Energy-Efficient Resource Allocation for Machine-Type Communications in Smart Grid based on a Matching with Externalities Approach

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ABSTRACT Machine-type communication plays a critical role in the reliable operation of smart grid. To overcome the problem of spectrum scarcity, the massive number of machine-type devices (MTDs) are allowed to reuse the spectrum resource allocated to the cellular users (CUs) opportunistically. However, the complicated interference caused by channel reusing and the energy efficiency (EE) issues pose new challenges on resource allocation. In this paper, we investigate the problem of EE maximization for MTDs via jointly optimizing channel selection and power control. A two-stage optimization algorithm is proposed based on many-to-one matching with externalities. In the first stage, each MTD is temporally allocated to a predefined transmission power, and then the channel selection optimization problem is solved by matching with externalities to derive the matching relationship between MTDs and resource blocks (RBs). In the second stage, the power control optimization problem is solved by the nonlinear fractional programming algorithm based on the established matching relationship obtained in the first stage. Simulation results demonstrate that the proposed algorithm outperforms the other two heuristic algorithms distinctly.

INDEX TERMS machine-type communication, energy efficiency, resource allocation, matching with externalities, nonlinear fractional programming.

I. INTRODUCTION

A. MOTIVATION

MACHINE-type communication plays an important role in smart grid. With the large-scale deployment of millions of machine-type devices (MTDs), the operation status of energy generation, transmission, transformation, delivery, and consumption can be monitored and controlled on a real-time basis [1]. As a new communication paradigm, machine-type communication enables the seamless integration with 4G or 5G cellular networks, short-sized packets access, and discontinuous transmissions [2], [3]. And in June 2013 machine-type communication was chosen as Work Item and it will be included in 3GPP release 12 standard [4]. However, considering the characteristics of short-sized packets and discontinuous transmission, it is wasteful to allocate limited orthogonal resource blocks for machine-type communications [5]. Therefore, to support a massive number of MTDs, a promising solution is to allow them to reuse the spectrum resources of cellular users (CUs) [6]. In this new paradigm, the practical implementation of machine-type communication in smart grid still faces several challenges, which are summarized as follows.

Energy efficiency (EE) issues: EE is critical for machine-type communication to maintain reliable connectivity and effective coverage [7], [8]. In practical, most MTDs are usually equipped with low-capacity batteries and are expected to operate for long period of time without the requirement for battery replacement [9]. The sudden power outage during operations may cause data loss or even network collapse. Therefore, how to optimize power control of MTDs from an
energy-efficient perspective is critical.

**Interference management issues:** Machine-type communication needs intermittent uplink resources to report data transmission. When MTDs are allowed to reuse the spectrum resources of cellular users (CUs) in an opportunistic manner, MTDs will cause co-channel interference to CUs. To make it more worse, a MTD also faces interference from other MTDs which reuse the same resource block (RB) simultaneously. As a result, the channel selection decision of a MTD not only depends on the channel status, but also depends on the utilities for all MTDs. In addition, there exists externalities such as the "peer effect" are created among MTDs when RBs are reused by multiple MTDs.

**Joint resource allocation issues:** The multi-dimensional resources such as RBs and power have to be jointly allocated based on dynamic channel states and interference levels. However, channel selection and power control are coupled together. On one hand, the optimal power control strategies vary among different channel selection schemes, which will affect cellular network utilities. On the other hand, the power control strategies has to not only meet the transmission requirements but also take into account co-channel interference between MTDs and CUs, which affects the channel selection schemes of MTDs.

### B. CONTRIBUTION

In this paper, we study how to maximize the EE of MTDs via the joint optimization of channel selection and power control based on various practical constraints including stringent quality of service (QoS) requirements, transmission power, and RB reusing. The formulated joint optimization problem is NP-hard which cannot be solved by using polynomial-time algorithms [10], due to the coupling of channel selection and power control.

To provide a tractable solution, we propose a two-stage energy-efficient resource allocation algorithm by combining matching with externalities and nonlinear fractional programming. The original joint optimization problem is converted to a many-to-one matching problem between MTDs and RBs, which is solved in two stages. In the first stage, each MTD is temporally allocated to a predefined transmission power, and then the channel selection optimization problem is solved by matching with externalities via swapping the matching pairs for better EE performance to derive the matching relationship between MTDs and RBs. In the second stage, given a particular matching obtained in the first stage, the power control optimization problem is solved by the nonlinear fractional programming algorithm. The main contributions of this article are summarized as follows:

- Joint optimization problem formulation, transformation and decoupling: a joint channel selection and power control optimization problem under the various practical constraints is formulated. The formulated problem is a mixed integer nonlinear programming (MINLP) problem, in which the continuous variables for power control and the integer variables for channel selection need to be optimized jointly. To solve the MINLP problem, a many-to-one matching model between MTDs and RBs is introduced. In this way, the joint channel selection and power control problem can be decoupled into two subproblems and solved in a tractable way.
- Channel selection optimization: the utilities of MTDs are defined as the achievable energy efficiency based on the predefined transmission power. However, the value of the utilities of MTDs not only depend on the matched RB, but also on other MTDs that are matched with the same RB, namely, externalities exist in the proposed matching model. The swap operation between any two MTDs to exchange their matched RBs for better EE performance is adopted. Then, the channel selection optimization strategy can be derived in an energy effective manner.
- Power control optimization: given a particular matching, the power control optimization problem is firstly modeled as a noncooperative game due to the intercorrelation and interactions among MTDs. Then the transformed nonconvex optimization problem with fraction-form is solved by the nonlinear fractional programming algorithm, and the optimal power control strategy will be derived until the power control variables obtained in each round are extremely close, that’s to say, it has converged to a Nash equilibrium.
- Analysis and verification: simulation results demonstrate the superior performance and the convergence of the proposed approach. Furthermore, the proposed algorithm can derive the significant EE performance and outperforms the other two heuristic algorithms remarkably.

### C. ORGANIZATION

The remaining parts of the paper are organized as follows. A summary of related works is reviewed in Section II. Section III describes the overall system model. The energy-efficient joint channel selection and power control optimization problem is formulated in Section IV. Section V presents the proposed two-stage energy-efficient resource allocation algorithm. Simulation results are given in Section VI. Section VII concludes the article.

### II. RELATED WORKS

Several works in the literature have addressed the coexistence of machine-type communication underlay transmissions in the IoT [11]–[15], which provide autonomous connectivity among machines without human intervention to create new service. The limited channel resources impel fixed data aggregator (FDA) to schedule resources besides data aggregation, hence, a resource allocation scheme was proposed in [11] to dynamically allocate channels to the MTD subject to their QoS requirements. To address the issue about both overload detection and contention resolution, a context-aware dynamic resource allocation (CADRA) mechanism was proposed in [12] for further improving the random access per-
formance in a dynamic world. Other works as [13], in order to address the performance degradation caused by concurrent and massive access attempts of MTD in LTE systems, a joint optimal physical random access channel (PRACH) resource allocation and access control mechanism was proposed.

Although significant improvement in resource allocation can be achieved by the above works, the energy consumption is ignored during the resource allocation design. There have been some works investigating energy-efficient resource allocation strategies for machine-type communication underlying cellular networks such as [16]–[19]. In [16], to minimize the total energy consumption of the network Yang et al. jointly optimize power control and time allocation while taking into account circuit power consumption. And in [17], Li et al. introduced mobile edge computing (MEC) into virtualized cellular networks with machine-type communications to decrease the energy consumption and optimize the computing resource allocation as well as improve the computing capability. A more evolved situation appears in [18] where a joint massive access control and resource allocation (RA) scheme was investigated to minimize total EC in both flat- and frequency-selective fading channel.

However, most of the previous works assumed that any MTD is willing to follow the suggested resource allocation decision even though better utility can be achieved by disrupting it. Moreover, compared to other different optimization approaches for resource allocation problem from the energy efficient perspective such as coalitional game [20], Stackelberg game [21], and multi-player noncooperative game [22], etc., matching theory is an efficient, flexible, and low-complexity solution to tackle such problems [23].

Matching-based energy-efficient algorithms for machine-type communication were proposed in [24]–[27]. In [24], to maximize the quality of experience (QoE) of machine-to-machine (M2M) communication, matching algorithm is utilized to formulate the joint power optimization and sub-channel selection problems as a two-dimensional combinatorial optimization problem. And in [25], Alamouti et al. investigated a joint power and resource allocation scheme to minimize the total uplink transmit power for all users based on matching theory. It’s noted that one RB can be reused by multiple MTDs helps to reduce overhead signals and increases network capacity with fewer resources. But there only exists few literatures taking into account many-to-one scenarios via joint optimization for the power control and allocation of resource from the perspective of energy efficiency. For instance, to improve the spectrum efficiency in cellular networks, Hmilas et al. in [26] considered resource sharing by letting co-channel transmission over an RB (up to a maximum number of transmitters). And in [27], in order to maximize the system sum rate under the constraints of the signal to interference plus noise ratio (SINR) for both transmitter and cellular user equipments, a novel resource allocation algorithm was proposed based on a many-to-many two-sided matching game.

However, the above-mentioned works whose methods cannot directly solve the joint optimization problem considered in our work. Unlike most of the existing works, we consider a multi resource sharing case where a sub-channel can be reused by multiple MTDs, and the problem of channel selection between MTDs and RBs was formulated as a mixed integer non-linear problem (MINLP). Nevertheless, the problem of channel selection is solved by a matching with externalities approach while power control is solved by nonlinear fractional programming [26].

III. SYSTEM MODEL

As presented in Fig. 1, we consider a scenario of the uplink machine-type communication underlying a single cellular network, where a BS installed with the omnidirectional antenna is located in the center of the cell, and the MTDs are distributed randomly over the cell. Other works (e.g., [28]) have demonstrated that the reuse of the uplink channels has more performance gains than the sharing of downlink channel in wireless networks. We adopt the block fading channel model [29], in which the channel state is considered to be fixed at a given time block, and changes independently across different time blocks.

We consider that there are N MTDs and K CUs, the sets of which are denoted as $\mathcal{MTD}_N = \{MTD_1, ..., MTD_n, ..., MTD_N\}$ and $\mathcal{C}_K = \{C_1, ..., C_k, ..., C_K\}$, respectively. The definitions of all the variables are summarized in Table 1. We assume that the spectrum resources of the cellular network are divided into time-frequency RBs, namely, the orthogonal partitioning of spectrum resources is adopted, and each CU transmits on a single subchannel or RB. This way, the co-channel interference will not exist among CUs. The set of RBs is denoted as $\mathcal{RB}_K = \{RB_1, ..., RB_k, ..., RB_K\}$. It is noted that the RB allocated to CU $C_k$ is denoted as $RB_k$. For the uplink spectrum reusing scenario, the MTDs transmit data to the BS by reusing the RBs allocated to CUs, which is referred to as channel selection. To improve spectrum efficiency, multiple MTDs can reuse the same RB allocated to a CU. In this way, CU will suffer from the co-channel interference from MTDs which are reusing the RB allocated to this CU, and
TABLE 1: Nomenclature

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
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<tbody>
<tr>
<td>$N$</td>
<td>Number of MTDs</td>
</tr>
<tr>
<td>$K$</td>
<td>Number of CUs (RBs)</td>
</tr>
<tr>
<td>$S_{N \times K}$</td>
<td>Channel selection decision</td>
</tr>
<tr>
<td>$s_{n,k}$</td>
<td>The $(n,k)$-th element of $S_{N \times K}$</td>
</tr>
<tr>
<td>$P_n$</td>
<td>Power control decision</td>
</tr>
<tr>
<td>$p_{n}$</td>
<td>Transmission power of MTD $MTD_n$</td>
</tr>
<tr>
<td>$p_{n,c}$</td>
<td>Circuit power of MTD $MTD_n$</td>
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<tr>
<td>$p_{n,\text{min}}$</td>
<td>Lower bound power of $p_n$</td>
</tr>
<tr>
<td>$p_{n,\text{max}}$</td>
<td>Upper bound power of $p_n$</td>
</tr>
<tr>
<td>$p_{n,\text{opt}}$</td>
<td>Optimal transmission power of MTD $MTD_n$</td>
</tr>
<tr>
<td>$p_{n,\text{total}}$</td>
<td>Total power consumption of MTD $MTD_n$</td>
</tr>
<tr>
<td>$g_{k,0}$</td>
<td>Channel gain for the link from CU $C_k$ to the BS</td>
</tr>
<tr>
<td>$g_{n,0}$</td>
<td>Channel gain for the link from MTD $MTD_n$ to the BS</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Pathloss constant</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Pathloss exponent</td>
</tr>
<tr>
<td>$\delta_{k,0}$</td>
<td>Fast-fading gain that follows an exponential distribution</td>
</tr>
<tr>
<td>$\delta_{k,0}^{\text{slow}}$</td>
<td>Slow-fading gain that follows a log-normal distribution</td>
</tr>
<tr>
<td>$\delta_{k,0}^{\text{n}}$</td>
<td>Transmission distance from CU $C_k$ to the BS</td>
</tr>
<tr>
<td>$\gamma_{k,0}$</td>
<td>Received SINR of CU $C_k$</td>
</tr>
<tr>
<td>$\gamma_{n,0,k}$</td>
<td>Received SINR of MTD $MTD_n$</td>
</tr>
<tr>
<td>$\gamma_{k,\text{min}}$</td>
<td>SINR threshold of CU $C_k$</td>
</tr>
<tr>
<td>$\gamma_{n,\text{min}}$</td>
<td>SINR threshold of MTD $MTD_n$</td>
</tr>
<tr>
<td>$R_{n,0,k}$</td>
<td>Channel transmission rate of the link from $MTD_n$ to BS</td>
</tr>
<tr>
<td>$B_k$</td>
<td>Channel bandwidth of RB $RB_k$</td>
</tr>
<tr>
<td>$\eta_{n,k}$</td>
<td>Energy efficiency of MTD $MTD_n$</td>
</tr>
<tr>
<td>$T$</td>
<td>Data transmission duration</td>
</tr>
<tr>
<td>$U_n$</td>
<td>Utility value of MTD $MTD_n$</td>
</tr>
</tbody>
</table>

MTD will suffer from the co-channel interference from other MTDs which are also reusing this RB.

We consider a specific example that both $MTD_n$ and $MTD_{n'}$ transmit data to the BS by utilizing $RB_k$ allocated to $C_k$. On account of uplink spectrum reusing, the BS will suffer from the co-channel interference caused by $MTD_n$ and $MTD_{n'}$ when receiving data from $C_k$, and suffer from the co-channel interference caused by $C_k$ and other MTDs that also reuse $RB_k$, i.e., $MTD_n$, when receiving data from $MTD_n$. Here, we concentrate on a scenario that the same RB can be reused by up to $q_k$ MTDs, where $q_k \geq 1$, and a single MTD can only reuse at most one RB. The more complicated scenario that a single MTD can reuse multiple RBs can be developed by simply extending our proposed model. The channel selection decision is defined as follows.

**Definition 1. (Channel Selection Decision)** The channel selection decision is denoted by an $N \times K$ matrix $S_{N \times K}$. Here, the $(n,k)$-th element of $S_{N \times K}$, i.e., $s_{n,k}$ is a binary variable. Particularly, $s_{n,k} = 1$ denotes that $MTD_n$ will reuse $RB_k$ to transmit data to the BS and $s_{n,k} = 0$, otherwise.

**Definition 2. (Power Control Decision)** The power control decision is denoted by a vector $P_n$, where $P_n = \{p_n|n \in N\}$. The element of $P_n$, i.e., $p_n$, denotes the transmission power of $MTD_n$, which is a continuous variable that needs to be optimized.

In the following subsections, the data transmission and energy consumption models are elaborated in detail.

A. DATE TRANSMISSION MODEL

The perfect channel state information (CSI) is assumed to be available during the period of data transmission. For the adopted channel model, both the fast fading effects and slow fading effects due to shadowing, multipath propagation, and pathloss are considered [30], [31]. Therefore, the channel gain for the link from $C_k$ to the BS is defined as

$$g_{k,0} = \omega \delta_{k,0} \zeta_{k,0} d_{k,0}^{-\alpha},$$

where $\alpha$ and $\omega$ represent the pathloss exponent and pathloss constant, respectively. The fast-fading gain that follows an exponential distribution is denoted as $\delta_{k,0}$, and the slow-fading gain that follows a log-normal distribution is denoted as $\zeta_{k,0}$. $d_{k,0}$ denotes the transmission distance from $C_k$ to the BS.

We assume that $MTD_n$ transmits data to the BS by reusing the RB of CU $C_k$, i.e., $s_{n,k} = 1$. For the cellular link, when $C_k$ transmits data to the BS, the signal to interference plus noise ratio (SINR) of $C_k$ under this assumption is given by

$$\gamma_{k,0} = \frac{p_c g_{k,0}}{p_{n,c} g_{n,0} + \sum_{n' \neq n} p_{n',c} g_{n',0} + N_0},$$

where $p_c$ and $p_{n,c}$ denote the transmission power of $C_k$ and $MTD_n$, respectively. $p_{n',c}$ ($n' \neq n$) denotes the transmission power of $MTD_{n'}$, which also reuses $RB_k$ to transmit data to the BS. $g_{n,0}$ and $g_{n',0}$ represent the channel power gain of the interference links from $MTD_n$ to the BS and $MTD_{n'}$, the BS, respectively. $N_0$ denotes the additive white Gaussian noise.

When $MTD_n$ transmits data to the BS by reusing $RB_k$, the received SINR of $MTD_n$ is given by

$$\gamma_{n,0,k} = \frac{p_c g_{k,0}}{p_{n,c} g_{n,0} + \sum_{n' \neq n} p_{n',c} g_{n',0} + N_0},$$

According to the Shannon theorem [32], the achievable channel transmission rate of the link from $MTD_n$ to the BS is given by

$$R_{n,0,k} = B_k \log_2 (1 + \gamma_{n,0,k}),$$

where $B_k$ is the channel bandwidth of $RB_k$.

B. ENERGY CONSUMPTION MODEL

The power consumption of $MTD_n$ is composed of two parts: the circuit power $p_{n,c}$ and the transmission power $p_n$. For simplicity, the value of the circuit power $p_{n,c}$ is the same for all $MTD_n \in MTD_N$, namely, $p_{n,c}$ is regarded as a constant. Therefore, the total power consumption of $MTD_n$ is given by

$$p_{n,\text{total}} = p_{n,c} + p_n.$$  

(5)

The energy efficiency (bits/Joule) of $MTD_n$, which is defined as the total bits transmitted by per joule [30], is given by

$$\eta_{n,k} = \frac{R_{n,0,k} T}{p_{n,\text{total}} T} = \frac{R_{n,0,k}}{p_n}.$$  

(6)
where $T$ is the data transmission duration.

By substituting (4) and (5) into (6), $\eta_{n,k}$ can be rewritten as

$$
\eta_{n,k} = \frac{B \log_2(1 + \gamma_{n,0,k})}{p_{n,c} + p_n}.
$$

**IV. PROBLEM FORMULATION**

In the machine-type communication networks, the crucial research challenge is how to jointly optimize channel selection and power control for each MTD from an energy efficiency perspective under various practical constraints, such as the constraints of transmission power, QoS provisioning, and spectrum reusing.

The sets of indices are denoted as $\mathcal{N} = \{1, \ldots, n, \ldots, N\}$ and $\mathcal{K} = \{1, \ldots, k, \ldots, K\}$, respectively. Besides, the set of optimization variable is denoted as $\{S_{n \times K}, \mathcal{P}_n\}$, where $\mathcal{P}_n = \{p_n | n \in \mathcal{N}\}$. Thus, the formulated problem is to minimize joint energy-efficiency and power control problem is given as follows:

**P1**: \[
\begin{align*}
\max & \sum_{S_{n \times K}, \mathcal{P}_n} \sum_{n=1}^{N} \sum_{k=1}^{K} s_{n,k} \eta_{n,k}(p_n) \\
\text{s.t.} & C_1 : s_{n,k} \gamma_{n,k}, \forall k \in \mathcal{K},

c_2 : s_{n,k} \gamma_{n,k} \leq s_{n,k} \gamma_{n}, \forall n \in \mathcal{N}, k \in \mathcal{K},
\end{align*}
\]

with constraints $C_3$, $C_4$, $C_5$, and $C_6$.

where $C_1$ and $C_2$ denote the QoS requirements of CUs and MTDs, respectively. $C_3$ is the transmission power constraint, where $p_{n,min}$ and $p_{n,max}$ denote the lower and upper bounds of $p_n$. $C_4$ specifies that the indicator of the channel selection decision is binary. $C_5$ guarantees that any MTD can reuse at most one RB. $C_6$ specifies that each RB can be reused by at most $q_k$ MTDs. The power control optimization problem is solved based on the established matching relationship obtained in the first stage.

**V. TWO-STAGE ENERGY-EFFICIENT RESOURCE ALLOCATION ALGORITHM**

In this section, we introduce the energy-efficient joint channel selection and power control algorithm for machine-type communication.

**A. PROBLEM TRANSFORMATION**

It is infeasible to derive the optimal solution of problem P1 in polynomial-time because of the following two reasons: 1) the formulated problem P1 is a mixed integer nonlinear programming (MINLP) problem, in which continuous variables $\{p_n\}$ and integer variables $\mathcal{S}_{\mathcal{N} \times \mathcal{K}}$ need to be optimized jointly; 2) the objective function for P1 is generally nonconvex due to the form of the summation of a number of fractions, leading the convex optimization algorithm cannot be utilized.

The channel selection optimization variable $s_{n,k}$ leads the original problem to a two-dimensional matching problem between $N$ MTDs and $K$ RBs, which can be denoted as a triple $(\mathcal{MTR}, \mathcal{RB}, \mathcal{U})$. Here, $\mathcal{MTR}$ and $\mathcal{RB}$ denote the sets of matching participants, and $\mathcal{U}$ denotes the set of matching utility. The two-dimensional many-to-one matching is defined as follows.

**Definition 3. (Many-to-one Matching)** Given the sets of $\mathcal{MTR}$ and $\mathcal{RB}$, the matching $\mu$ represents a many-to-one correspondence from the set $\mathcal{MTR} \cup \mathcal{RB}$ onto the set $\mathcal{MTR} \cup \mathcal{RB}$ such that:

1) $\mu(MTR_n) \in \mathcal{RB} \Rightarrow \mu(MTR_n) \neq \emptyset, \forall MTR_n \in \mathcal{MTR}_N$;

2) $|\mu(MTR_n)| \leq 1$, $|\mu(RB_k)| \leq q_k$.

which guarantee that any MTD can reuse at most one RB, and each RB can be reused by at most $q_k$ MTDs.

Therefore, deriving the optimal solution of P1 is composed of two stages. In the first stage, any $MTR_n \in \mathcal{MTR}_N$ is temporally allocated to a predefined transmission power $\bar{p}_n$, which is set as the maximum transmission power under the practical constraints, and then channel selection optimization problem is solved to derive the matching relationship between MTDs and RBs. In the second stage, the power control optimization problem is solved based on the established matching relationship obtained in the first stage.

**B. FIRST-STAGE CHANNEL SELECTION BASED ON MATCHING WITH EXTERNALITIES**

In the many-to-one matching model between MTDs and RBs, the utility value of $MTR_n$ when it reuses $RB_k$, is defined as the achievable energy efficiency based on $\bar{p}_n$, which is calculated as

$$
U_n | \mu(MTR_n) = RB_k = \bar{\eta}_{n,k} | \mu(MTR_n) = RB_k.
$$

The binary preference relation “$\succ$” is utilized to compare the different utility values for MTDs. For example, $RB_k \succ MTR_n RB_k'$ represents that $MTR_n$ can achieve higher utility when matching with $RB_k$ than $RB_k'$. In other words, $MTR_n$ prefers $RB_k$ to $RB_k'$, which can be represented as

$$
RB_k \succ MTR_n RB_k',
\iff U_n | \mu(MTR_n) = RB_k > U_n | \mu(MTR_n) = RB_k', \forall n \in \mathcal{N}, k, k' \in \mathcal{K}, k \neq k'.
$$

It is not difficult to find that the utility $U_n$ is a function with regards to the interference from both CU $C_k$ and other MTDs reusing the same RB $RB_k$. Therefore, the following observation can be made.

**Remark 1.** Externalities exist in the proposed matching model, in which the value of the utility of $MTR_n$ not only depends on the matched RB, but also on other MTDs that are matched with the same RB, i.e., $RB_k$. 

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Algorithm 1 Matching Theory with Externalities

1: **Input**: $MTD_N, RB_K, \bar{p}_n$;
2: **Output**: $\mu$;
3: **Initialization**: MTDs and RBs are matched with each other randomly under the constraints $C_1 \sim C_6$;
4: for $MTD_n \in MTD_N$ do
5: Search for another RB $RB_{k'}$ that is matched with other MTDs or still being single;
6: if $(MTD_n, MTD_{n'})$ forms a swap-blocking pair then
7: Update the current matching state $\mu$;
8: Update the number of MTDs matched with each RB;
9: else
10: Keep the current matching state;
11: end if
12: Repeat until there is no swap-blocking pair.
13: end for

This type of matching is referred to as matching with externalities, in which each participant has a dynamic utility value relevant to the decision strategies of all participants. Inspired by the housing allocation problem in [33], an extended many-to-one matching problem with externalities is proposed.

The swap operation which enables the participants to exchange their respective matching partner may lead a more effective matching result. Hence, the swap operation between any two MTDs to exchange their corresponding matching RBs is adopted. For the two matching pairs $(MTD_n, RB_k)$ and $(MTD_{n'}, RB_{k'}) (n \neq n', k \neq k')$, the concept of swap is defined as follows:

$$\mu_{MTD_n'} = \{\mu \setminus \{(n, k), (n', k')\}\} \cup \{(n', k'), (n, k)\}. \quad (11)$$

That is to say, the operation of swap enables $MTD_n$ and $MTD_{n'}$ to exchange their corresponding matched RBs, i.e., $RB_k$ and $RB_{k'}$, while keeping the matching relationship between other MTDs and RBs unchanged. It is noted that one of the MTDs involved in the swap operation can be a "hole", which means that the RB involved in the swap has not been matched with any MTD. The single MTD is therefore allowed to move to all the available vacancies.

According to the concept of the swap, the swap will occur when the following condition is satisfied:

$$U_n \mid_{\mu(MTD_n) = RB_k} - U_n \mid_{\mu(MTD_n) = RB_{k'}} \geq \delta_U, \quad (12)$$

where $\delta_U$ is a positive value. Namely, the swap will be executed when the utilities of participants can be increased. Here, $(MTD_n, MTD_{n'})$ is called the swap-blocking pair. The concrete process of the matching is described in Algorithm 1 in detail.

Remark 2. The matching will achieve stability when there is no swap-blocking pair.

Proof: Assuming that there exists a swap-blocking pair $(MTD_n, MTD_{n'})$ that satisfies (11), and the matching state has achieved stable. However, the matching algorithm will not terminate until all the swap-blocking pairs have been eliminated according to the Algorithm 1. Therefore, the present formulated matching state is not the final matching, and will be carried out sequentially, which causes conflict with the assumption.

C. SECOND-STAGE POWER CONTROL OPTIMIZATION BASED ON NONLINEAR FRACTIONAL PROGRAMMING

In this section, we introduce an iterative optimization algorithm for power control based on the nonlinear fractional programming and noncooperative game theory.

1) Noncooperative-Game-Based Utility Modeling

Obtaining the maximum energy efficiency of all MTDs is equal to guarantee that any $MTD_n \in MTD_N$ has achieved its corresponding maximum achievable energy efficiency. Therefore, based on the matching relationship between MTDs and RBs obtained in the first stage, $P_1$ can be solved through solving the following problem:

$$\begin{aligned}
P_2: \max_{p_n} & \quad \eta_{n, k}(p_n) \\
\text{s.t.} & \quad C_1 \sim C_3. \quad (13)
\end{aligned}$$

However, there are still two critical challenges when solving the optimization problem of (13). Firstly, from (3) and (7), $p_n g_{n,0}$ and the interference term, i.e., $p_{n'} g_{n',0}$, are intercorrelated together, both of which need to be optimized. Secondly, the problem formulated in (13) is still nonconvex with respect to the optimization variable, i.e., $p_n$, because of the fractional form of $\eta_{n, k}$.

To overcome the first challenge, a game-theoretic method is adopted to model the power control problem as a noncooperative game $G$. MTDs are considered as selfish and rational, i.e., any $MTD_n \in MTD_N$ only cares about its individual utility $\eta_{n, k}$. The noncooperative game $G$ can be denoted as $G = (MTD_N, A, \eta)$, where $A = \{A_1,...,A_n,...,A_N\}$ represents the set of strategies that an MTD can adopt, and $\eta = \{\eta_{1, k},...\eta_{n, k},...\eta_{N, k}\}$ represents the set of energy efficiency that an MTD can achieve, i.e., the achieved utility. For instance, if $A_n = \{0, p_{n, max}\}$, then $MTD_n$ is permitted to adopt the value of $p_n$ from the interval $[0, p_{n, max}]$.

2) Objective Function Transformation

To solve the second challenge, the nonlinear fractional programming is adopted to transform the original nonconvex problem $P_2$ with fraction-form into an equivalent convex one based on the following theorem.

Theorem 1. Defining $q_{n,0, k}$ as the optimal objective value of (13), the optimal solutions $p^*_n$ to $P_2$ can be obtained if and only if

$$\begin{aligned}
\max_{p_n} & \quad B \log_2 \left(1 + \gamma_{n,0, k}(p_n)\right) - q_{n,0, k}(p_{n, c} + p_n) \\
= & \quad B \log_2 \left(1 + \gamma_{n,0, k}(p_n)\right) - q_{n,0, k}(p_0 + p^*_n) = 0. \quad (14)
\end{aligned}$$
Algorithm 2 Iterative Power Control Algorithm

1: Input : $MTD_N, RB_K$.
2: Output : $p_n$.
3: for $MTD_N \in MTD_N$ do
4: for $RB_K \in RB_K$ do
5: Initialization : initialize $q_{n,0,k}^{l-1,*}$, $q_{n,l,0,k}^{l-1,*}$, $p_{n}^{l-1,*}$, and maximum tolerance $\delta$ and $\Gamma$, set $t = 1$, $l = 1$.
6: Solve the problem for optimizing the power control variable $p_n$ based on $p_{n}^{l-1,*}$ by utilizing (22).
7: if $B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l-1,*}))/\gamma_{n,0,k}(p_{n}^{l-1,*}) + p_{n}^{l-1,*}) > \delta$ then
8: $t = t + 1$, return to line 6, update $q_{n,0,k}^{l-1} = B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l-1,*}))/\gamma_{n,0,k}(p_{n}^{l-1,*})$.
9: else
10: $p_{n}^{l,*} = p_{n}^{l-1,*}, q_{n,0,k}^{l,*} = q_{n,0,k}^{l-1}$.
11: Solve the problem for optimizing the power control variable $p_n'$ based on $p_{n}^{l,*}$ by utilizing (22).
12: end if
13: if $B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l-1,*}))/\gamma_{n,0,k}(p_{n}^{l-1,*}) + p_{n}^{l-1,*}) > \delta$ then
14: $t = t + 1$, return to line 11, update $q_{n,0,k}^{l-1} = B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l-1,*}))/\gamma_{n,0,k}(p_{n}^{l-1,*})$.
15: else
16: $p_{n}^{l,*} = p_{n}^{l-1,*}, q_{n,0,k}^{l,*} = q_{n,0,k}^{l-1}$.
17: end if
18: if $q_{n,0,k}^{l-1} - q_{n,0,k}^{l-1,*} > \Gamma, q_{n,0,k}^{l-1} - q_{n,0,k}^{l-1,*} > \Gamma$ then
19: $l = l + 1$, return to line 6.
20: end if
21: end for
22: end for

Proof: Theorem 1 can be proved by exploring the properties of nonlinear fractional programming [34]. A similar proof can be found in [10].

Therefore, the transformed equivalent problem is formulated as follows.

**P3** : $\max_{p_n} B \log_2(1 + \gamma_{n,0,k}(p_{n})) - \gamma_{n,0,k}(p_{n}) + p_{n}$

s.t. $C_1 \sim C_3$.

(15)

3) Iterative Optimization for Power Control

Therefore, solving (15) is equal to solve (13). Nevertheless, it is noted that $q_{n,0,k}^{*}$ in (15) is still unknown. Then, the iterative algorithm based on Dinkelbach method is adopted to iteratively derive the unknown value of $q_{n,0,k}^{*}$, which is elaborated in Algorithm 2. The iteration indexes of Dinkelbach method and noncooperative game are denoted as $t$ and $l$, respectively. Two loops are contained in Algorithm 2: the inner loop is the Dinkelbach method, which is executed to derive the optimal power control strategy for each MTD, and the outer loop is the noncooperative game, which is executed to guarantee the achieved power control strategy can converge to a Nash equilibrium [34], i.e., no MTD is able to unilaterally achieve better performance via deviating from it.

At the $t$-th iteration of the $l$-th round game, the optimal power control variable, i.e., $p_{n}^{l,t,*}$, is obtained according to the value of $q_{n,0,k}$ derived in the $(t-1)$-th iteration, i.e., $q_{n,0,k}^{l-1}$, by getting the solution of the following problem:

**P4** : $\max_{p_n} B \log_2(1 + \gamma_{n,0,k}(p_{n})) - q_{n,0,k}^{l-1} + p_{n}$

s.t. $C_1 \sim C_3$.

(16)

In each iteration, the value of $q_{n,0,k}$ can be updated as

$q_{n,0,k}^{l} = B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l}))/\gamma_{n,0,k}(p_{n}^{l})$.

(17)

The Dinkelbach iteration will terminate when

$B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l}))/\gamma_{n,0,k}(p_{n}^{l}) + p_{n}^{l} \leq \delta$.

(18)

where $\delta$ is the maximum tolerance.

To utilize the Lagrange dual decomposition, the constraints $C_1$ and $C_3$ are combined into a simpler constraint, which is given by

$\hat{C}_1 : \gamma_{n,0,k}(p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l}) - \gamma_{n,0,k}(p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l} + p_{n}^{l}) \leq \delta$.

(19)

The Lagrangian associated with **P4** is given by

$L(p_{n}^{l}, p_{n}, \beta_{n}, \theta_{n}) = \begin{vmatrix}
B \log_2(1 + \gamma_{n,0,k}(p_{n}^{l}))/\gamma_{n,0,k}(p_{n}^{l}) + \beta_{n}(p_{n}^{l}) + \theta_{n}(p_{n}^{l})
\end{vmatrix}

min \left\{ \gamma_{n,0,k}(p_{n}^{l}) - \gamma_{n,0,k}(p_{n}^{l}), \gamma_{n,0,k}(p_{n}^{l}) + \theta_{n}(p_{n}^{l}) \right\}$.

(20)

where $\beta_{n}$ and $\theta_{n}$ are the vectors of Lagrange multipliers associated with constraint $\hat{C}_1$, and the vector of Lagrange multiplier with respect to constraint $C_2$ is defined as $p_{n}$. By utilizing the Lagrange dual decomposition, (20) can be decomposed as follows:

$\min_{(p_{n}^{l}, \beta_{n}, \theta_{n} \geq 0)} \max_{(p_{n}^{l}, \beta_{n}, \theta_{n})} L(p_{n}^{l}, p_{n}, \beta_{n}, \theta_{n})$.

(21)

The inner power control optimization problem can be solved via setting the first-order derivative of $L(p_{n}^{l}, p_{n}, \beta_{n}, \theta_{n})$ associated with $p_{n}^{l}$ as zero. The optimal value $p_{n}^{l,t,*}$ can be given by

$p_{n}^{l,t,*} = \left[ \begin{vmatrix}
B \log_2(c(p_{g,k,0} + N_0 + \sum_{n' \in N, n' \neq n} s_{n',k}p_{n',g_{n',0}})) + \gamma_{n,0,k}(p_{n}^{l}) + \gamma_{n,0,k}(p_{n}^{l}) + \theta_{n}(p_{n}^{l})
\end{vmatrix}

min \left\{ \gamma_{n,0,k}(p_{n}^{l}) - \gamma_{n,0,k}(p_{n}^{l}), \gamma_{n,0,k}(p_{n}^{l}) + \theta_{n}(p_{n}^{l}) \right\} + \theta_{n}(p_{n}^{l}) \right] + \theta_{n}(p_{n}^{l})$.

(22)
TABLE 2: Simulation Parameters

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell radius $r (m)$</td>
<td>50</td>
</tr>
<tr>
<td>Pathloss constant $\omega$</td>
<td>0.01</td>
</tr>
<tr>
<td>Fast-fading gain $\delta$</td>
<td>8</td>
</tr>
<tr>
<td>Slow-fading gain $\gamma$ (dB)</td>
<td>3</td>
</tr>
<tr>
<td>Pathloss exponent $\alpha$</td>
<td>4</td>
</tr>
<tr>
<td>Maximum distance between MTDs and CUs $d_{max} (m)$</td>
<td>$35 \sim 35$</td>
</tr>
<tr>
<td>One-sided power spectral density of the additive white Gaussian noise $N_0$ (dBm)</td>
<td>-114</td>
</tr>
<tr>
<td>Transmission power range $p_{n, min}$ and $p_{n, max}$ (dBm)</td>
<td>0-23</td>
</tr>
<tr>
<td>Circuit power consumption $p_{n,c}$ (dBm)</td>
<td>20</td>
</tr>
</tbody>
</table>

FIGURE 2: A snapshot of CU-MTD network with $K$ CUs, $N$ MTDs ($K = 5$, $N = 10$)

of the game and the previous round are extremely close, namely, the corresponding optimal power control variable $p_n$ has converged to a Nash equilibrium.

VI. NUMERICAL RESULTS

In this section, we evaluate the proposed algorithm through simulations. The simulation parameters are summarized in Table 2. The cell radius is 50 meters. The location of CUs and MTDs are randomly distributed throughout the cell. The proposed algorithm is compared with several heuristic algorithms, i.e., exhaustive algorithm, random matching, and random matching with power control. In particular, MTDs are allowed to reuse the RBs of CUs randomly under the optimal transmission power for the third algorithm.

A snapshot of $K = 5$ and $N = 10$ is shown in Fig. 2. Fig. 3 shows the sum energy efficiency performance of MTDs versus the number of RBs with $N = 5$. Simulation results demonstrate that the proposed algorithm can approach the optimal performance achieved by the exhaustive algorithm with a much lower complexity, and achieve better performance compared with the other two heuristic algorithms. To be specific, when $K = 7$, the performance of proposed algorithm outperforms the second algorithm by 30.7%, while the proposed algorithm outperforms the first algorithm by 62%. Moreover, it is apparently that the energy efficiency performance increases monotonically with the number of RBs. The reason lying behind is that the MTD will have a higher probability to match with a more preferred RB from a larger amount of RBs. However, when the number of RBs reaches a certain number, the increment of performance is not significant because all MTDs have been matched.

Fig. 4 shows the sum energy efficiency performance of MTDs versus the number of MTDs with $K = 3$. Simulation results demonstrate that the proposed algorithm can achieve better performance compared with the other two heuristic algorithms. When $N = 7$, the energy efficiency performance of the proposed algorithm can achieve up to 93% comparing the optimum performance. In comparison, the performance improvements of the other two heuristic algorithms are only 71% and 54%, respectively. Moreover, it is apparently that the energy efficiency performance increases monotonically when the number of MTDs is not large. The reason is that the RBs of CUs are not fully utilized by the MTDs. However, when the number of MTDs reaches a certain number, the performance increment is not significant since all the RBs have reached the maximum capacity to be reused, the increase of energy efficiency can only be achieved by swapping the MTDs.

Fig. 5 shows the sum energy efficiency performance of MTDs versus the quota of CUs with $K = 3$ and $N = 5$. When $q \leq 2$, it is apparently that the energy efficiency performance increases monotonically with the quota of CUs. To be specific, the sum energy efficiency performance of the proposed algorithm at $q = 2$ is double that of at $q = 1$. The reason is that the capacity of each CU is not sufficient to support all the MTDs to be matched, to be specific, there are at most $q \times N$ MTDs are allowed to reuse all the RBs. However, when $q > 2$, the sum energy efficiency is almost constant because all the MTDs have been matched with the RBs, and the small increments of energy efficiency can only be achieved through swap matching.

Fig. 6 shows the sum energy efficiency performance of MTDs versus the minimum value of SINR of base station $\gamma_{min}$ with $K = 3$ and $N = 5$. It is noted that when $\gamma_{min} = 25$ dBm, $\gamma_{min}$ barely affects energy efficiency performance of MTDs since the transmission power of MTDs can be set to a relative suitable value under the constraint of $C_1 \sim C_3$. However, when $25$ dBm $< \gamma_{min} \leq 30$ dBm, the sum energy efficiency of MTDs decreases monotonically with $\gamma_{min}$ since the achievable channel transmission rate of the link from MTDs to the BS gained by per unit increment of transmission power cannot compensate for the increased energy consumption. When $\gamma_{min} = 30$ dBm, the sum energy efficiency decreases to zero since MTDs are not able to transmit data to the BS effectively due to the terrible channel condition.

Fig. 7 shows the sum energy efficiency performance of MTDs versus the number of Dinkelbach iterations. Based on the power control algorithm, the initial value of $q_{n,0,k}$ is...
set as a small positive number $q_{n,0,k} = 0.0001$. With the proceeding of the algorithm, $q_{n,0,k}$ is slowly converting to the optimum value. It is noted that it only takes 2 iterations to converge to the optimum value. In addition, the number of CUs and MTDs barely affects the convergence performance of the proposed algorithm.

**VII. CONCLUSIONS**

In this paper, we studied the energy-efficient resource allocation problem for machine-type communications. A two-stage energy efficient joint channel selection and power control optimization algorithm by combining a matching with externalities approach and nonlinear fractional programming method was proposed. As shown in Fig. 3, the simulation results show that the proposed algorithm outperforms the other two heuristic algorithms. For example, the proposed algorithm outperforms the other two algorithms by 30.7% and 62% when $N = 5, K = 7$, respectively. In future works, we will investigate a more complicated many-to-many matching scenario in which each MTD can reuse multiple RBs, and multiple MTDs are allowed to reuse the same RB.

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**REFERENCES**


FIGURE 7: Sum energy efficiency performance of MTDs versus the number of Dinkelbach iterations
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