint of stored energy E_k^s with finite-sized battery as

$$E_k^s = \min\left(E_k^0 + E_k^{EH}, E_k^{tot}\right), \tag{4}$$

where E_k^0 is the residual energy in the battery of the relay before EH process and E_k^{EH} denotes the harvested energy in a slot.

III. UTILITY-OPTIMIZED STABLE MATCHING FOR RELAY NETWORKS WITH FINITE-ALPHABET INPUTS

In this section, firstly, we create a number of clusters for a large scale EH relay networks with finite alphabet inputs by K-means algorithm. Next, the optimal power bought from the relay by user can be obtained to maximize the utility function of the user node with our iterative optimization method. Then, we establish mutual preference matrices between the users and the relays, and then present a proposed utility-based stable matching algorithm of EH relay network with finite alphabet inputs, which aims at deriving a sub-optimal utility optimization result of the network. Finally, we analyze the implementation and the convergence of the algorithm.

A. CLUSTERS CREATING FOR LARGE SCALE RELAY NETWORKS

In large scale network scenarios, the interference is a serious issue, and it is difficult to access the state information of all the nodes in a network for optimizing the system performance. Therefore, we adopt the clustering scheme, which first divide all the nodes into C clusters, and then perform optimization strategy within a cluster. We use K-means algorithm to decide the cluster member and choose the node closest to the centroid as the cluster head. To get the tradeoff between the resource utilization efficiency and the reduction of the interference, resources are orthogonal within a cluster and are reused between the clusters.

Let look into one cluster $c \in \psi$, where $\psi = \{1, 2, \cdots, C\}$ denotes the set of clusters. Cluster c is composed of T users and K relays. The T users and K relays in the cluster can be denoted by the set $\chi = \{1, 2, \cdots, T\}$ and $\omega = \{1, 2, \cdots, K\}$, respectively. Without loss of generality, the noise power of all the links is set the same and can be denoted as σ^2. The intra-cluster interference can be eliminated by orthogonal resource allocation schemes such as OFDMA.

Considering the inter-cluster interference, the Signal to Interference plus Noise Ratios (SINRs) can be expressed as

$$\gamma_{i,k} = \frac{p_i \left|h_{i,k}\right|^2}{\sigma^2 + I_{i,k}}, \tag{5}$$

$$\gamma_{i,d} = \frac{p_i \left|h_{i,d}\right|^2}{\sigma^2 + I_{i,d}}, \tag{6}$$

and

$$\gamma_{k,d} = \frac{p_{i,k} \left|h_{k,d}\right|^2}{\sigma^2 + I_{k,d}}, \tag{7}$$

where $I_{i,k} = \sum_{j \neq i, j \in \mu} p_j \left|h_{j,k}\right|^2$, $I_{i,d} = \sum_{j \neq i, j \in \mu} p_j \left|h_{j,d}\right|^2$ and $I_{k,d} = \sum_{j \neq i, l \neq k, j \in \mu, k \in \nu} p_{j,l} \left|h_{l,d}\right|^2$ $(i \in \chi,\, k \in \omega)$ denote total inter-cluster interference caused by the set of other clusters that reuse the same channel.

Therefore, the SINR at the output of the maximal-ratio combining (MRC) is given by [24]

$$\gamma_{i,k,d} = \min\left(\gamma_{i,k}, \gamma_{i,d} + \gamma_{k,d}\right). \tag{8}$$

The achieved information rate at the output of MRC with finite-alphabet inputs is given by [16]

$$R_{i,k,d}\left(p_{i,k}\right) = \frac{1}{2}\log_2 M - \frac{1}{2M}\sum_{m=1}^{M}\log_2\sum_{n=1}^{M}\exp\left(g_{mn}\left(p_{i,k}\right)\right), \tag{9}$$

where $g_{mn}\left(p_{i,k}\right) \triangleq -\gamma_{i,k,d}|(x_m - x_n)|^2/2$ and the signal x_m, x_n are drawn from a discrete M-ary modulating constellation, such as PSK, PAM or QAM.

B. OPTIMAL POWER BOUGHT FROM A RELAY NODE

We assume that all the nodes including the users and the relays are selfish and rational whose objectives are to maximize their own utility. As the users can be modeled as an energy buyer, the utility function of user i is given by:

$$U_{i,k}^{u}\left(p_{i,k}\right) = g_i R_{i,k,d}\left(p_{i,k}\right) - \eta_k p_{i,k}, \tag{10}$$

where $R_{i,k,d}\left(p_{i,k}\right)$ and g_i denote the information rate at the output of MRC with finite-alphabet inputs of relay k and unit information rate gain of user i respectively, η_k represents the price per unit of the power purchased by user i from relay k.

Relays can be modeled as an energy seller that aim at maximizing their own profits. The utility function of each relay $k \in \omega$ can be defined as

$$U_{i,k}^{r}\left(p_{i,k}\right) = \left(\eta_k - c_k\right) p_{i,k}, \tag{11}$$

where $c_k = \left|E_k^{tot}/E_k^{s}\right|^{\beta}/\lambda_k$ denotes the cost of per unit of power, which is introduced so that the energy efficiency becomes higher and the variable β represents the exponent [34]. Besides, the relay with more adequate stored energy E_k^s and higher average energy arrivals rate λ_k will offer a lower price.

Considering the fairness between user i and relay k, the utility function of the matching pair can be defined as

$$\begin{aligned} U_{i,k}^{N}\left(p_{i,k}\right) &= w^u U_{i,k}^{u}\left(p_{i,k}\right) + w^r U_{i,k}^{r}\left(p_{i,k}\right) \\ &= w^u\left(g_i R_{i,k,d} - \eta_k p_{i,k}\right) + w^r\left(\eta_k - c_k\right) p_{i,k}, \end{aligned} \tag{12}$$

where w^u and w^r denote the weight factor of $U_{i,k}^{u}\left(p_{i,k}\right)$ and $U_{i,k}^{r}\left(p_{i,k}\right)$ respectively.

The energy consumption of the matching pair is given by

$$E_{i,k}\left(p_{i,k}\right) = \frac{1}{2}\tau p_i + \frac{1}{2}\tau p_{i,k}, \tag{13}$$

the first term and the second term represent the amount of energy consumption of the user and the relay during the cooperative transmission of a data block, respectively.

We define the energy efficiency as the ratio of utility to energy consumption. The energy efficiency of the matching pair is given by

$$U_{i,k}^{EE}\left(p_{i,k}\right) = \frac{U_{i,k}^{N}\left(p_{i,k}\right)}{E_{i,k}\left(p_{i,k}\right)}. \tag{14}$$

We first prove that $R_{i,k,d}\left(p_{i,k}\right)$ is a concave function of $p_{i,k}$. It can be shown that $\log\sum_n\left(g_n\right)$ is convex whenever g_n is convex [35]. Thus $\frac{1}{M}\sum_{m=1}^{M}\log_2\sum_{n=1}^{M}\exp\left(g_{mn}\left(p_{i,k}\right)\right)$ is convex with the operation of positive weighted sum. Therefore, $R_{i,k,d}\left(p_{i,k}\right)$ is a concave function of $p_{i,k}$.

With a limited-storage battery, the maximum transmit power $p_k^{\max}$ of the relay k depends on the stored energy E_k^s. Then we can get another constraint of power bought from relay k:

$$\frac{1}{2}\tau p_k^{\max} \leq E_k^s. \tag{15}$$

Algorithm 1 Maximizing the Utility Function with respect to the Power Bought from Relay

Initialize :
  Set the price of power η_k and the stored energy E_k^s. Initialize $a = 0, b = E_k^s$, the golden ratio $\varphi = \frac{1}{2}(-1+\sqrt{5})$ and tolerance $\varepsilon > 0$.
Repeat
  Update $p_a := b - \varphi(b-a)$ and $p_b := a + \varphi(b-a)$.
  Calculate the utility of user $U_{i.k}^u(p_a, \eta_k)$ and $U_{i.k}^u(p_b, \eta_k)$.
  If $U_{i.k}^u(p_b, \eta_k) < U_{i.k}^u(p_a, \eta_k)$, set $b = p_b$. Otherwise set $a = p_a$.
Until $|a-b| < \varepsilon$.
Output :
  The optimal power $p_{i,k}^* = \frac{1}{2}(a+b)$ bought from relay.

Based on the current prices of all relays, the users chooses to purchase the optimal power quantity to maximize their utilities. According to the principle of utility maximization, the utility of user i's maximization problem can be expressed as follows when user i chooses relay k as its candidate:

$$P1: \min_{p_{i,k}} -U_{i,k}^u(p_{i,k}) = -g_i R_{i,k,d} + \eta_k p_{i,k} \tag{16a}$$

$$s.t.\ 0 \le \frac{p_{i,k}}{2} \le E_k^s, \tag{16b}$$

$$E_k^s = \min\left(E_k^0 + E_k^{EH}, E_k^{tot}\right). \tag{16c}$$

It has been shown that $R_{i,k,d}(p_{i,k})$ is a concave function of $p_{i,k}$. Furthermore, the problem P1 is convex because the objective function is convex and the constraint functions are affine. The optimal solution of the problem P1 is illustrated in Algorithm 1 and the optimal power $p_{i,k}^*$ of each user $i \in \chi$ bought from relay k can be given by:

$$p_{i,k}^* = \arg\max_{p_{i,k}} \left(U_{i,k}^u(p_{i,k})\right). \tag{17}$$

C. STABLE MATCHING ALGORITHM FOR RELAY NETWORKS

If user i chooses relay k as its candidate, the utility of user i and relay k can be obtained by $U_{i,k}^u{}^*(p_{i,k}^*)$ and $U_{i,k}^r{}^*(p_{i,k}^*)$ according to (17), respectively.

For the purpose of exposition, we denote the utility function vector of user i as $\mathbf{U}_i^u = [U_{i,1}^u{}^*, \cdots, U_{i,K}^u{}^*]^T$. Thus, the utility function matrix of all users can be denoted by

$$\mathbf{U}^u = [\mathbf{U}_1^u, \cdots, \mathbf{U}_T^u]^T, \tag{18}$$

in the same way, we can denote the utility function matrix of all relays as

$$\mathbf{U}^r = [\mathbf{U}_1^r, \cdots, \mathbf{U}_K^r]^T, \tag{19}$$

where $\mathbf{U}_k^r = [U_{1,k}^r{}^*, \cdots, U_{T,k}^r{}^*]^T$ represents the utility function vector of relay k.

Here we consider a one-to-one matching model between nodes, each relay can be matched to at most one user. In this paper, each user selects the single optimal relay for communication and one relay serves single user at the same time. If a user can not be matched, i.e., $T > K$, then it directly transmits information to the destination node. The utility between user i and destination node d can be calculated by

$$\begin{aligned} U_{i,d}^u &= g_i R_{i,d} \\ &= g_i(\log_2 M - \frac{1}{M}\sum_{m=1}^{M}\log_2\sum_{n=1}^{M}\exp\left(g_{mn}(p_i)\right)), \end{aligned} \tag{20}$$

and the energy consumption is given by

$$E_{i,d}\left(p_{i,k}\right) = \tau p_i. \tag{21}$$

We investigate the one-to-one stable matching between the users and the relays, the matching matrix of networks Θ can be denoted by

$$[\Theta]_{i,k} = \begin{cases} 1 & \text{match user } i \text{ with relay } k \\ 0 & \text{otherwise} \end{cases}, \quad \forall i \in \chi, \forall k \in \omega. \tag{22}$$

According to the establishment of utility function matrices, the matching problem to maximize the utility of matching pairs with stable result can be expressed as follows

$$P2: \max_{\Theta}(w^u \mathrm{Tr}(\Theta(\mathbf{U}^u)^T) + w^r \mathrm{Tr}(\mathbf{U}^r\Theta)) \tag{23a}$$

$$s.t. \sum_{k=1}^{K}[\Theta]_{i,k} = 1, \quad 1 \le i \le T, \tag{23b}$$

$$\sum_{i=1}^{T}[\Theta]_{i,k} = \{0, 1\}, \quad 1 \le k \le K, \tag{23c}$$

where $\mathrm{Tr}(*)$ denotes the sum of all of the diagonal entries of a matrix. The constraint (23b) restricts the number of relay each user can select, that is, each user can only select one relay. The constraint (23c) ensures that each relay can only be selected by one user. It is a typical constrained combinatorial optimization problem with multiple objectives. Each node has K candidates, so the computational complexity to get the globally optimal matching result of problem P2 is $\mathcal{O}(K!/(K-T)!)$, which is a Non-deterministic Polynomial (NP) problem. We proposed a stable matching scheme by exploiting an improved GS algorithm [27] to get a sub-optimal result with complexity $\mathcal{O}(KT)$, and the GS algorithm is illustrated in Algorithm 2.

Both the users and relays are selfish and rational and they will try their best to maximize their own utility. Therefore, the preference values of the sellers and buyers can be formulated as their utility. Let $\theta_i = \{U_{i,1}^u{}^*\left(p_{i,1}^*\right), \cdots, U_{i,K}^u{}^*(p_{i,K}^*)\}$ denotes the set of utility when user i matches with each relay. Thus the preference vector of user i can be denoted by $\mathbf{p}_i^u = [r_1, \cdots, r_K]^T$ with θ_i in descending order, which satisfies $U_{i,r_1}^u{}^*\left(p_{i,r_1}^*\right) \ge U_{i,r_2}^u{}^*\left(p_{i,r_3}^*\right) \ge \cdots \ge U_{i,r_K}^u{}^*\left(p_{i,r_K}^*\right)$. Thus, we can denote the preference matrix of all the users as

$$\mathbf{P}^u = \left[\mathbf{p}_1^u, \cdots, \mathbf{p}_i^u, \cdots, \mathbf{p}_T^u\right]^T. \tag{24}$$

Algorithm 2 Stable Matching Algorithm for Relay Networks

Initialize :
  Set the preference matrices of users $\mathbf{P}^u = [\mathbf{p}_1^u, \cdots, \mathbf{p}_T^u]^T$ and relays $\mathbf{P}^r = [\mathbf{p}_1^r, \cdots, \mathbf{p}_K^r]^T$. Initialize the matching matrix $\Theta = \mathbf{0}_{T\times K}$ and preference level vector of all the users $\upsilon = \mathbf{1}_{1\times T}$.
Repeat
  for $i \in \chi$ **do**
    Obtain i-th row of Θ which is $\mathbf{0}_{1\times K}$.
    Choose user i's the most preferred relay as its candidate by $[\upsilon]_i$, the number of which is $k = [\mathbf{P}^u]_{i,[\upsilon]_i}$.
    Set $[\Theta]_{i,k} = 1$.
    Choose user i's new candidate by updating $[\upsilon]_i := [\upsilon]_i + 1$.
  end for
  for $k \in \omega$ **do**
    Calculate i-th column of Θ .
    if $\sum_{i=1}^{T} [\Theta]_{i,k} > 1$ **then**
      Choose relay k's most preferred user l by $\mathbf{P}^r$ among its candidates.
    else
      if $\sum_{i=1}^{T} [\Theta]_{i,k} = 1$ **then**
        Choose relay k's the only candidate user l.
      end if
    end if
      Set $[\Theta]_{l,k} = 1$ and $[\Theta]_{-l,k} = 0$.
  end for
  Calculate rank(Θ).
Until rank(Θ) $= L$.
Output :
  The optimal matching matrix Θ^*.

Similarly, the preference matrix of relays when matching with the users can be denoted by

$$\mathbf{P}^r = [\mathbf{p}_1^r, \cdots, \mathbf{p}_k^r, \cdots, \mathbf{p}_K^r]^T, \tag{25}$$

where $\mathbf{p}_k^r = [u_1, \cdots, u_T]^T$ represents the preference vector of relay k, which satisfies $U_{u_1,k}^{r\ *}\left(p_{u_1,k}^*\right) \geq U_{u_2,k}^{r\ *}\left(p_{u_2,k}^*\right) \geq \cdots \geq U_{u_T,k}^{r\ *}\left(p_{u_T,k}^*\right)$.

After obtaining the preference matrices, the stable matching algorithm based on the GS algorithm can be obtained, and the steps are as follows:

1) In the first iteration in Algorithm 2, each user $i \in \chi$ proposes the most preferred relay according to the preference matrix $\mathbf{P}_i^u$. Then each relay $k \in \omega$ chooses the most preferred user and rejects other users on the basis of $\mathbf{P}_k^r$.
2) The rejected users will rechoose their most preferred relay as candidate among those who have not rejected them before. Then each relay will update its most preferred choice and reject other users by comparing the held candidates with the new proposals.
3) Finally the algorithm will end when every user is either matched to a relay or has been rejected by all relays, i.e. the stable matching between the users and relays is derived when

$$\text{rank}(\Theta) = L, \tag{26}$$

where $L = min(T, K)$.

The algorithm enables the users and relays to continuously update the optimal candidates in each iteration instead of the absolute match, so that the current matching result can be continuously updated through subsequent iterations, and finally a better matching result is achieved. Instead of random matching, better results emerge by proceeding the proposed stable matching algorithm.

Based on the matching model and the stable matching algorithm, the process of matching between nodes can be summarized into two steps. First, the users and relays obtain the stable matching results between them according to Algorithm 2. The result can be that every user is either matched to a relay or has been rejected by all relays. Second, the user, which is rejected by all relays, directly transmits information to the destination node.

IV. ANALYSIS OF THE PROPOSED ALGORITHM

This section analyzes the implementation, the convergence, the complexity, and the traffic overhead of the proposed algorithm.

A. IMPLEMENTATION

In this paper, coordinators are used to allocate orthogonal resources. The cluster header can act as the coordinator for each cluster. The range of i and k mentioned below is set to χ and ω, respectively. The implementation steps of the proposed relay selection method are as follows:

1) *Collect information.* For each cluster, user i collects the local information, such as $h_{i,k}$, $h_{i,d}$, $I_{i,k}$, $I_{i,d}$, and $P_{i,k}$. In addition to local information, user i is also required to collect the information transmitted from relay k, including η_k, E_k^s, $I_{k,d}$ and $h_{k,d}$. Relay k is also required to collect the information transmitted from user i, including $P_{i,k}$.
2) *Calculate optimal power.* After collecting enough information, user i calculates the optimal power $p_{i,k}^*$ bought from relay k according to algorithm 1.
3) *Build preference vector.* According to Section III-C, user i builds the preference vector $\mathbf{P}_i^u$ and relay k builds the preference matrix $\mathbf{P}_k^r$ by utilizing their existing information.
4) *Take actions.* After building the preference vectors, nodes perform matching process according to algorithm 2 until every user is either matched to a relay or has been rejected by all relays.

B. CONVERGENCE

The optimal utility function $U_{i,k}^u$ is a basis for judging user i's preference for relay k, and the optimal utility function $U_{i,k}^r$ is a basis for judging relay k's preference for user i. According to their preferences, the users choose their most preferred relay as candidate among those who have not rejected them before, and the relays update their most preferred choice and reject other users by comparing the held candidates with the new proposals in each iteration. The algorithm will end when no user is rejected, i.e. all users have been matched with a different relay.

C. COMPLEXITY

This paper investigates the utility optimization by clustering, optimizing power and stable matching. For clustering, we use K-means algorithm, the complexity is $\mathcal{O}((S+N)CL)$, where L represents the number of iterations required to converge. For optimizing power, we use one dimensional research method, i.e., Algorithm 1, the complexity is in the order of $\mathcal{O}(IJ)$, where I and J are the maximum numbers of iterations required for reaching convergence and solving the utility optimization problem. Before stable matching, we establish preference matrices, since it involves two sorting, the complexity is $\mathcal{O}(KT\log(KT))$ taking T users and K relays into consideration. For stable matching, i.e., Algorithm 2, we use an improved GS algorithm with polynomial time complexity $\mathcal{O}(KT)$ [27].

D. TRAFFIC OVERHEAD

We analyze the traffic overhead in one cluster, which is composed of T users and K relays. The algorithm is implemented in a distributed fashion. Thus, the traffic overhead mainly comes from the exchange of information. The users and the relays need to collect information to calculate the power bought from the relays and establish their preference lists. Moreover, they need to transmit messages to make choices.

Users have to obtain the channel state information (CSI) to calculate the power bought from the relays. To this end, firstly, each relay and the BS broadcast N_T bit reference signal. Thus, the users can get the CSI from the relays and the BS to them, and the relays can get the CSI from the BS to them. Due to the assumption of channel reciprocity, the corresponding uplink CSI would be got. Then, each relay broadcasts the obtained CSI via N_H bit information. After obtaining the necessary CSI, the users also need to collect other information, such as the price per unit of the power, the stored energy. Therefore, each relay uses N_I bit information to broadcast them.

Once the users have received the above information, they calculate the optimal power bought from the relays, and broadcast it via N_P bit information.

So far, the users and the relays have collected all necessary information to perform stable-matching algorithm. Firstly, the users and the relays establish their preference lists. Then, the matching process starts. The process can be mapped onto the connection control process [36]. For establishing connection in the networks, the process are as follows. The users transmit a *ConnectionRequest* message to the relays. If the relays accept the connection, they send a *ConnectionSetup* message to the users and the users return a *Connection-Complete* message. Otherwise, the relays respond with the message *ConnectionReject*. For releasing connection in the networks, the relays send the message *ConnectionRelease* message.

We analyze the signaling overhead for the stable-matching. There are three cases during the iteration. The case A is that the users make requests to the relays which are idle, of course, the relays will accept the requests, thus, the number of messages exchanged is 3. The case B is that the users make requests to the relays which are connected, and they establish successful connections, the number of messages exchanged is 4. The case C is that the users make requests to the relays which are connected, and they fail to make connections, the number of messages exchanged is 2.

The total signaling overhead can be obtained by

$$\begin{aligned}\Omega_{pro} = (K+1)N_T + KN_H + KN_I + TN_P \\ + K_M(3N_A + 4N_B + 2N_C), \quad (27)\end{aligned}$$

where N_A, N_B, N_C are the number of case A, case B and case C, respectively; K_M is the number of bits for all messages.

Obviously, the overhead of the system increases with the increase of the number of the nodes. However, the computational complexity of the distributed algorithm is significantly lower than the centralized one and it achieves a substantial performance gain compared to the conventional algorithms.

We characterize the traffic overhead based on the percentage of signaling transmission time to channel coherence time, which is given by

$$\Omega_{per} = \frac{\Omega_{pro}}{IT_c}, \quad (28)$$

where I is the bit rate, and $T_c = 0.423c/(vf_C)$ represents the channel coherence time [37]; v is defined as the moving speed, f_C represents the carrier frequency, and c is denoted as the speed of light.

V. SIMULATIONS

This section examines the performance of the proposed stable matching algorithm for large scale EH relay networks with finite-alphabet inputs. With finite alphabet inputs, matching algorithms are depicted for performance comparison with other schemes. We compare the performance with six schemes, to present simply, we termed them as follows:

- **SMP** : the scheme adopts stable matching algorithm in practical systems with finite alphabet inputs.
- **SDP** : the scheme adopts shortest distance algorithm in practical systems with finite alphabet inputs.
- **RMP** : the scheme adopts random matching algorithm in practical systems with finite alphabet inputs.
- **RMA** : the scheme adopts random matching algorithm, but the optimal power allocation is calculated based on the assumption of Gaussian inputs, which is not practical.

TABLE 1. **Simulation parameters.**

Parameter	**Value**
S	60
N	140
α	2
p_i	20 dbm
σ^2	-13 dbm
λ_k	2 J/s, $\forall k \in \nu$
E_k^0	1 J, $\forall k \in \nu$
E_k^{tot}	5 J, $\forall k \in \nu$
g_i	40, $\forall i \in \mu$
π_k	5, $\forall k \in \nu$
β	1
w^u	0.7
w^r	0.3
E_k^0	1 J, $\forall k \in \nu$
E_k^{tot}	5 J, $\forall k \in \nu$
C	5
N_T	8
N_H	8
N_I	8
N_P	8
K_M	8
f_C	2.0 GHz

- **SDA** : the scheme adopts short distance algorithm, but the optimal power allocation is calculated based on the assumption of Gaussian inputs, which is not practical.
- **ESP** : the scheme adopts exhaustive search algorithm in practical systems, which considers all the permutation and combination of one-to-one matching.

We consider a large scale relay network shown in Fig. 1.The price per unit of the power purchased by user from relay k can be obtained by $\eta_k = \pi_k E_k^{tot}/(\lambda_k E_k^s)$, where the variable π_k denotes the factor of the price. The detailed systems parameters are listed in Table 1. We consider the performance of the proposed stable matching algorithm from the aspect of ergodic utility of the matching pairs. The results are averaged over 30 simulations. For each simulation, user nodes and relay nodes are distributed randomly in relay network with $S = 60$, $N = 140$, and we divide the user and relay nodes into five clusters, the snapshot is shown in Fig. 2. The proposed algorithm is verified from the aspect of utility and the running time of matching pairs of the system.

Fig. 3 and 4 compare the ergodic utility of the matching pairs of different schemes with QPSK and 16QAM inputs, respectively. We set the user node power $p_i(\forall i \in \mu)$ from 10 dbm to 30 dbm. The other simulation parameters are the same as in Table 1. From the two figures, we first see that the trend of the curves for the five algorithm with QPSK and 16QAM inputs are virtually the same, which illustrates the consistency within the user node power range. In addition, we observe that the utility of the matching pairs of all schemes are increasing with the user's node power p_i. This is because as p_i increases, the SINR increases, thus the rate at the output of MRC rises, so does the systems's utility of the matching pairs. Moreover, larger cardinality M also result in higher utility of the matching pairs. This is because that larger cardinality M provides more signal points contained in

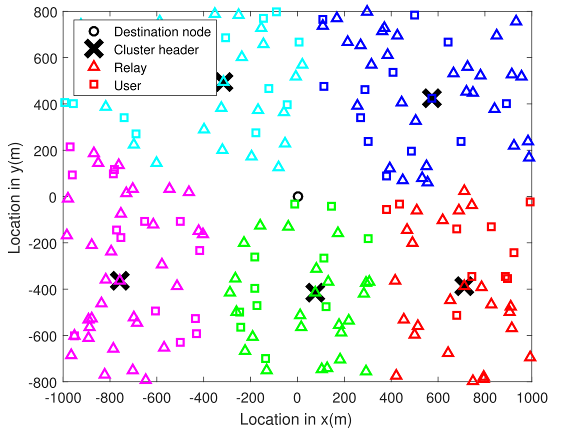

FIGURE 2. **A snapshot of multiple clusters.**

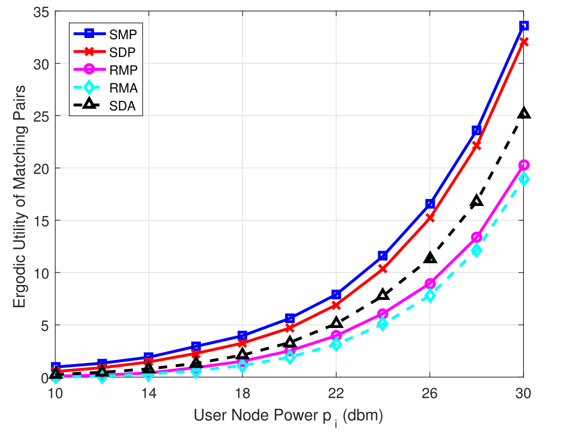

FIGURE 3. **Ergodic utility of the matching pairs versus user node power p_i for different schemes with QPSK inputs.**

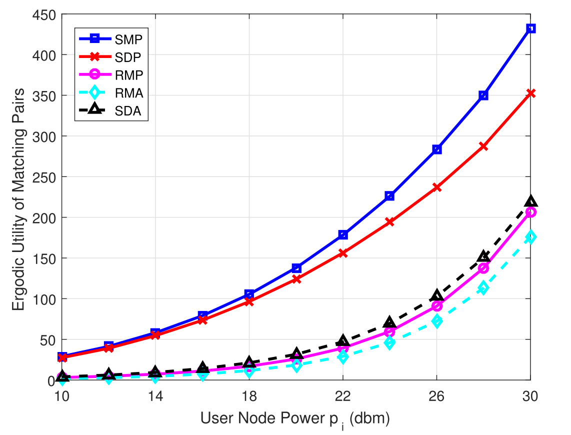

FIGURE 4. **Ergodic utility of the matching pairs versus user node power p_i for different schemes with 16QAM inputs.**

the modulated signal constellation. We also observe that the proposed SMP scheme can achieve a substantial performance gain with QPSK and 16QAM inputs, which demonstrates the effectiveness of this algorithm. Throughout the tested p_i range, the proposed SMP scheme outperforms the other four schemes, and the performance gain becomes larger when

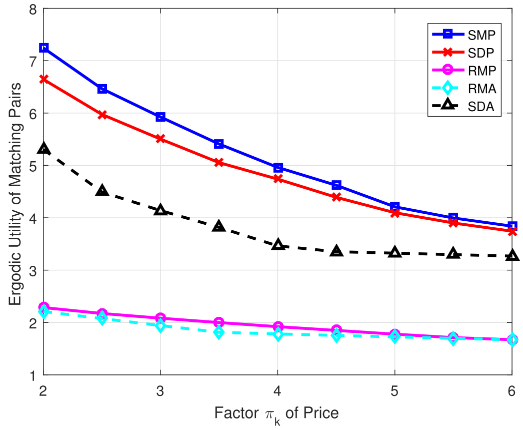

FIGURE 5. Ergodic utility of the matching pairs versus factor π_k of price for different schemes with QPSK inputs.

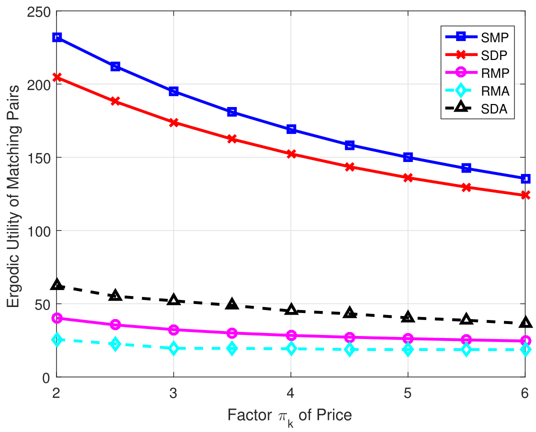

FIGURE 6. Ergodic utility of the matching pairs versus factor π_k of price for different schemes with 16QAM inputs.

p_i increases. Finally, it is shown that the RMA and SDA algorithms lead to a significant performance loss if they are directly applied with finite alphabet inputs. RMA algorithm even has the worst performance among all the five algorithms.

Fig. 5 and 6 show the ergodic utility of the matching pairs versus factor π of price for different schemes. We set the factor $\pi_k(\forall k \in \nu)$ of price from 2 to 6. The other simulation parameters are the same as in Table 1. We observe that the utility of the matching pairs of all the schemes decreases with the price growth. The reasons are two folds. Firstly, the price per unit of the power purchased by users rises with the increasing of the factor of the price. Furthermore, users are willing to buy less power to minimize its payment, which will reduce the rate as well as utility of the matching pairs with finite-alphabet inputs. It is also observed that the proposed SMP scheme performs best and the RMA performs worst within the tested π_k range. In addition, the SDP scheme offers a second-best performance. The reason lies that, it considers statistic CSI in stead of the full one which exploits less information of the practical systems. Moreover, the performance of the proposed scheme is much better than the SDP, RMP, RMA and SDA schemes, especially when the cardinality M is large, i.e., inputs are 16QAM inputs.

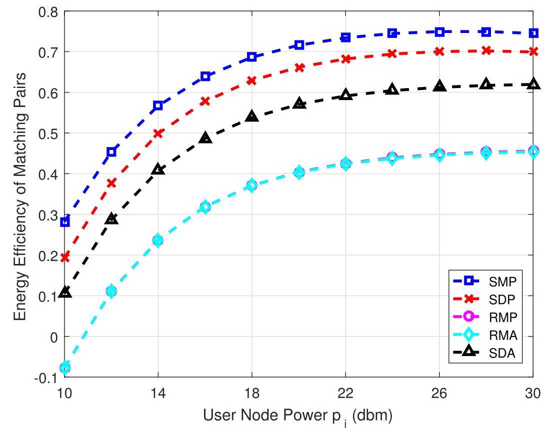

FIGURE 7. Energy efficiency of the matching pairs versus user node power p_i for different schemes with QPSK inputs.

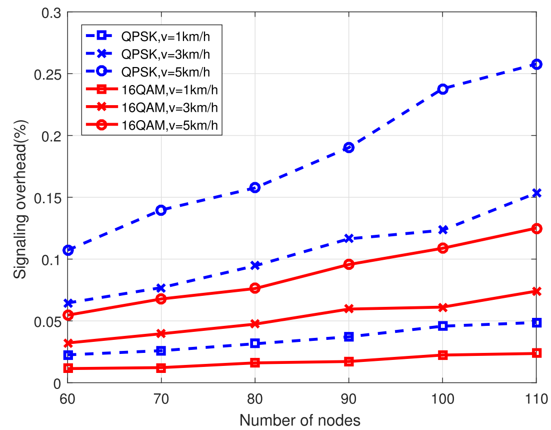

FIGURE 8. The percentage of signaling transmission time to channel coherence time versus the number of nodes.

Fig. 7 shows the energy efficiency of the matching pairs versus user node power for different schemes. We set the user node power $p_i(\forall i \in \mu)$ from 10 dbm to 30 dbm. The other simulation parameters are the same as in Table 1. We can see that throughout the tested p_i range, the performance of the proposed algorithm outperforms the other four schemes. For instance, the performance of the proposed algorithm is better than the SDP, SDA, RMP, and RMA by 7.14%, 20.97%, 57.89%, and 59.57%, respectively, when $p_i = 30$ dbm.

Fig. 8 shows the percentage of signaling transmission time to channel coherence time. We set the total number of nodes from 60 to 110, with the ratio of the number of users to the number of relays is 3:7. The bit rate is set to 50 Mbps for QPSK inputs, and 100 Mbps for 16QAM inputs. The other simulation parameters are the same as in Table 1. From the simulation result, we observe that the signaling transmission time is significantly shorter than the channel coherence time, which illustrates low signaling overhead and the practicality of our proposed scheme. Moreover, we can see that the signaling overhead increases with the increasing number of nodes, due to the fact that more nodes have more information to exchange. We also see that the increasing modulation order

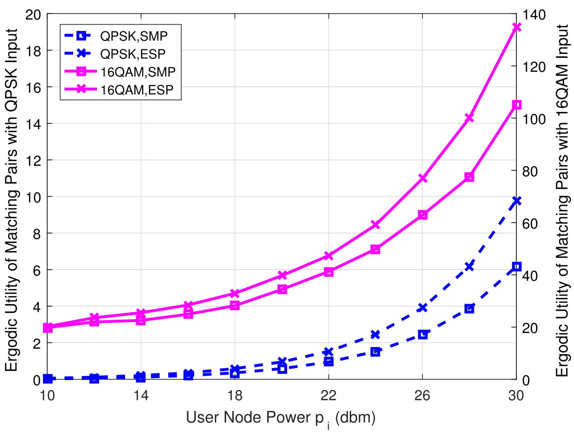

FIGURE 9. Ergodic utility of the matching pairs versus user node power p_i for different schemes.

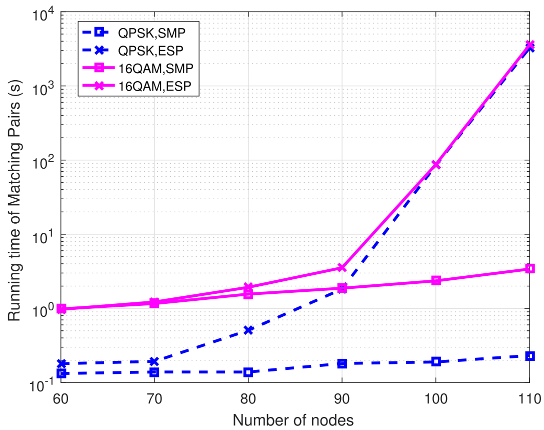

FIGURE 10. Running time of the matching pairs versus the number of nodes for different schemes.

leads to a lower signaling overhead, this is because for higher modulation order, the bit rate is larger. For a given modulation order, the signaling overhead increases with the increasing speed, the reason lies that faster mobility results in the smaller channel coherence time.

Fig. 9 shows the performance of ESP and SMP schemes. We set the user node power $p_i(\forall i \in \mu)$ from 10 dbm to 30 dbm. Considering the simulation time, we set node number $S = 24$, $N = 56$. The other simulation parameters are the same as in Table 1. From fig. 9, we can see that the SM scheme performs close to the optimal one in practical systems, which demonstrates the effectiveness and suboptimal of the SM scheme.

Fig. 10 shows the running time versus the total number of nodes for ESP and SMP schemes. We set the total number of nodes from 60 to 110, the corresponding ratio of the number of users to the number of relays is 3:7. The other simulation parameters are the same as in Table 1. We observe that the running time of the SM scheme is less than that of the ES scheme, and the time gap between the two schemes becomes larger when the number of nodes increases. When the total number of nodes is 80, the utility performance can be seen in Fig. 9.

VI. CONCLUSION

In this paper, we investigated the utility optimization problem for energy harvesting (EH) large scale relay networks with finite-alphabet inputs, which includes the determining of the power bought from the relays and the stable matching scheme. First, we proposed the clustering scheme, where the users and relays were divided into groups. Then, we performed optimization strategy within the clusters. First, optimal power was obtained to maximize the utility of users by an iterative optimization method. Second, the mutual preference matrices between the users and relays were established based on the principle of utility maximization. Third, an improved stable matching algorithm for large scale relay networks was proposed by exploiting GS algorithm with lower complexity. The implementation and convergence of the GS algorithm were analyzed. The simulation results verified that the proposed algorithm achieves better performance and achieve higher energy efficiency compared with other conventional algorithms, and incurs low signaling overhead. Moreover, the proposed algorithm performs closely to the ES method in practical systems, while the running time of it is much less than the ES scheme.

REFERENCES

[1] L. Davoli, L. Belli, A. Cilfone, and G. Ferrari, "From micro to macro IoT: Challenges and solutions in the integration of IEEE 802.15.4/802.11 and sub-GHz technologies," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 784–793, Apr. 2018.

[2] K. Shafique, B. A. Khawaja, M. D. Khurram, S. M. Sibtain, Y. Siddiqui, M. Mustaqim, H. T. Chattha, and X. Yang, "Energy harvesting using a low-cost rectenna for Internet of Things (IoT) applications," *IEEE Access*, vol. 6, pp. 30932–30941, 2018.

[3] A. S. Adila, A. Husam, and G. Husi, "Towards the self-powered Internet of Things (IoT) by energy harvesting: Trends and technologies for green IoT," in *Proc. 2nd Int. Symp. Small-Scale Intell. Manuf. Syst. (SIMS)*, Apr. 2018, pp. 1–5.

[4] G. Pan, H. Lei, Y. Yuan, and Z. Ding, "Performance analysis and optimization for SWIPT wireless sensor networks," *IEEE Trans. Commun.*, vol. 65, no. 5, pp. 2291–2302, May 2017.

[5] J. Ye, H. Lei, Y. Liu, G. Pan, D. B. da Costa, Q. Ni, and Z. Ding, "Cooperative communications with wireless energy harvesting over Nakagami- *m* fading channels," *IEEE Trans. Commun.*, vol. 65, no. 12, pp. 5149–5164, May 2017.

[6] J. Men, J. Ge, and C. Zhang, "A joint relay-and-antenna selection scheme in energy-harvesting MIMO relay networks," *IEEE Signal Process. Lett.*, vol. 23, no. 4, pp. 532–536, Apr. 2016.

[7] R. Yousaf, R. Ahmad, W. Ahmed, and A. Haseeb, "Fuzzy power allocation for opportunistic relay in energy harvesting wireless sensor networks," *IEEE Access*, vol. 5, pp. 17165–17176, 2017.

[8] A. Bletsas, A. Khisti, D. P. Reed, and A. Lippman, "A simple cooperative diversity method based on network path selection," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 3, pp. 659–672, Mar. 2006.

[9] A. Bletsas, H. Shin, and M. Z. Win, "Cooperative communications with outage-optimal opportunistic relaying," *IEEE Trans. Wireless Commun.*, vol. 6, no. 9, pp. 3450–3460, Sep. 2007.

[10] D. Mishra and S. De, "Utility maximization models for two-hop energy relaying in practical RF harvesting networks," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, Paris, France, May 2017, pp. 41–46.

[11] Y. Wang, X. Su, D. Choi, and C. Choi, "Coordinated scheduling algorithm for system utility maximization with heterogeneous QoS requirements in wireless relay networks," *IEEE Access*, vol. 4, pp. 8351–8361, 2016.

[12] A. H. Mohsenian-Rad, J. Huang, M. Chiang, and V. W. S. Wong, "Utility-optimal random access: Reduced complexity, fast convergence, and robust performance," *IEEE Trans. Wireless Commun.*, vol. 8, no. 2, pp. 898–911, Feb. 2009.

[13] H. Joung, H.-S. Jo, C. Mun, and J.-G. Yook, "Generalized gradient scheduling for vector network utility maximization," *IEEE Commun. Lett.*, vol. 17, no. 1, pp. 111–114, Jan. 2013.
[14] R. Aggarwal, M. Assaad, C. E. Koksal, and P. Schniter, "Joint scheduling and resource allocation in the OFDMA downlink: Utility maximization under imperfect channel-state information," *IEEE Trans. Signal Process.*, vol. 59, no. 11, pp. 5589–5604, Nov. 2011.
[15] C. Xiao and Y. R. Zheng, "On the mutual information and power allocation for vector Gaussian channels with finite discrete inputs," in *Proc. IEEE GLOBECOM*, New Orleans, LO, USA, Nov./Dec. 2008, pp. 1–5.
[16] W. Zeng, Y. R. Zheng, M. Wang, and J. Lu, "Linear precoding for relay networks: A perspective on finite-alphabet inputs," *IEEE Trans. Wireless Commun.*, vol. 11, no. 3, pp. 1146–1157, Mar. 2012.
[17] C. Xiao, Y. R. Zheng, and Z. Ding, "Globally optimal linear precoders for finite alphabet signals over complex vector Gaussian channels," *IEEE Trans. Signal Process.*, vol. 59, no. 7, pp. 3301–3314, Jul. 2011.
[18] W. Zeng, C. Xiao, M. Wang, and J. Lu, "Linear precoding for finite-alphabet inputs over MIMO fading channels with statistical CSI," *IEEE Trans. Signal Process.*, vol. 59, no. 6, pp. 3134–3148, Jun. 2012.
[19] W. Zeng, C. Xiao, and J. Lu, "A low-complexity design of linear precoding for MIMO channels with finite-alphabet inputs," *IEEE Wireless Commun. Lett.*, vol. 1, no. 1, pp. 38–41, Feb. 2012.
[20] F. Pérez-Cruz, M. R. D. Rodrigues, and S. Verdú, "MIMO Gaussian channels with arbitrary inputs: Optimal precoding and power allocation," *IEEE Trans. Inf. Theory*, vol. 56, no. 3, pp. 1070–1084, Mar. 2010.
[21] J. Harshan and B. S. Rajan, "On two-user Gaussian multiple access channels with finite input constellations," *IEEE Trans. Inf. Theory*, vol. 57, no. 3, pp. 1299–1327, Mar. 2011.
[22] Q. Zhang, X. Zhu, L. Wu, and K. Sandrasegaran, "A coloring-based resource allocation for OFDMA femtocell networks," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Shanghai, China, Apr. 2013, pp. 673–678.
[23] A. Abdelnasser, E. Hossain, and D. I. Kim, "Clustering and resource allocation for dense femtocells in a two-tier cellular OFDMA network," *IEEE Trans. Wireless Commun.*, vol. 12, no. 3, pp. 1628–1641, Mar. 2014.
[24] B. Wang, Z. Han, and K. J. R. Liu, "Distributed relay selection and power control for multiuser cooperative communication networks using Stackelberg game," *IEEE Trans. Mobile Comput.*, vol. 8, no. 7, pp. 975–990, Jul. 2009.
[25] A. Leshem, E. Zehavi, and Y. Yaffe, "Multichannel opportunistic carrier sensing for stable channel access control in cognitive radio systems," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 1, pp. 82–95, Jan. 2012.
[26] O. Naparstek, S. M. Zafaruddin, A. Leshem, and E. Jorswieck, "Distributed energy efficient channel allocation," 2014, *arXiv:1401.1671*. [Online]. Available: https://arxiv.org/abs/1401.1671
[27] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: Fundamentals and applications," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 52–59, May 2015.
[28] X. Tang, D. Hong, and W. Chen, "Content replication scheme using stable matching in vehicular networks," in *Proc. Int. Conf. Identificat., Inf. Knowl. Internet Things (IIKI)*, Beijing, China, Oct. 2016, pp. 351–356.
[29] M. Hasan and E. Hossain, "Distributed resource allocation for relay-aided device-to-device communication under channel uncertainties: A stable matching approach," *IEEE Trans. Commun.*, vol. 63, no. 10, pp. 3882–3897, Oct. 2015.
[30] R. Mochaourab, B. Holfeld, and T. Wirth, "Distributed channel assignment in cognitive radio networks: Stable matching and walrasian equilibrium," *IEEE Trans. Wireless Commun.*, vol. 14, no. 7, pp. 3924–3936, Jul. 2015.
[31] Z. Zhou, M. Dong, K. Ota, and Z. Chang, "Energy-efficient context-aware matching for resource allocation in ultra-dense small cells," *IEEE Access*, vol. 3, pp. 1849–1860, 2015.
[32] S. Arabi, E. Sabir, T. Taleb, and M. Sadik, "The right content for the right relay in self-organizing delay tolerant networks: A matching game perspective," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Paris, France, May. 2017, pp. 1–6.
[33] P. Mitran, "On optimal online policies in energy harvesting systems for compound Poisson energy arrivals," in *Proc. IEEE Int. Symp. Inf. Theory*, Jul. 2012, pp. 960–964.
[34] F. Ke, S. Feng, and H. Zhuang, "Relay selection and power allocation for cooperative network based on energy pricing," *IEEE Commun. Lett.*, vol. 14, no. 5, pp. 396–398, May 2010.
[35] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
[36] *Radio Resource Control (RRC) Protocol Specification (Release 15)*, document 3GPP TS 38.331 V15.4.0, 3GPP, Dec. 2018.
[37] A. Goldsmith, *Wireless Communications*. Cambridge, U.K.: Cambridge Univ. Press, 2005.

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