A Matching-Game-Based Energy Trading for Small Cell Networks with Energy Harvesting

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***Abstract*—Deploying small cells in cellular networks, as a technique for capacity and coverage enhancement, is an indispensable characteristic of future cellular networks. In this paper, a novel online decentralized algorithm for enabling energy trading in multi-tier cellular networks with selfish energy harvesting capable base stations (BSs) is proposed. A BS uses the non-renewable energy when it cannot harvest sufficient energy to serve its connected users. To minimize the non-renewable energy consumption, we establish a framework for trading energy such that BSs with energy deficit are stimulated to compensate their energy shortage with the extra harvested energy of other BSs. BSs with energy deficit are assigned to BSs with extra harvested energy by using matching theory. The extra harvested energy is distributed by the smart grid. Along with energy trades, BSs gain more profit and their utility functions enhance. Simulation results show that the waste of energy due to limited batteries and the non-renewable energy consumption decreases considerably when the proposed algorithm is applied.**

I. Introduction

The exponential growth in the wireless data traffic has motivated the need for new approach that can boost the capacity and coverage of wireless networks [1]. To solve this problem, small cells are appeared to reduce distance between transmitters and receivers, and therefore, they can improve the overall wireless quality-of-service (QoS). This new type of cellular networks differ from traditional macro-cellular networks in many ways. Small cells have lower power consumption and cover smaller areas. Depending on their capabilities, small cell BSs are classified into different types such as microcells, picocells and femtocells. Deploying small cells raises many technical challenges in terms of resource allocation, outage management, distributed optimization and implementation. One of the fundamental challenges in small cell networks is power management. In contrast to traditional cellular networks, Base Stations (BSs) of small cell networks differ in transmission power. Therefore, power management in this kind of cellular network is different from traditional networks. The power control of small cells has been studied, for instance, in [2], [3]. The decentralized power control of the femtocell network is considered in [2], where higher traffic load increases power consumption. Minimizing the transmit power of two-tier networks is considered in [3], where users connected to different tiers share the same spectrum. In addition, green cellular networks have attracted lots of attention recently which is a way to reduce using fossil energy resources and it leads to the reduction of green house gases [4], [5]. Energy harvesting receivers are considered in [6] where channel state information is used in order to find an adaptive energy beamforming to supply energy to receivers.

As a green technology, small cells with energy harvesting capabilities are alluring recent attention. In [7], a heterogeneous network is studied where BSs in different tiers are self-powered. If a BS has not harvested sufficient energy, it is kept OFF for charging energy, and connected users to it are served by neighbouring ON BSs. The availability region for a set of general uncoordinated operational strategies is characterized. The energy cooperation between two cellular BSs which are equipped with harvesting and hybrid modules is explored in [8]. In [8], the energy arrival and demanded energy are considered to be deterministic and the optimal energy cooperation policy of BSs is found. The joint design and combination of the physical layer technique of the coordinated multi-point (CoMP) with two way energy trading is studied in [9], where BSs are connected to the smart grid. In contrary to these solutions which considers trade with smart grid, in our framework, the harvested energy is not traded between the BS and the grid. We propose a framework for energy exchange among BSs by which one can combat the effect of the intermittent nature of the harvested energy from non-renewable source. A non-cooperative Stackelberg game between the residential units of energy and the shared facility controller is proposed in [10] to explore how both entities can benefit from their energy trading with each other and the grid. Optimal energy management decisions to minimize the total electricity cost and the operation delay is investigated in [11] where users are connected to smart grid.

In this paper, we propose a novel online decentralized algorithm for reduction of the non-renewable energy consumption in multi-tier cellular networks with energy harvesting capability where the harvested and the demanded energy from BSs are stochastic. To reduce the non-renewable energy consumption, selfish BSs are motivated to trade their extra harvested energy with BSs that have not harvested sufficient energy. We define BSs utility functions, and we find the prices of energy trades accordingly. We propose appropriate transaction fees for energy trades and by using it, we control prices of energy trades to keep BSs with energy deficit motivated to trade energy. As long as energy trades are profitable for involved BSs, the extra harvested energy is shared to reduce the non-renewable energy consumption. It is shown that the price of each energy trade is Nash equilibrium. We demonstrate that the price of the harvested energy shared by BSs per Joule is cheaper than the price of a unit of energy of the non-renewable energy. Therefore, BSs with energy deficit are motivated to buy required energy from other BSs. By using the matching theory, BSs with energy deficit are matched to BSs with the extra harvested energy. It is assumed that both the harvested energy by a BS and the demanded energy from a BS are correlated in time. BSs with high extra harvested energy sell their energy at lower prices. This leads to selling extra energy quickly which prevents the possible waste of energy due to the limited battery capacities. Moreover, the priority for buying energy is assigned to BSs with high energy deficit which increase energy distribution fairness. The cost of installing large batteries is removed as the proposed algorithm is applied.

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II. System Model

Consider the downlink of a multi-tier cellular wireless network consisting a number of BSs, classified into K tiers. Each BS belongs to tier k is with a maximum transmit power of P_k. Serving connected users causes the power depletion in BSs, and we ignore other types of energy consumption at BSs. We assume that locations distribution of BSs operating in different tiers is approximated as independent Poisson Points Processes (PPPs) with density λ_k. Each BS is equipped with an individual energy harvesting module and an energy storage device. We assume that the BSs belonging to a given tier k have a similar battery capacity c_k. In the considered network, the distribution of the users location also follows a PPP with density λ_u. Here, users are allowed to connect to a BS of different tiers. Depending on tiers densities and transmit power, the average number of users connected to a BS of tier k is given by [7]:

$$N_k = \frac{P_c \lambda_u P_k^{\frac{2}{\gamma}}}{\sum\limits_{j=1}^{K} \lambda_j P_j^{2/\gamma}}. \tag{1}$$

where P_c is the coverage probability. The coverage probability denotes the portion of the users connected to a BS with SIR above than a threshold. The path loss exponent is shown by γ, which typically lies in the range of $2 \leq \gamma \leq 6$. To find the above formula in [7], it is considered that shadowing attenuates transmitted signals and it follows a lognormal distribution with the same mean and variance for all tiers.

A. Demanded Energy Model

The traffic rate demand of user m connected to the i^{th} BS of tier k at time slot t is denoted by $R_{i,k}^m(t)$ and it is constant in each time slot. Users may request different rates through time slots. The total rate that BS i in tier k has to serve is $R^{i,k}(t) = \sum_{m=1}^{N^{i,k}(t)} R_{i,k}^m(t)$, where $N^{i,k}(t)$ denotes the number of connected users and it is a Poisson random variable [12]. Its mean value is given in (1). The requested rates of users are considered to be stochastic. The consumed power of the i^{th} BS of tier k at time slot t to provide user m with rate $R_{i,k}^m(t)$ is denoted by $p_{i,k}^m(t)$. Due to the stochastic nature of demanded rates of connected users, the consumed power at BSs is stochastic. The consumed power to serve each user connected to a BS can be modeled as an arbitrary correlated process due to the correlation in user traffic and usage patterns [8]. Serving all connected users to a BS consumes $p^{i,k}(t) = \sum_{m=1}^{N^{i,k}(t)} p_{i,k}^m(t)$ Watt. Hence, $p^{i,k}(t)$ is a function of two kinds of random variables, $p_{i,k}^m(t)$, $\forall m$, and $N^{i,k}(t)$. The consumed energy at time slot t is obtained as $\int_0^T p^{i,k}(t)\,du = T\,p^{i,k}(t) = T\,\sum_{m=1}^{N^{i,k}(t)} p_{i,k}^m(t)$ where T is the time slot duration and the demanded power is constant in each time slot. The energy stored in the battery of the BS i in tier k at time slot t is denoted by $e^{i,k}(t)$. The shortage of energy in the BS battery necessitates buying energy from other BSs or using the energy of the non-renewable source.

B. Harvested Energy Model

The harvested energy by each BS can be modeled as an arbitrary correlated random process. The total amount of the harvested energy at the i^{th} BS of tier k during time slot t is $\mu^{i,k}(t)$. If the harvested energy by a BS is more than its needs, the extra energy is stored at the BS battery. The energy is wasted when the BS tries to store more energy than its battery capacity. Therefore, the BS that has harvested energy more than its needs is motivated to trade its extra energy. In the considered model, BSs are allowed to sell the extra harvested energy to the BSs that have energy shortage. If a BS which is in need of energy finds no seller BS, it has to use the non-renewable energy to serve connected users. It is also assumed that BSs are connected to the smart grid. The smart grid is a technology that enables more precise measurement of the electric power by using digital devices which can communicate with each other. When the BSs trade their energy by using the smart grid, the smart grid operator charges a cost for such service. This cost is an increasing function of distances as well as the amount of the shared energy [13]. When two BSs trade energy, the energy is transferred by the smart grid and no energy is consumed by BSs while they trade energy. Each BS knows distances between itself and other BSs. The stored energy is updated as

$$e^{i,k}(t+1) = \tag{2}$$
$$\min\left\{\max\left\{e^{i,k}(t) - T\,p^{i,k}(t), 0\right\} + \mu^{i,k}(t) \pm E_T(t+1), c_k\right\},$$

where $E_T(t+1)$ is the amount of the traded (shared) energy at the beginning of time slot $t+1$ and it is added if the BS is buyer, or it is subtracted if the BS is seller. In (2), the maximum stored energy in the battery is equal to the battery capacity. Furthermore, the BS can not use more energy than the stored amount from its battery. To enable a BS to compensate its energy deficit by the harvested energy of other BSs, a framework for the energy trading is established in the following section.

III. Energy Trading Scheme among BSs Using a Matching-Game-Based Algorithm

Energy harvesting is not a reliable method to supply energy to BSs as a result of uncertainty in environmental conditions. In order to minimize the non-renewable energy consumption, we stimulate BSs to share their extra harvested energy. At the beginning of each time slot, every BS broadcasts a message to the other BSs. This message contains the information of the tier the BS belongs to, its battery level and the amount of extra or needed energy to serve connected users in that time slot. Based on these information, all BSs are classified into two categories, i.e, seller BSs and buyer BSs. Seller BSs have extra stored energy and buyer BSs are with the energy shortage problem. The set of the seller BSs of tier k is $\mathcal{S}_k = \{s_k^1, s_k^2, \ldots, s_k^{n_k}\}$ and the set of all buyer BSs of tier k' is $\mathcal{B}_{k'} = \{b_{k'}^1, b_{k'}^2, \ldots, b_{k'}^{n'_{k'}}\}$, where n_k and $n'_{k'}$ are the number of seller BSs and buyer BSs of tiers k and k', respectively. The set of seller BSs is $\mathcal{S} = \bigcup_{k=1}^{K} \mathcal{S}_k$. The set of buyer BSs is $\mathcal{B} = \bigcup_{k'=1}^{K} \mathcal{B}_{k'}$. Since it is known that a BS is seller or buyer at the beginning of the time slot t, one can display the battery level, the number of connected users and the demanded power from a BS by using the BS index in the set of sellers or buyers of the tier that the BS belongs to, $\mathcal{S}_k$ or $\mathcal{B}_{k'}$. Consequently, $e^{s_k^i}(t)$, $N^{s_k^i}(t)$ and $p^{s_k^i}(t)$ are used for a seller BS s_k^i in tier k, and $e^{b_{k'}^j}(t)$, $N^{b_{k'}^j}(t)$ and $p^{b_{k'}^j}(t)$ are used for a buyer BS $b_{k'}^j$ of tier k', respectively. The amount of energy that a seller BS s_k^i from any tier $k \in \{1, 2, \ldots, K\}$ wants to sell at time slot t is

$$\rho^{s_k^i}(t) \quad = \quad e^{s_k^i}(t) - T\,p^{s_k^i}(t). \tag{3}$$

A buyer BS $b_{k'}^j$ from any tier $k' \in \{1, 2, \ldots, K\}$ wants to buy the following amount of energy at time slot t

$$\rho^{b_{k'}^j}(t) \quad = \quad \left| e^{b_{k'}^j}(t) - T\,p^{b_{k'}^j}(t) \right|. \tag{4}$$

The total extra energy stored in BSs of the network at time slot t is $\sum\limits_{k=1}^{K} \sum\limits_{i=1}^{n_k} \rho^{s_k^i}(t)$ and the total needed energy of BSs with energy deficit in the network is $\sum\limits_{k'=1}^{K} \sum\limits_{j=1}^{n'_{k'}} \rho^{b_{k'}^j}(t)$. Each BS serves a number of users connected to it, and the consumed energy to serve them costs a known price of ζ units of money per Joule for users. A BS receives requests from users at the beginning of each time slot. Deployed BSs in the network are considered to be selfish. In other words, regardless of other BSs, a BS wants to earn money by serving connected users to maximize its utility function. Selfish BSs do not share energy to help BSs with energy deficit. Earning money from other BSs is an incentive for a seller BS to share its extra energy.The smart grid usage to trade energy is not free for BSs. The cost of transferring energy by the smart grid depends on the distance between the seller BS and the buyer BS in meters, denoted by $g^{s_k^i, b_{k'}^j}$, and the amount of shared energy among them. It is assumed that the cost of energy transfer is a linear function of the amount of transferred energy, $E_T(t)$, and an arbitrary increasing cost function of distance denoted by $\Gamma(g^{s_k^i, b_{k'}^j})$. The cost of sharing $E_T(t)$ Joule energy is captured by $E_T(t)\Gamma(g^{s_k^i, b_{k'}^j})$ and it is paid by the buyer BS. Consider that a seller BS s_k^i is operating in the k^{th} tier and it consumes $p^{s_k^i}(t)$ Watt to serve users. Its utility function at time slot t is defined as follows

$$U^{s_k^i}(\eta(E_T(t)), t) \quad = \quad \zeta \, T \, p^{s_k^i}(t) + \eta(E_T(t)), \qquad (5)$$

where $\eta\,(E_T(t))$ is the price of $E_T(t)$ units of shared (traded) energy. In the next subsection, the appropriate value of $\eta(E_T(t))$ is obtained by using a game-theoretic approach. The seller BS has enough energy to serve users connected to it. Consequently, it serves $N^{s_k^i}(t)$ users and it sells its extra energy to gain utility of size $\eta(E_T(t))$. Similarly, we define the utility function of buyers. The buyer BS gains utility by serving connected users to it which consumes $Tp^{b_{k'}^j}(t)$ Joule. The energy of the buyer BS is not enough to serve all connected users. The utility function of a buyer BS at time slot t is obtained as follows

$$U^{b_{k'}^j}(\eta(E_T(t)), t) =$$
$$\zeta \, T \, p^{b_{k'}^j}(t) - \eta(E_T(t)) - E_N(t)\psi - E_T(t) \, \Gamma(g^{s_k^i, b_{k'}^j}), \qquad (6)$$

where $E_N(t) = \rho^{b_{k'}^j}(t) - E_T(t)$ is the non-negative amount of energy which is not obtained from other BSs and purchased from the non-renewable source. The price that the buyer BS pays to the non-renewable source is $E_N(t)\psi$ where ψ is the price of a Joule of the non-renewable energy. We assume that ψ should satisfy the condition $\zeta + \max_{g^{s_k^i, b_{k'}^j}} \Gamma(g^{s_k^i, b_{k'}^j}) < \psi$, $\forall s_k^i \in \mathcal{S}$, $\forall b_{k'}^j \in \mathcal{B}$. This inequality is used to show that the non-renewable energy is more expensive than the shared energy of other BSs, and thus, a buyer BS is motivated to compensate its energy deficit by the extra stored energy of other BSs.

We study the pricing of the shared (traded) energy, and it is shown that the energy sharing between BSs reduces the consumption of the non-renewable energy. In order to enable BSs to pay money, a *Credit Clearance Service* (CCS) has been used [14], [15], where all BSs have credit accounts with initial fund. After the seller and the buyer BSs agree on a price, the price, their tiers, their battery levels, the needed energy of the buyer and the extra energy of the seller are submitted to the CCS as the trade characteristics. The CCS moves the money from the buyer BS credit account to the seller BS credit account according to the agreed price. The CCS controls the agreed prices as well. Distances among BSs are known by the CCS. Assume that the buyer BS $b_{k'}^j$ starts negotiating with the seller BS s_k^i as rational game players. Since the buyer BS wants to compensate all its energy deficit, the amount of the shared energy is the minimum of the extra stored energy in the seller BS and the needed energy of the buyer BS, $\min\{\rho^{s_k^i}(t), \rho^{b_{k'}^j}(t)\}$. The BS s_k^i proposes a price to the BS $b_{k'}^j$ to maximize its utility function. The utility function of the BS s_k^i is an increasing linear function of $\eta(E_T(t))$, and thus, by proposing a higher price, it increases its utility function. The BS s_k^i can obtain the utility function of the BS $b_{k'}^j$, since the BS $b_{k'}^j$ broadcasts its tier, battery level and its amount of needed energy at the beginning of time slots. Moreover, the cost of transferring energy by the smart grid and the amount of shared energy is known. If the price is more or equal than $E_T(t)\psi - E_T(t)\,\Gamma(g^{s_k^i, b_{k'}^j})$, the BS $b_{k'}^j$ does not accept it. The reason is that this price makes a lower or equal utility than buying energy from the non-renewable source, i.e.,

$$\zeta \, T \, p^{b_{k'}^j}(t) - \eta(E_T(t)) - E_N(t)\psi - E_T(t) \, \Gamma(g^{s_k^i, b_{k'}^j})$$
$$\leq \zeta \, T p^{b_{k'}^j}(t) - E_T(t)\psi - E_N(t)\psi. \qquad (7)$$

To restrict the proposed price by a seller BS and motivate buyer BSs to exploit the renewable energy, we use the transaction fee concept introduced in [15] which is a paid money by the BS s_k^i to the CCS for updating accounts after the agreement. The utility function of the seller BS is revised as

$$U^{s_k^i}(\eta(E_T(t)), t) = \zeta \, T \, p^{s_k^i}(t) + \eta(E_T(t)) - F(\eta(E_T(t))), \quad (8)$$

where $F(\eta(E_T(t)))$ is the transaction fee. According to seller and buyer battery levels, the needed energy of the buyer and the extra energy of the seller, the CCS can find the BSs utility functions and the price of the shared energy. Using the transaction fee, the CCS is able to affect the proposed price of the seller BS to keep the buyer BS motivated to use the shared energy and avoid wasting of the harvested energy. When the extra stored energy in the battery of the seller BS is near to the battery capacity, the proportion of the extra stored energy of the seller BS to its battery capacity, $\frac{\rho^{s_k^i}(t)}{c_k}$, is near to one. Based on the battery level, two cases are considered. In the first case, $\frac{\rho^{s_k^i}(t)}{c_k}$ is less than ϑ where ϑ is an arbitrary parameter such that $0 \leq \vartheta \leq 1$. In the other case, $\frac{\rho^{s_k^i}(t)}{c_k} \geq \vartheta$. In this case, the CCS forces the seller BS to offer lower prices. It leads to selling the extra energy faster which reduces possible waste of energy in the next time slots due to the correlation between harvested energy values. As the battery capacity of the seller BS affects the price of the shared energy, BSs are classified into tires. We propose appropriate transaction fees for both cases and find prices of energy trades accordingly in [16] which are *Nash equilibrium*.

IV. Matching Buyer BSs to Seller BSs

Based on the broadcasting BSs tiers, battery levels and the extra or needed energy, buyer BSs start to find the price of the shared energy with each rational seller BS as explained in previous section. Next, buyer BSs rank seller BSs according to the amount of the shared energy with each of the seller BSs and its price. Assigning a number of buyer BSs to a seller BS in order to buy energy can be well formulated as a many-to-one matching problem. In the many-to-one matching problem, a subset of buyer BSs $\mathcal{B}$ is assigned to a seller BS. A buyer BS is assigned to one seller BS at most. In this problem, many-to-one matching is a two-sided matching. The reason is that all involved BSs belong to one of the two sets, sellers and buyers. Matching is defined in [17] as:

Definition 1: Let $\mathcal{S}$ be a set of $\sum_{k=1}^{K} n_k$ sellers and $\mathcal{B}$ be a set of $\sum_{k'=1}^{K} n'_{k'}$ buyers. A matching is a mapping ϕ from the set $\mathcal{S} \cup \mathcal{B}$ into the set of all subsets of $\mathcal{S} \cup \mathcal{B}$ such that: (1) $|\phi(b_{k'}^j)| \leq 1$ and $\phi(b_{k'}^j) \in \mathcal{S} \cup \emptyset$ for all $b_{k'}^j \in \mathcal{B}$, (2) $\phi(b_{k'}^j) \in 2^{\mathcal{B}} \cup \emptyset$ for all $s_k^i \in \mathcal{S}$,

TABLE I. SUMMARY OF THE PROPOSED MATCHING ALGORITHM

Phase 1 - Initialization:

Each BS broadcasts its tier, the amount of energy in its battery and the amount of energy it wants to sell or to buy to other BSs.

Sellers are stored in the set $\mathcal{S}$. Buyers are stored in the set $\mathcal{B}$.

Phase 2 - Matching Buyer BSs to Seller BSs

repeat:

Each buyer BS finds the amount of the shared energy and its price with every seller BSs.

Each buyer BS ranks seller BSs according to its preference.

Each buyer BS sends a request to the first ranked seller BS.

Each seller BS ranks requested BSs with respect to its preference.

repeat:

A random seller accepts the first ranked requested buyer.

The extra amount of energy in the seller is updated.

The accepted buyer BS is removed from the ranked list.

The energy trade is saved and its characteristics are submitted to the CCS.

until the seller extra energy is finished or all requested BSs are processed

If a buyer BS buys its needed energy, it is removed from $\mathcal{B}$.

If a seller BS sells all its extra energy, it is removed from $\mathcal{S}$.

The CCS updates credit accounts according to submitted trade characteristics.

BSs in sets $\mathcal{S}$ and $\mathcal{B}$ broadcast their tiers, the amount of energy in their batteries and the amount of energy they want to sell or to buy.

until the set $\mathcal{S}$ is empty or the set $\mathcal{B}$ is empty.

Phase 3 - The energy Distribution

The energy distribution is done according to saved energy trades.

and (3) $\phi(b_{k'}^j) = s_k^i$ if and only if $b_{k'}^j$ is in $\phi(s_k^i)$ for all $s_k^i \in \mathcal{S}$ and for all $b_{k'}^j \in \mathcal{B}$.

In the above definition, $|\mathcal{A}|$ denotes the cardinality of the set $\mathcal{A}$. Moreover, $\phi(b_{k'}^j) = \emptyset$ means that the buyer $b_{k'}^j$ is not successful in finding a seller BS and it is not matched.

A. Utility-Based Preferences

Each buyer BS $b_{k'}^j$ has a strict, transitive, and complete preference relation $\succ_{b_{k'}^j}$ over the members in $\mathcal{S}$. The same argument holds for preference of members in $\mathcal{S}$ which is denoted by $\succ_{s_k^i}$ over members of the set $\mathcal{B}$. In order to obtain the preferences of each BS, defined utility functions in previous section are used. Based on the derived price of the shared energy between a seller BS and a buyer BS, the buyer BS searches for a seller BS that makes its utility maximum compared to other BSs. Therefore, $\forall s_1, s_2 \in \mathcal{S}$ and $\forall b_{k'}^j \in \mathcal{B}$, a buyer preference is

$$U^{b_{k'}^j}(\eta(E_{T_1}), t) > U^{b_{k'}^j}(\eta(E_{T_2}), t) \Leftrightarrow s_1 \succ_{b_{k'}^j} s_2, \qquad (9)$$

where $\eta(E_{T_i})$ is the shared energy price between the seller s_i and the buyer $b_{k'}^j$. According to its preference, a buyer BS ranks sellers. The first ranked seller BS is the most wanted seller BS to buy energy in the view of the buyer BS. Each buyer BS requests the most wanted seller BS. Similarly, $\forall s_k^i \in \mathcal{S}$ and $\forall b_1, b_2 \in \mathcal{B}$, the preference relation of a seller is defined as

$$U^{s_k^i}(\eta(E'_{T_1}), t) > U^{s_k^i}(\eta(E'_{T_2}), t) \Leftrightarrow b_1 \succ_{s_k^i} b_2, \qquad (10)$$

where $\eta(E'_{T_i})$ is the shared energy price between the BS s_k^i and the BS b_j. Using (10), a seller BS ranks requested buyer BSs. In the next subsection, we propose a matching-game-based algorithm in order to assign buyer BSs to seller BSs. The proposed algorithm matches buyer BSs to seller BSs such that BSs preferences are satisfied as much as possible.

B. The Proposed Matching-Game-Based Algorithm

In the first phase of the algorithm, each BS broadcasts its tier, battery level and the extra or needed energy, and BSs are divided into two groups, i.e., sellers and buyers. In phase 2, buyer BSs rank seller BSs according to their preference relations. Next, they send a request to the first ranked seller BS, simultaneously. Seller BSs receive a number of requests and they rank requested BSs according to their preferences due to the fact that seller BSs can calculate the price of the shared energy according to the broadcasting. After ranking requested BSs, a random seller accepts l top ranked requested buyer BSs such that the total requested shared energy with l buyers is less or equal to its extra stored energy and the total requested shared energy with $l+1$ buyers is more than its extra stored energy. If a seller depletes its extra energy by selling, it is removed from $\mathcal{S}$. Similarly, if a buyer BS compensates its energy deficit, it is removed from $\mathcal{B}$. Successful energy trades are saved and the CCS updates credit accounts. BSs in sets $\mathcal{S}$ and $\mathcal{B}$ broadcast the amount of energy in their batteries and the amount of energy they want to sell or to buy as well as their tiers, and the phase 2 is iterated until $\mathcal{S} = \emptyset$ or $\mathcal{B} = \emptyset$. In the phase 3 of the algorithm, the extra harvested energy is distributed according to saved energy trades. Summary of the proposed algorithm is given in Table I. We assume a buyer BS never requests more than its energy deficit. If it sends a request more than its needed energy and a seller BS accepts its request, the buyer BS reduces the amount of the extra energy for sell. This action of a buyer BS results in additional number of iterations. Therefore, the seller BS is prevented to help other buyer BSs. To force players to agree on a price fast, utilities of players, when agreement is not reached, are considered to be equal in all iterations of the algorithm.

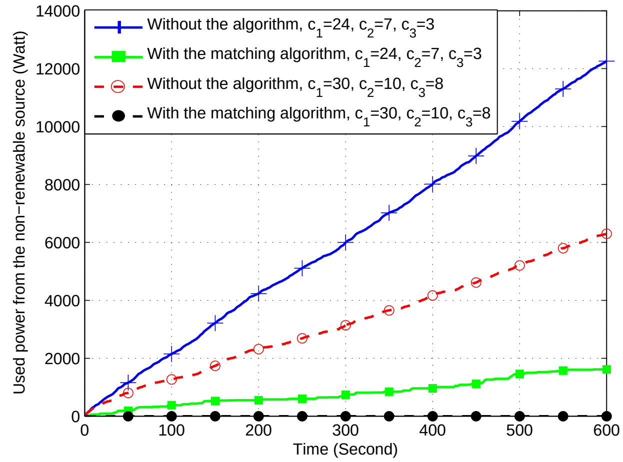

Fig. 1. Comparison of the non-renewable power consumption in the network with and without applying the algorithm by different battery capacities. Means of harvested energy of different tiers are $[23.3, 5.8, 1.1]$ Joule.

Definition 2: Suppose that $M(\mathcal{S}, \mathcal{B})$ is the set of all possible matchings. A many-to-one matching is blocked if $\exists\ \phi' \in M(\mathcal{S}, \mathcal{B}), s_k^i \in \mathcal{S}$ and $b_{k'}^j \in \mathcal{B}$ s.t. $\phi'(b_{k'}^j) \succ_{b_{k'}^j} \phi(b_{k'}^j)$ and $\phi'(s_k^i) \succ_{s_k^i} \phi(s_k^i)$. Many-to-one matching is stable if there is no subset of buyer BSs and a seller BS in which the matching is blocked.

Since buyer BSs request seller BSs according to their preference relations, seller BSs are chosen by buyer BSs and seller BSs accept request according to their preferences the matching can not be blocked. Therefore, the matching is stable [18], and in each iteration, a number of seller and buyer BSs are removed from $\mathcal{S}$ and $\mathcal{B}$. Consequently, the proposed algorithm converges.

V. PERFORMANCE RESULTS

In this section, the performances of the matching-game-based algorithm is evaluated through simulations. We consider a three-tier small cell network, including macrocells (tier 1), microcells (tier 2) and picocells (tier 3). BSs of tiers are distributed according to PPPs with densities $[\frac{1}{500^2}, \frac{3}{500^2}, \frac{5}{500^2}]$ m^{-2}, respectively, in a 1.35 km $\times$ 1.35 km area. Moreover, users distribution follows

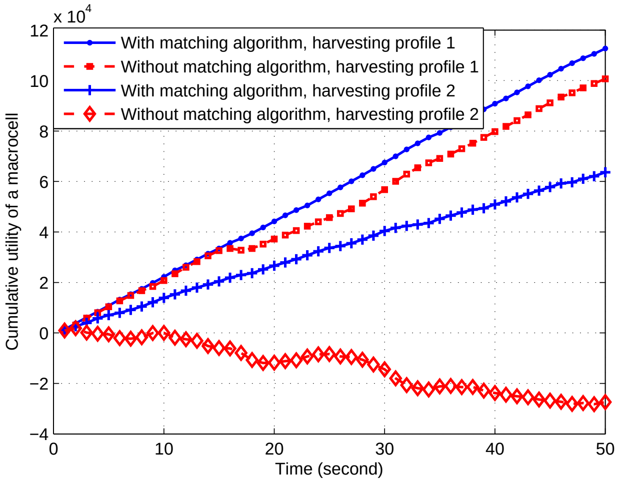

Fig. 2. The cumulative utilities of a macrocell when matching algorithm is applied. Means of the harvested energy of different tiers in the first profile (corresponding to two below curves) are $[20.1, 4.5, 1]$ Joule. Means of the harvested energy of different tiers in the second profile are $[23.3, 5.8, 1.1]$ Joule.

a PPP with density $\frac{80}{500^2}$ m^{-2}. The transmit power of BSs, depending on their tier, sorted as $[40, 6.3, 1]$ Watt. The path-loss exponent is considered to be 4, the coverage probability is 0.65 and the time slot duration is one second. We consider $\vartheta = 0.7$ and $\beta = 0.4$. The cost of transferring one Joule by the smart grid is $\Gamma(g^{s_k^i, b_{k'}^j}) = \sqrt[4]{g^{s_k^i, b_{k'}^j}}$. Means of the demanded power of users connected to different tiers during a time slot are $[22.5, 5, 0.85]$ Watt, respectively. Gaussian processes are correlated by Cholesky decomposition method. Both the harvested energy and the demanded energy at each time slot are correlated by their previous values at the last time slot and two previous time slot. The effect of the proposed matching-game-based algorithm, and battery capacities of tiers on the consumed non-renewable power is depicted in Fig. 1. The sum of the harvested energy of BSs in the network in all time slots are more than the demanded energy from BSs in the network. Thus, the stored energy in BSs of the network is sufficient to serve connected users in all time slots. However, the harvested energy by a BS is not enough in some time slots due to its stochastic nature. By using the proposed algorithm, the consumed power from the non-renewable source is reduced considerably as it compensate energy deficit of BSs with the available extra stored energy. In the initial time slots, the larger battery capacity is not influential. The reason is that the extra stored energy is less than battery capacity. As more time slots are elapsed, the extra stored energy increases, and the larger battery capacities become more helpful. The proposed algorithm distributes the extra stored energy among BSs with energy deficit instead of storing the extra energy in the batteries. Hence, BSs require smaller batteries to store energy when the algorithm is applied. Applying the algorithm removes the cost of installing large batteries. When the algorithm is not applied, the non-renewable energy consumption increases as the harvested energy is wasted in limited batteries. The run time of the algorithm for 600 time slots is less than 4 seconds.

The cumulative utilities of a macrocell from serving connected users and energy trades, when the demanded energy profile is common and two different energy harvesting profiles are considered, are shown in Fig. 2. In this figure, we compare the cumulative utilities in the presence of the proposed algorithm and without it. The utility of the BS is found from (7) and (8) in each time slot. The gained utility from serving connected users is 100 units of money per consumed Joule. The non-renewable source offers 300 units of money per consumed Joule. When the proposed algorithm is not applied, the macrocell gains negative utility values in some time slots due to the high price of the non-renewable energy. To stop negative utility, the macrocell can deploy larger batteries which is an additional cost. Although higher ζ can avoid negative utility, increasing ζ is out of a BS control. Since the shared energy price per unit is always lower than ζ, and ψ is three times more than ζ, negative utility values can be avoided in time slots by using the algorithm. In Fig. 2, the mean of the harvested energy of a BS is less than the mean of the demanded energy in profile 1, and the mean of the harvested energy of a BS is more than the mean of the demanded energy in profile 2. In both cases, the cumulative utility increases as the matching-game-based algorithm is applied.

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