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Joint Device Association and Power Coordination for H2H and IoT Communications in Massive MIMO Enabled HCNs

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ABSTRACT The integration of massive multiple-input and multiple-output (MIMO) enabled heterogeneous cellular networks (HCNs) and Internet of Things (IoT) is a promising treatment for future networking paradigms. In such networks, the human-to-human (H2H) devices and IoT devices have some distinct service requirements. Specifically, the former mainly concentrates on downlink throughput, but the latter pays more attention to uplink power consumption. Based on this, we design a device association mechanism (scheme) to achieve a tradeoff between these two performance metrics under devices' association requirements. Through some appropriate adjustments of weighting parameters, different types of devices can improve their performance metrics of interest. At last, such a scheme is formulated as a network-wide logarithmic utility maximization problem in a nonlinear and combinatorial form. To solve it, we develop two types of association algorithms, whose primary difference lies in the treatment of weighting parameters. Then, we show the corresponding convergence and computation complexity analyses for them. Finally, we investigate the impacts of weighting parameters, the BS power and the number of antennas on some certain performance metrics of designed algorithms and other existing one. The simulation results show that the designed algorithms can meet different devices' association requirements by properly adjusting weighting parameters.

INDEX TERMS Heterogeneous cellular networks (HCNs), massive MIMO, Internet of Things (IoT), human-to-human (H2H), device association, power coordination, downlink and uplink (DUL).

I. INTRODUCTION

The Internet of Things (IoT) is a new paradigm envisioned as the global network of smart devices capable of interacting with each other. Such these devices mainly involve sensors, actuators, mobile terminals and so on, which can support home security and safety, health and fitness monitoring, energy management and other services [1]–[3]. To support IoT communications, a favorable measure may be the implementation of IoT devices in a cellular network [4].

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With rapid growth of IoT devices and mobile terminals, there exist a higher pressure of accommodating IoT and human-to-human (H2H) communications [5], [6] on the network operators in a cellular network. To meet the service demand of IoT and traditional H2H devices, heterogeneous cellular networks (HCNs) consisting of disparate base stations (BSs) may be a good option, which have been widely regarded as a more spectrum-efficient and energy-efficient networking paradigm [7]. As we know, HCNs enhance the network coverage and relieve the flow congestion by deploying some low-power nodes at each macrocell [8]. Such these nodes mainly include pico BSs (PBSs), femto BSs (FBSs) and so on, whose main difference lies in the transmit power,

propagation characteristic, backhaul and deployment cost. As revealed in [4], [9], small cells based HCNs can provide the desirable seamless connectivity for the evolving IoT. That is to say, the integration of HCNs and IoT is a promising operation for future networking paradigms.

To further enhance the spectrum efficiency, the massive multiple-input and multiple-output (MIMO) technology is often utilized at macro BSs (MBSs) of HCNs. Under the implementation of a large number of antennas, such these BSs can transmit independent data streams to multiple users with resource share simultaneously [10].

The device association, selecting one or several BSs for some device (user) to optimize some certain performance metrics (e.g., signal strength, biasing signal strength [11], energy efficiency [12]–[15], rate utility [16], etc.), has been considered as one of crucial challenges in HCNs. In addition, it may be more complicated and difficult for designers to develop some device association mechanisms for the emerging H2H/IoT enabled HCNs since the H2H and IoT devices involve some distinct association requirements. Specifically, the H2H devices may pay more attention to downlink throughput because the most of them require some high data transmission rates especially for some interactive video services, but the IoT devices may need to keep a close eye on uplink power consumption since they are often in a battery-operated work pattern and expect some long battery lifetimes [7].

The traditional signal strength-based association mechanisms, e.g., maximal reference signal receiving power (RSRP) association [17], may be unsuitable for H2H/IoT enabled HCNs because the disparate transmit power causes an unbalanced load distribution and finally insufficient resource utilization [18], [19]. Although the implementation of a large-scale antenna array can bring the increment of spectrum efficiency, it may result in a more unbalanced load distribution among disparate BSs. Evidently, the design of some good association mechanisms in the massive MIMO enabled HCNs is meaningful, and the one in H2H/IoT enabled HCNs with massive MIMO is also urgent. Considering the different association requirements of H2H and IoT devices, designers may need to develop some mechanisms with coupling downlink and uplink (DUL) associations [4], [7]. Next, we will mainly concentrate on the design of some coupling DUL association mechanisms in the existing efforts.

A. RELATED WORK

In [18], Andrews *et al.* thought that asymmetric DUL is the one of major implementation constraints of association mechanisms for load balancing in traditional HCNs, and joint DUL association mechanisms should be designed to achieve a good system performance. To this end, many designers have already made some efforts to develop this type of association mechanisms.

Under the resource constraints, Chen and Hu in [20] designed an association mechanism to minimize the uplink power and resource consumption but maximize the system

load for HCNs, and finally achieved a goal of optimizing the downlink system throughput and uplink energy consumption. Unlike the centralized implementation of association mechanism designed in [20], Zhou *et al.* [21] tried to optimize a network-wide utility with respect to the downlink throughput and uplink power for HCNs, and designed an effective distributed algorithm. To minimize the DUL energy consumption for cloud radio access networks, Luo *et al.* in [22] jointly performed the user association and beamforming. However, such a treatment may be unreasonable since the user association takes place at a large-scale time slot and utilizes a slow-fading channel, but the latter takes place at a small-scale time slot and uses a fast-fading channel. In [23], Liu *et al.* proposed a backhaul-aware association mechanism with coupling DUL to achieve a tradeoff between the network delay and the power consumption for hybrid energy sources enabled HCNs. Such a mechanism tried to minimize the DUL traffic delay, and reduce the uplink power consumption of users and the downlink on-grid power consumption at the same time. In a new perspective, Liu *et al.* in [24] developed an association mechanism to achieve the optimal log-scale DUL energy efficiencies for HCNs. In addition, other designers in [25] mainly concentrated on the DUL throughput maximization under some quality-of-service (QoS) constraints.

To further improve the spectrum efficiency, MBSs employ a large number of antennas in HCNs. In such networks, most designers concentrated on a type of associations with maximizing network-wide rate utility [26]–[31]. In addition, some ones focused on energy-efficient associations with maximizing the aggregate utility of energy efficiencies [12], the design of association mechanisms with power consumption minimization [32], [33], and the development of association algorithms with a tradeoff between energy efficiency and spectral efficiency [34]. However, such these works were mainly interesting in the downlink or uplink systems. So far, there may be only one association design that concentrated on the whole energy efficiency maximization for uplink and downlink.

With rapid growth of IoT devices and the integration of IoT and HCNs, the design of association mechanisms in H2H/IoT enabled HCNs has received a certain amount of attention in recent years, but it is also relatively fewer than the one in HCNs. In [4], Elhatab *et al.* designed an association mechanism to maximize the downlink throughput and uplink energy efficiency, but minimize the uplink power consumption. Based on a game theoretic framework, authors developed a two-player bargaining algorithm. In another perspective, Elhatab *et al.* in [7] considered a QoS-aware opportunistic device association to achieve a goal of downlink throughput maximization and uplink power consumption minimization. It is easy to find that these designed association mechanisms in H2H/IoT enabled HCNs have considered some different association requirements of H2H and IoT devices.

In general, the aforementioned association mechanisms often jointly optimized some DUL performance metrics, and most of them (e.g., [7], [20], [22]–[24]) introduced some

weighting parameters to achieve a tradeoff between these metrics. In fact, the introduction of weighting parameters is beneficial to coupling and decoupling associations for DUL systems. In other words, these association mechanisms can be transformed into decoupling DUL ones [35]–[37] or coupling ones by properly adjusting the weighting parameters. Through such a treatment, network operators can choose an appropriate association manner according to practical requirements.

Unlike the existing efforts in the literature, we design an association mechanism with adjustable logarithmic utility maximization, which is tightly related to the downlink long-term rates and uplink power consumption. The introduction of downlink long-term rates is better for balancing network loads, and the uplink power consumption is achieved by performing an open loop power control under some required signal-to-noise ratios (SNRs). Unlike the most of coupling DUL association mechanisms, we also take account of a power coordination mechanism [38] to enhance the downlink system throughput and reduce the downlink energy consumption. In a final association mechanism, the H2H and IoT devices can adjust their weighting parameters to meet the corresponding association requirements. Certainly, they can also perform a decoupling or coupling DUL association by adjusting these parameters.

B. CONTRIBUTIONS AND ORGANIZATION

In this paper, we design an association mechanism to maximize a network-wide logarithmic utility of weighted downlink long-term rates and uplink power under the power coordination for H2H/IoT enabled HCNs with massive MIMO. It is easy to find that the main difference between such work and the efforts in [4], [7] lies in the following aspects. At first, the optimized performance metrics of them are different greatly. Secondly, the consideration of massive MIMO in this paper is an additional contribution that doesn't exist in [4], [7]. At last, the power coordination is also a good contribution in this paper, which is not involved in [4], [7].

To solve the formulated network-wide utility maximization problem, we develop two types of algorithms using Lagrange dual decomposition and two-side-scale (2.s.s.) function methods. In fact, the main difference of these two types of algorithms lies in the treatment of weighting parameters. In general, the main contributions in this paper can be listed as follows.

① **Association Design in A Relatively New Paradigm.** So far, there are very few efforts toward the association design for H2H/IoT enabled HCNs with massive MIMO in the literature. In such networks, none of existing efforts take account of a power coordination measure to improve the downlink system throughput and reduce the downlink power consumption.

② **Association With Power Coordination for Identical Weights (APCIW).** In the association design, we find that the finally formulated problem is in a nonlinear and mixed-integer form, and hard to tackle. In addition, the

different weighting parameters make the development of effective algorithms more difficult. To solve this type of problem, we assume that all devices have the same weighting parameters. After such a treatment, we can design a feasible algorithm for the association subproblem using a dual decomposition method, and develop an effective one for the power coordination subproblem using a 2.s.s. function method. Finally, the whole problem can be solved by alternately performing these subalgorithms.

③ **Association With Power Coordination for Distinct Weights (APCDW).** Although the treatment of weighting parameters in APCIW simplifies the algorithm design for an association subproblem, it may be unfavourable for accommodating different association requirements of H2H and IoT devices. In view of this, we try to design another association algorithm under some different weighting parameters of devices. To this end, we first need to obtain an upper bound of original optimization problem through some relaxation operation. After that we can design the corresponding algorithms for the association and power coordination subproblems using some similar methods in APCIW.

④ **Convergence and Computation Complexity Analyses.** Similar to the most of existing efforts in the literature, although we cannot prove the convergence of alternating process, we can verify it by numerical simulation. In addition, we can definitely give some convergence analyses for the algorithms designed for device association and power coordination subproblems. At last, we investigate the computation complexities of all algorithms in detail, and give some feasible operations to improve the executive efficiencies of designed algorithms.

The rest of this paper is organized as follows. In Section II, we give some detailed descriptions for H2H/IoT enabled HCNs with massive MIMO. In Section III, an association mechanism is presented to maximize an adjustable network-wide utility of downlink long-term rates and uplink power under the power coordination. In Section IV, two types of algorithms are designed to solve the problem formulated in the association mechanism. In Section V, some convergence and computation complexity analyses are provided for the designed algorithms. In Section VI, we investigate the association performance of designed algorithms through numerical simulation. At last, some further discussions and conclusions are made in Section VII.

Notations: Uppercase boldface letters (e.g., \mathbf{X}) denote matrices and lowercase ones (e.g., \mathbf{x}) represent vectors. Assume that $\mathbf{x} \succcurlyeq \mathbf{y}$ if $x_s \geq y_s$ for any s , and $\mathbf{x} \preccurlyeq \mathbf{y}$ if $x_s \leq y_s$ for any s . $[z]_x^y = \min\{\max\{z, x\}, y\}$ and $[z]^+ = \max\{z, 0\}$. In addition, $|z|$ represents an absolute value of z , $\|\mathbf{Z}\|$ denotes a 2-norm of \mathbf{Z} .

II. SYSTEM MODEL

Without loss of generality, we mainly concentrate on two-tier HCNs with co-existing H2H and IoT devices, which are illustrated in Fig. 1. Significantly, the expanded region is caused by some device association mechanism (e.g., range

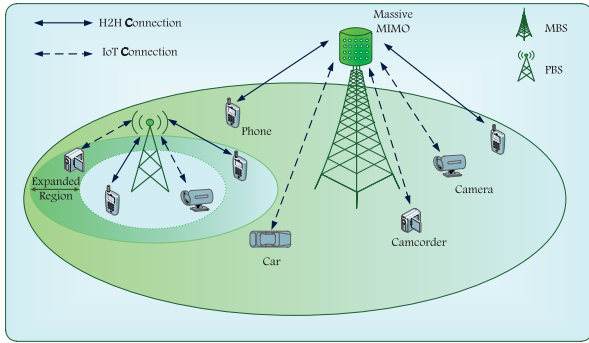


FIGURE 1. H2H/IoT enabled two-tier HCNs with massive MIMO.

extension [40]). In such networks, any MBS implements A antennas, but any PBS just configures one antenna [12], [34]. To mitigate the interference between uplink and downlink accesses, we assume that they utilize different time/frequency resources [39]. In addition, all BSs are assumed to utilize the same frequency resource in the uplink or downlink, and they equally assign it to their associated users and serve these users under the round-robin scheduling (RRS). At last, we assume that any MBS can simultaneously transmit at most D ($1 \ll D \ll A$) downlink data streams on the same frequency resource, and the linear zero-forcing beamforming is used for the downlink transmission with massive MIMO [12], [34].

Assume that there are S BSs including $|\mathcal{S}_1|$ MBSs and $|\mathcal{S}_2|$ PBSs in the set $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, and M devices used for H2H and IoT communications in the set \mathcal{M} . Then, the downlink signal-to-interference-plus-noise ratio (SINR) received by device m from BS s is given by

$$\text{SINR}_{sm}^{DL} = \begin{cases} \frac{p_s h_{sm}}{\sum_{i \in \mathcal{S}_1, i \neq s} p_i h_{sm} + \Theta}, & \forall s \in \mathcal{S}_2, \forall m \in \mathcal{M}, \\ \frac{B p_s h_{sm}}{\sum_{i \in \mathcal{S}_1, i \neq s} p_i h_{sm} + \Theta}, & \forall s \in \mathcal{S}_1, \forall m \in \mathcal{M}, \end{cases} \quad (1)$$

where p_s represents the transmit power of BS s ; h_{sm} denotes the average channel gain between BS s and device m ; Θ represents the additive noise power; $B = (A - D + 1)/D$, and it is a scaling factor of any SINR_{nk} due to the equal power allocation and array gain from massive MIMO under the Rayleigh channel fading [12]; \mathcal{S}_s represents the set \mathcal{S} excluding BS s . Then, the downlink achievable rate received by device m from BS s is given by

$$r_{sm}^{DL} = \begin{cases} D \log_2 (1 + \text{SINR}_{sm}^{DL}), & \forall s \in \mathcal{S}_1, \forall m \in \mathcal{M}, \\ \log_2 (1 + \text{SINR}_{sm}^{DL}), & \forall s \in \mathcal{S}_2, \forall m \in \mathcal{M}, \end{cases} \quad (2)$$

Under the open loop control [20], the uplink transmit power q_{sm} of device m associated with BS s can be given by

$$q_{sm} = \min \left\{ \kappa \Theta / h_{sm}, 10^{\bar{q}_m / 10} \right\}, \quad (3)$$

where \bar{q}_m denotes the maximal allowed (transmit) power of device m in dBm; κ represents a target SNR on the whole frequency range of each BS.

To proceed, we give the following definitions.

Definition 1: Under RRS, the downlink data (long-term) rate of device m associated with BS s can be written as $R_{sm}^{DL} = r_{sm}^{DL} / \sum_{m \in \mathcal{M}} x_{sm}$, where x_{sm} is a link usage (association) indicator between device m and BS s , and it takes 1 if device m selects BS s , 0 otherwise.

Definition 2 [41], [42]: If there exist $(1/c) \varphi_s(\mathbf{p}) \leq \varphi_s(\boldsymbol{\rho}) \leq c \varphi_s(\mathbf{p})$ for any $s, c > 1, \mathbf{p} = \{p_1, p_2, \dots, p_S\}$ and $\boldsymbol{\rho} = \{\rho_1, \rho_2, \dots, \rho_S\}$ satisfying $(1/c) \mathbf{p} \preceq \boldsymbol{\rho} \preceq c \mathbf{p}$, a function $\varphi_s(\mathbf{p})$ used for updating the power is two-side-scale (2.s.s.) with respect to \mathbf{p} for any s .

It is easy to find that downlink data rates are closely related to the link signal strength between devices and selected BSs, and the load levels of these BSs. In the association design, such a performance metric can be used as a crucial parameter for balancing network loads. Next, we will focus on the design and solving of an association problem for H2H/IoT enabled HCNs with massive MIMO under the power coordination.

III. PROBLEM FORMULATION FOR ASSOCIATION WITH POWER COORDINATION

To balance the network loads and thus sufficiently utilize the system resources, long-term rates need to be integrated into a DUL association design, especially for a downlink system. As shown in Definition 1, downlink long-term rates are closely related to the achievable rates of devices and the loads of associated BSs. Evidently, the introduction of long-term rates in a DUL association design can avoid a bad situation that most of devices are attracted by high-power BSs, and very few devices can be served by low-power BSs. In order to further enhance the network throughput and reduce the energy consumption in the downlink, a power coordination measure is considered in the association phase. For the uplink, the open loop power control with guaranteed SNRs is integrated into the device association.

Since the rate of increase in logarithmic utility function $U = \log(R_{sm}^{DL})$ decreases with increasing R_{sm}^{DL} monotonically, the lower data rate R_{sm}^{DL} is more favored and the higher one is suppressed in such a logarithmic utility function. That is to say, some low-rate users associated with the overloaded BSs should be favored, which means these users may need to be connected to the underloaded BSs for load balancing. Based on this, we uniformly utilize a logarithmic utility function in the design of association mechanisms.

At last, we design an association mechanism to maximize an adjustable logarithmic utility of weighted downlink long-term rates and uplink power under the power coordination for H2H/IoT enabled HCNs with massive MIMO. Mathematically, it can be formulated as

$$\begin{aligned} & \max_{\mathbf{X}, \mathbf{p}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ \alpha w_m \log R_{sm}^{DL} - \beta (1 - w_m) q_{sm} \right\} \\ & \text{s.t. } C_1 : \sum_{s \in \mathcal{S}} x_{sm} = 1, \quad \forall m \in \mathcal{M}, \\ & C_2 : 0 \leq p_s \leq \bar{p}_s, \quad \forall s \in \mathcal{S}, \\ & C_3 : x_{sm} \in \{0, 1\}, \quad \forall s \in \mathcal{S}, \forall m \in \mathcal{M}, \end{aligned} \quad (4)$$

where $\mathbf{X} = \{x_{sm}, \forall s \in \mathcal{S}, \forall m \in \mathcal{M}\}$; $\mathbf{p} = \{p_s, \forall s \in \mathcal{S}\}$;

$$\alpha = \left| \sum_{m \in \mathcal{M}} \log \bar{r}_{sm}^{DL} \right|^{-1}, \quad \beta = \left| \sum_{m \in \mathcal{M}} 10^{\bar{q}_m/10} \right|^{-1}, \quad (5)$$

$$\bar{r}_{sm}^{DL} = \begin{cases} D \log_2 (1 + B \bar{p}_s h_{sm} / \Theta), & \forall s \in \mathcal{S}_1, \forall m, \\ \log_2 (1 + \bar{p}_s h_{sm} / \Theta), & \forall s \in \mathcal{S}_2, \forall m, \end{cases} \quad (6)$$

$$s_m = \arg \max_{s \in \mathcal{S}} \bar{r}_{sm}^{DL}, \quad \forall m \in \mathcal{M}. \quad (7)$$

In (4), α and β represent the upper bounds of downlink throughput (sum rate) and uplink power consumption (sum power) respectively; w_m is a weighting parameter of device m ; \bar{p}_s denotes the maximal allowed (transmit) power of BS s ; s_m represents a BS selected by device m , which has the highest upper bound of achievable rates among all possible serving BSs; the constraint C_1 ensures a single association for any device, and the constraint C_2 shows the allowed maximal and minimal power of BS s .

In the reality, the weighting parameters may often be regarded as the priorities of devices. By adjusting these parameters properly, different types of devices can achieve some distinct association requirements or high device fairness. Certainly, all devices can perform the coupling or decoupling DUL association under some special weighting parameters. Specifically, in the decoupling DUL association, the devices let their weighting parameters be 1 and then perform the downlink association, or they let these parameters be 0 and then perform the uplink association; in the coupling DUL association, all devices can attain a tradeoff between downlink rate experience and uplink power consumption when their weighting parameters are not 1 or 0.

In order to find some good weighting parameters maximizing the objective function of problem (4), a common approach is to search feasible solution space with very small granularity when all devices have equal weighting parameters, but some intelligent algorithms (e.g., genetic algorithm, particle swarm algorithm, etc.) may be a better option when all devices have distinct weighting parameters. Once these parameters are given, the problem (4) can be solved using a centralized algorithm. In addition, when a search of these parameters is regarded as a parameter configuration, the problem (4) with distinct weighting parameter configurations can be well tackled by different computation unites in a parallel manner.

Next, we will concentrate on the solution of (4). Evidently, through some simple operations, it can be further transformed into

$$\begin{aligned} \max_{\mathbf{X}, \mathbf{p}} \quad & \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ U_{sm} - \alpha w_m \log \sum_{k \in \mathcal{M}} x_{sk} \right\} \\ \text{s.t.} \quad & C_1, C_2, C_3, \end{aligned} \quad (8)$$

where $U_{sm} = \alpha w_m \log r_{sm}^{DL} - \beta (1 - w_m) q_{sm}$.

Evidently, the problem (8) is in a nonlinear and mixed-integer form, and its optimization variables \mathbf{X} and \mathbf{p} are also coupling. To achieve the global solutions of (8), it is required to fully search the feasible downlink power space

with a tiny granularity along with all possible association combinations. At a relatively small association slot, such a solving process may be infeasible, even for a centralized control system. To solve it, an alternate optimization approach is widely advocated, which alternately optimizes the downlink transmit power and association index.

IV. ALGORITHM DESIGN FOR ASSOCIATION WITH POWER COORDINATION

Under the alternate optimization, we develop two types of effective association algorithms, whose main difference lies in the treatment of weighting parameters.

A. ASSOCIATION WITH POWER COORDINATION FOR IDENTICAL WEIGHTS

At first, we consider the algorithm design for an association with power coordination under identical weights (APCIW). When all devices adopt the same weights, the problem (8) can be converted into

$$\begin{aligned} \max_{\mathbf{X}, \mathbf{p}} F(\mathbf{X}, \mathbf{p}) &= \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ U_{sm} - \alpha w \log \sum_{k \in \mathcal{M}} x_{sk} \right\} \\ \text{s.t.} \quad & C_1, C_2, C_3, \end{aligned} \quad (9)$$

where $U_{sm} = \alpha w \log r_{sm}^{DL} - \beta (1 - w) q_{sm}$.

Next, we can solve the problem (9) by utilizing an alternate optimization approach.

1) DEVICE ASSOCIATION

When the optimal transmit power \mathbf{p} is found, the problem (9) can be simplified into

$$\begin{aligned} \max_{\mathbf{X}} \quad & \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ U_{sm} - \alpha w \log \sum_{k \in \mathcal{M}} x_{sk} \right\} \\ \text{s.t.} \quad & C_1, C_3. \end{aligned} \quad (10)$$

To solve the problem (10), we need to consider the following two cases.

① Association with $w = 0$

When $w = 0$, the problem (10) can be simplified into

$$\left\{ \min_{\mathbf{X}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} q_{sm} \right\} \quad \text{s.t. } C_1, C_3. \quad (11)$$

It is evident that the problem (11) can be further simplified into

$$s_m = \arg \min_{s \in \mathcal{S}} q_{sm}, \quad \forall m \in \mathcal{M}, \quad (12)$$

which means any device m selects some BS with maximal q_{sm} among all possible association combinations.

② Association with $w \neq 0$

For $w \neq 0$, with the help of an auxiliary parameter $\mathbf{y} = \{y_1, y_2, \dots, y_S\}$, the problem (10) can be further converted into

$$\begin{aligned} \max_{\mathbf{X}, \mathbf{y}} G(\mathbf{X}, \mathbf{y}) &= \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} U_{sm} - \alpha w \sum_{s \in \mathcal{S}} y_s \log y_s \\ \text{s.t.} \quad & C_1, C_3, C_4 : \sum_{m \in \mathcal{M}} x_{sm} = y_s, \quad \forall s \in \mathcal{S}, \\ & C_5 : y_s \leq M, \quad \forall s \in \mathcal{S}. \end{aligned} \quad (13)$$

Theorem 1: After the introduction of a Lagrange multiplier $\boldsymbol{\mu} = \{\mu_1, \mu_2, \dots, \mu_S\}$ for the second constraint of (13), a decomposable dual form of (13) can be achieved by

$$\min_{\boldsymbol{\mu}} H(\boldsymbol{\mu}) = I(\boldsymbol{\mu}) + J(\boldsymbol{\mu}), \quad (14)$$

where

$$I(\boldsymbol{\mu}) = \begin{cases} \max_{\mathbf{X}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \{U_{sm} - \mu_s\} \\ \text{s.t. } C_1, C_3, \end{cases} \quad (15)$$

$$J(\boldsymbol{\mu}) = \begin{cases} \max_{\mathbf{y}} A(\mathbf{y}) = \sum_{s \in \mathcal{S}} y_s \{\mu_s - \alpha w \log y_s\} \\ \text{s.t. } C_5. \end{cases} \quad (16)$$

Proof: After a Lagrange multiplier $\boldsymbol{\mu}$ is introduced for the auxiliary constraints, a partial Lagrange function of (13) can be given by

$$\begin{aligned} \mathcal{L}(\mathbf{X}, \mathbf{y}, \boldsymbol{\mu}) = & \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} U_{sm} - \alpha w \sum_{s \in \mathcal{S}} y_s \log y_s \\ & + \sum_{s \in \mathcal{S}} \mu_s \left(y_s - \sum_{m \in \mathcal{M}} x_{sm} \right). \end{aligned} \quad (17)$$

Then, a dual function can be given by

$$H(\boldsymbol{\mu}) = \begin{cases} \max_{\mathbf{X}, \mathbf{y}} \mathcal{L}(\mathbf{X}, \mathbf{y}, \boldsymbol{\mu}) \\ \text{s.t. } C_1, C_3, \end{cases} \quad (18)$$

and a dual problem can be represented as

$$\min_{\boldsymbol{\mu}} H(\boldsymbol{\mu}). \quad (19)$$

Now, we can easily find that the optimization variables \mathbf{X} and \mathbf{y} are decoupling in (19), and can be tackled separately. It means we can break the dual problem (19) into two parts that can be solved under optimal \mathbf{X} and \mathbf{y} respectively. That is to say, $H(\boldsymbol{\mu})$ can be decomposed into $I(\boldsymbol{\mu})$ and $J(\boldsymbol{\mu})$. \square

It is evident that the optimal \mathbf{X} in (15) can be found by

$$s_m = \arg \max_{s \in \mathcal{S}} \{U_{sm} - \mu_s\}, \quad \forall m \in \mathcal{M}. \quad (20)$$

According to an extreme value principle $\partial A / \partial y_s = 0$, we can find the optimal \mathbf{y} of (16), and give it by

$$y_s^{t+1} = \min \left\{ e^{(\mu_s^t - \alpha w) / \alpha w}, M \right\}, \quad \forall s \in \mathcal{S}, \quad (21)$$

where $e \approx 2.71828$; t denotes an iteration index.

After introducing a subgradient method [43], a multiplier μ_s for BS s can be updated by

$$\mu_s^{t+1} = \mu_s^t - \xi_1 \left(y_s^t - \sum_{m \in \mathcal{M}} x_{sm}^t \right), \quad (22)$$

where ξ_1 is a sufficiently small fixed stepsize.

Until now, a whole solving process of (13) can be provided, and summarized in Algorithm 1. That is to say, the association subproblem (13) can be solved by taking some steps mentioned in Algorithm 1.

In general, the association subproblem in (10) can be solved by using the rule (12) if weighting parameter w is equal to zero, or utilizing Algorithm 1 in other cases. Next, we will concentrate on the solving process of power coordination subproblem in (9).

Algorithm 1 Association Subalgorithm

- 1: **Initialization:** $t = 0$; $\boldsymbol{\mu}^t$.
- 2: **Repeat:**
- 3: Initialize the association state: $\mathbf{X}^t = \mathbf{0}$.
- 4: Perform the device association using (20).
- 5: Calculate the auxiliary parameter \mathbf{y}^{t+1} using (21).
- 6: Update the multiplier $\boldsymbol{\mu}^{t+1}$ using (22).
- 7: Update the iteration index: $t = t + 1$.
- 8: **Until** t reaches T_1 iterations.

2) POWER COORDINATION

In this section, we consider a common problem that can be used for modeling the power coordination under identical and distinct weighting parameters. When $w_m \neq 0$ for any device m , and the optimal association index \mathbf{X} is given, the problem (4) can be converted into

$$\begin{aligned} \max_{\mathbf{p}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ \alpha w_m \log R_{sm}^{DL} - \beta (1 - w_m) q_{sm} \right\} \\ \text{s.t. } C_2, \end{aligned} \quad (23)$$

and it is equivalent to

$$\left\{ \max_{\mathbf{p}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} w_m \log R_{sm}^{DL} \right\} \text{ s.t. } C_2. \quad (24)$$

By relaxing the optimization objective of (24), we can obtain its upper bound, i.e.,

$$\left\{ \max_{\mathbf{p}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \chi_{sm} r_{sm}^{DL} \right\} \text{ s.t. } C_2, \quad (25)$$

where $\chi_{sm} = x_{sm} w_m / (\vartheta + \sum_k x_{sk})$; ϑ takes a small enough constant (e.g., 10^{-30}) to avoid "0/0";

$$\chi_{sm} = \begin{cases} D w_m x_{sm} / (\vartheta + \sum_k x_{sk}), & \forall s \in \mathcal{S}_1, \forall m \in \mathcal{M}, \\ x_{sm} w_m / (\vartheta + \sum_k x_{sk}), & \forall s \in \mathcal{S}_2, \forall m \in \mathcal{M}, \end{cases} \quad (26)$$

It is noteworthy that $\sum_k x_{sk}$ includes x_{sm} . Evidently, the latter must be 0 if the former is equal to 0. In such a case, χ_{sm} should not exist in the optimization objective of (25) for any BS s since there are no devices served by this BS. In addition, if x_{sm} takes 1, $\sum_k x_{sk}$ should be greater than or equal to 1. At this time, a small enough ϑ should have a negligible impact on χ_{sm} .

Under a common approximation $\log_2(1 + \text{SINR}_{sm}^{DL}) \approx \log_2 \text{SINR}_{sm}^{DL}$, the problem (25) can be converted into

$$\left\{ \max_{\mathbf{p}} L(\mathbf{p}) = \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \chi_{sm} \log \text{SINR}_{sm}^{DL} \right\} \text{ s.t. } C_2. \quad (27)$$

In $L(\mathbf{p})$, a coefficient $1/\log 2$ has been ignored, which has not any impact of (27).

To solve the non-convex problem (27), we first need to make some changes for optimization variables and finally

achieve its convex form [44]. Specifically, we let $\rho_s = \log p_s$ and $\bar{\rho}_s = \log \bar{p}_s$ for any s , and then have

$$\left\{ \max_{\rho} \mathcal{L}(\rho) = \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \chi_{sm} \log \Gamma_{sm}^{DL} \right\} \quad \text{s.t. } C_6, \quad (28)$$

where

$$\Gamma_{sm}^{DL} = \Gamma_{sm}^{DL}(\rho) = \frac{e^{\rho_s} h_{sm}}{\sum_{i \in \mathcal{B}_i} e^{\rho_i} h_{im} + \Theta}. \quad (29)$$

According to an extreme value principle $\partial \mathcal{L} / \partial \rho_s = 0$, we can achieve the optimal ρ of (28), and give it by

$$e^{\rho_s^{t+1}} = \frac{\sum_{m \in \mathcal{M}} \chi_{sm}}{\sum_{i \in \mathcal{B}_i} \sum_{m \in \mathcal{M}} h_{sm} \bar{h}_{im}(\rho^t)}, \quad \forall s \in \mathcal{S}, \quad (30)$$

where

$$\bar{h}_{im}(\rho^t) = \frac{\chi_{im}}{\sum_{k \in \mathcal{B}_i} e^{\rho_k^t} h_{km} + \Theta}. \quad (31)$$

Combining with the power constraints and box-constrained projection theorem in [44], we can attain a final power update rule for any s , i.e.,

$$\begin{aligned} p_s^{t+1} &= \varphi_s(\mathbf{p}^t) \\ &= \left[\mathcal{P}_s(\mathbf{p}^t) = \frac{\sum_{m \in \mathcal{M}} \chi_{sm}}{\sum_{i \in \mathcal{B}_i} \sum_{m \in \mathcal{M}} h_{sm} \lambda_{im}(\mathbf{p}^t)} \right]_0^{\bar{p}_s}, \end{aligned} \quad (32)$$

where

$$\lambda_{im}(\mathbf{p}^t) = \frac{\chi_{im}}{\sum_{k \in \mathcal{B}_i} p_k^t h_{km} + \Theta}. \quad (33)$$

Now, we can provide a detailed procedure to solve the power coordination subproblem (24), which is summarized in Algorithm 2.

Algorithm 2 Power Coordination Subalgorithm

- 1: **Initialization:** $t = 0$, and $\mathbf{p}^t = \{\bar{p}_s, \forall s \in \mathcal{S}\}$.
 - 2: **Repeat:**
 - 3: Update the downlink power \mathbf{p}^{t+1} using (32).
 - 4: Update the iteration index: $t = t + 1$.
 - 5: **Until** t reaches T_2 iterations.
-

According to the alternate optimization rule, we can now show a whole solving process of (9), which is summarized in Algorithm 3 (APCIW). It is easy to find that the outer loop alternately runs the association and power coordination subalgorithms until it converges or achieves the maximal number of iterations.

In fact, Algorithm 3 is designed to solve an association problem with power coordination under identical weights, and it may be used for a special case of H2H/IoT enabled HCNs, i.e., traditional HCNs. In view of different association requirements of H2H and IoT devices, we also need to design the corresponding algorithm for an association problem with power coordination under distinct weights.

Algorithm 3 APCIW

- 1: **Initialization:** $t = 0$.
 - 2: **Repeat (Outer Loop):**
 - 3: **If** $w = 0$
 - 4: Perform the device selection using rule (12).
 - 5: **Else**
 - 6: Perform the device selection using Algorithm 1.
 - 7: Perform the power coordination using Algorithm 2.
 - 8: **End If**
 - 9: Update the iteration index: $t = t + 1$.
 - 10: **Until** t reaches T_3 iterations.
-

B. ASSOCIATION WITH POWER COORDINATION FOR DISTINCT WEIGHTS

In this section, we concentrate on the algorithm design for an association with power coordination under distinct weights (APCDW). Through a relaxation operation, the problem (8) can be converted into

$$\begin{aligned} \max_{\mathbf{X}, \mathbf{p}} f(\mathbf{X}, \mathbf{p}) &= \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \left\{ \mathcal{U}_{sm} - \alpha w_m \log \sum_{k \in \mathcal{M}} w_k x_{sk} \right\} \\ \text{s.t. } &C_1, C_2, C_3. \end{aligned} \quad (34)$$

It is easy to find that the problem (34) may achieve an upper bound of (8). Similarly, we can solve the problem (34) by utilizing an alternate optimization approach.

1) DEVICE ASSOCIATION

When the optimal power \mathbf{p} is found, the problem (34) can be simplified into

$$\begin{aligned} \max_{\mathbf{X}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} &\left\{ \mathcal{U}_{sm} - \alpha w_m \log \sum_{k \in \mathcal{M}} w_k x_{sk} \right\} \\ \text{s.t. } &C_1, C_3, \end{aligned} \quad (35)$$

With the help of auxiliary parameter $\mathbf{z} = \{z_1, z_2, \dots, z_S\}$, the problem (35) can be further converted into

$$\begin{aligned} \max_{\mathbf{X}, \mathbf{z}} g(\mathbf{X}, \mathbf{z}) &= \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \mathcal{U}_{sm} - \alpha \sum_{s \in \mathcal{S}} z_s \log z_s \\ \text{s.t. } &C_1, C_3, C_7 : \sum_{m \in \mathcal{M}} w_m x_{sm} = z_s, \quad \forall s \in \mathcal{S}, \\ &C_8 : z_s \leq W, \quad \forall s \in \mathcal{S}, \end{aligned} \quad (36)$$

where $W = \sum_{m \in \mathcal{M}} w_m$ is an upper bound of z_s , and it is achieved by letting all devices select any BS s .

Theorem 2: After introducing a Lagrange multiplier $\boldsymbol{\eta} = \{\eta_1, \eta_2, \dots, \eta_S\}$ associated with the second constraint in (36), a decomposable dual form of (36) can be given by

$$\min_{\boldsymbol{\eta}} \mathcal{H}(\boldsymbol{\eta}) = \mathcal{I}(\boldsymbol{\eta}) + \mathcal{J}(\boldsymbol{\eta}), \quad (37)$$

where

$$\mathcal{I}(\boldsymbol{\eta}) = \left\{ \max_{\mathbf{X}} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} x_{sm} \{ \mathcal{U}_{sm} - w_m \eta_s \} \right\} \quad \text{s.t. } C_1, C_3, \quad (38)$$

and

$$\mathcal{J}(\boldsymbol{\eta}) = \begin{cases} \max_{\mathbf{z}} & \mathcal{A}(\mathbf{z}) = \sum_{s \in \mathcal{S}} z_s \{\eta_s - \alpha \log z_s\} \\ \text{s.t.} & C_8. \end{cases} \quad (39)$$

Proof: By following the proving process of Theorem 1, we can easily give the corresponding proof of Theorem 2. \square

It is evident that the primal optimal \mathbf{X} in (38) can be found by

$$s_m = \arg \max_{s \in \mathcal{S}} \left\{ \mathcal{U}_{sm} - w_m \eta_s \right\}, \forall m \in \mathcal{M}. \quad (40)$$

According to an extreme value principle $\partial \mathcal{A} / \partial z_s = 0$, the optimal \mathbf{z} of (39) can be updated by

$$z_s^{t+1} = \min \left\{ e^{(\mu_s^t - \alpha) / \alpha}, W \right\}, \forall s \in \mathcal{S}. \quad (41)$$

By employing a subgradient method, a multiplier η_s for BS s can be updated by

$$\eta_s^{t+1} = \eta_s^t - \xi_1 \left(z_s^t - \sum_{m \in \mathcal{M}} w_m x_{sm}^t \right). \quad (42)$$

Until now, the whole solving process of (36) can be given, and summarized in Algorithm 4.

Algorithm 4 Association Subalgorithm

- 1: **Initialization:** $t = 0; \boldsymbol{\eta}^t$.
 - 2: **Repeat:**
 - 3: Initialize the association state: $\mathbf{X}^t = \mathbf{0}$.
 - 4: Perform the device association using (40).
 - 5: Calculate the auxiliary factor \mathbf{z}^{t+1} using (41).
 - 6: Update the multiplier $\boldsymbol{\eta}^{t+1}$ using (42).
 - 7: Update the iteration index: $t = t + 1$.
 - 8: **Until** t reaches T_4 iterations.
-

Next, we will solve the power coordination subproblem in (34).

2) POWER COORDINATION

Once the optimal association index \mathbf{X} is given, the problem (34) can be converted into the problem (23) that can be solved by running Algorithm 2.

At last, according to the principle of alternate optimization, the whole solving process of (34) can be summarized in Algorithm 5 (APCDW).

Algorithm 5 APCDW

- 1: **Initialization:** $t = 0$.
 - 2: **Repeat (Outer Loop):**
 - 3: Perform the device selection using Algorithm 4.
 - 4: **If** $w_m \neq 0$ **for any device** m
 - 5: Perform the power coordination using Algorithm 2.
 - 6: **End If**
 - 7: Update the iteration index: $t = t + 1$.
 - 8: **Until** t reaches T_5 iterations.
-

In Algorithm 5, the device association and power coordination subalgorithms are carried out alternately until the whole process converges or achieves the maximal number of iterations.

Next, we will investigate the convergence and computation complexity of designed algorithms.

V. ALGORITHM ANALYSIS

At first, we discuss the convergence of all presented algorithms.

A. CONVERGENCE ANALYSIS

Significantly, some theoretical convergence proofs cannot be provided for the outer loops in Algorithms 3 and 5, which is similar to most efforts in the literature. However, we find that it is definitely convergent according to the simulation results. As for other subalgorithms, we can easily prove the corresponding convergence, whose theoretical proofs can be found in the following lemmas.

Lemma 1: After a few iterations, Algorithm 1 finally converges to the optimum of (14).

Proof: The first-order partial derivative of $H(\boldsymbol{\mu})$ with respect to μ_s for any s is calculated by

$$\partial H(\boldsymbol{\mu}) / \partial \mu_s = y_s(\mu_s) - \sum_{m \in \mathcal{M}} x_{sm}(\mu_s). \quad (43)$$

In reality, the number of devices is often limited, which means the bounded $y_s(\mu_s)$ and $\sum_{m \in \mathcal{M}} x_{sm}(\mu_s)$ in (43). Based on this, we can conclude that all subgradients of $H(\boldsymbol{\mu})$ are also bounded. That is to say, they meet

$$\sup_t \|\partial H(\boldsymbol{\mu}) / \partial \mu_s\| \leq \varepsilon, \quad \forall s \in \mathcal{S}, \quad (44)$$

where $\sup_t z$ represents a maximal estimate of z among all possible iterations; ε is a constant. Through a direct observation, we can find that the dual problem (14) meets the necessary conditions of convergence proofs in [43]. It means that we can prove Lemma 1 using some results in [43]. \square

Lemma 2: After a few iterations, Algorithm 4 finally converges to the optimum of (37).

Proof: By following the proving process of Lemma 1, we can easily prove Lemma 2. \square

Next, we will prove the convergence of Algorithm 3 using a 2.s.s. function. To this end, we first need to prove that $\varphi_s(\mathbf{p})$ is a 2.s.s. function with respect to \mathbf{p} for any BS s .

Lemma 3: For any BS s , $\varphi_s(\mathbf{p})$ is a 2.s.s. function with respect to \mathbf{p} .

Proof: To prove that $\varphi_s(\mathbf{p})$ is a 2.s.s. function with respect to \mathbf{p} for any BS s , we first need to prove $\mathcal{P}_s(\mathbf{p})$ and its upper and lower bounds are 2.s.s.

Assume that $(1/c)\mathbf{p} \preceq \boldsymbol{\rho} \preceq c\mathbf{p}$ for any s and $c > 1$. Then, we can easily deduce

$$(1/c)\lambda_{sm}(\mathbf{p}) \leq \lambda_{sm}(\boldsymbol{\rho}) \leq c\lambda_{sm}(\mathbf{p}), \forall s \in \mathcal{S}, \quad \forall m \in \mathcal{M}, \quad (45)$$

and thus achieve

$$(1/c)\mathcal{P}_s(\mathbf{p}) \leq \mathcal{P}_s(\boldsymbol{\rho}) \leq c\mathcal{P}_s(\mathbf{p}), \quad \forall s \in \mathcal{S}. \quad (46)$$

According to the definition of a 2.s.s. function in [41], we know that (46) means a 2.s.s. $\mathcal{P}_s(\mathbf{p})$ with respect to \mathbf{p} for any BS s . Similarly, it is easy to prove that the upper and lower bounds of $\mathcal{P}_s(\mathbf{p})$ in (32) are also 2.s.s.

Therefore, $\varphi_s(\mathbf{p})$ is a 2.s.s. function with respect to \mathbf{p} for any BS s . \square

Based on Lemma 3, we can now give the convergence proof for Algorithm 2.

Lemma 4: After a few iterations, Algorithm 2 converges to a unique fixed point.

Proof: As revealed in Lemma 3, we know that $\varphi_s(\mathbf{p})$ is a 2.s.s. function with respect to \mathbf{p} for any BS s . According to some results of a power update algorithm using a 2.s.s. function in [41], we can easily prove that Algorithm 2 converges to a unique fixed point after a few iterations. \square

Next, we will investigate the computation complexities of designed algorithms.

B. COMPLEXITY ANALYSIS

In this section, we mainly concentrate on the computation complexities of two types of algorithms, which are measured by counting the number of flops denoted as floating point operation [45], [46]. Specifically, a real addition, subtraction, multiplication or division is counted as one flop.

1 Complexity of Algorithm APCIW. At first, we consider Taylor's approximation of an exponent function, i.e., $e^z \approx 1 + z + \frac{1}{2}z^2 + \frac{1}{6}z^3$. In Algorithm 1, the step 4 has $2S$ real subtractions including S real comparisons for any device m , the step 5 has two real subtractions (including one real comparison), three real additions in an exponent function, five real multiplications (including three ones in an exponent function), and three divisions (including two ones in an exponent function) for any BS s , the step 6 has two real subtractions, $M - 1$ real additions, one real multiplication for any BS s . For each loop, Algorithm 1 may need $3MS + 15S$ flops. After T_1 iterations, Algorithm 1 may have a complexity of $\mathcal{O}(3MST_1 + 15ST_1) \approx \mathcal{O}(3MST_1)$.

In Algorithm 2, the main complexity comes from step 3. However, χ_{sm} and λ_{im} can be calculated before updating downlink power. It is evident that the computation of χ_{sm} may need M real additions, two real multiplications, one real division for any device m and any BS s , the one of λ_{im} may need S real additions, $S - 1$ real multiplications, one real division for any device m and any BS i . After attaining all χ_{sm} and λ_{im} , the computation of transmit power of BS s may need $MS + M - 2$ real additions, $MS - M$ real multiplications, one real division for any BS s . In general, the computation of all χ_{sm} and λ_{im} may need $M^2S + 2MS^2 + 4MS$ flops, and the computation of transmit power of BS s may need $2MS - 1$ flops. After T_2 iterations, Algorithm 2 may achieve a complexity of $\mathcal{O}(M^2ST_2 + 2MS^2T_2 + 4MST_2) \approx \max\{\mathcal{O}(M^2ST_2), \mathcal{O}(2MS^2T_2)\}$

Through a direct observation, we know that the computation complexity of Algorithm APCIW (i.e., Algorithm 3) is heavily dependent on w . Since there exist S comparisons

(subtractions) for any device m , the step 4 may need MS flops. That is to say, Algorithm 3 may achieve a complexity of $\mathcal{O}(MST_3)$ if w is equal to zero, where $T_3 = 1$. However, according to the complexity analyses of Algorithms 1 and 2, Algorithm 3 with $w \neq 0$ may achieve a complexity of $\max\{\mathcal{O}(M^2ST_2T_3), \mathcal{O}(2MS^2T_2T_3)\}$.

2 Complexity of Algorithm APCDW. In Algorithm 4, the step 4 may have S real multiplications, $2S$ real subtractions including S real comparisons for any device m , the step 5 has two real subtractions (including one real comparison), three real additions in an exponent function, three real multiplications in an exponent function, and three divisions (including two ones in an exponent function) for any BS s , the step 6 has two real subtractions, $M - 1$ real additions, $M + 1$ real multiplication for any BS s . For each loop, Algorithm 4 may need $5MS + 13S$ flops. After T_4 iterations, Algorithm 1 has a complexity of $\mathcal{O}(5MST_4 + 13ST_4) \approx \mathcal{O}(5MST_4)$.

It is easy to find that the computation complexity of Algorithm APCDW (i.e., Algorithm 5) is tightly related to w_m for any m . When w_m is equal to zero for any m , it may have a complexity of $\mathcal{O}(5MST_4T_5)$, where $T_5 = 1$. However, in other cases, it may achieve a complexity of $\max\{\mathcal{O}(M^2ST_2T_5), \mathcal{O}(2MS^2T_2T_5)\}$.

VI. PERFORMANCE EVALUATION

In H2H/IoT enabled HCNs, we deploy 7 MBSs, 30 devices and 5 PBSs at each macrocell. In addition, other essential parameters can be found in TABLE 1, where the inter-site distance represents the one between two MBSs; ℓ_{sm} denotes the distance between BS s and device m .

TABLE 1. Simulation parameters.

Parameter	Value	Parameter	Value
Inter-site distance	1000 m	\bar{p}_s for PBS s	30 dBm
System bandwidth	10 MHz	\bar{p}_s for MBS s	46 dBm
Parameter		Value	
Noise power spectral density			-174 dBm/Hz
Log-normal shadowing fading			Standard deviation of 8 dB
Pathloss between PBS s and device m			$140.7 + 36.7 \log_{10}(\ell_{sm} \text{ km})$
Pathloss between MBS s and device m			$128.1 + 37.6 \log_{10}(\ell_{sm} \text{ km})$

In [40], the range extension just concentrates on the link pathloss in the device association. Although it can greatly balance the network loads distributed among disparate BSs, it may result in a bad association performance due to the random shadowing fading. Based on this, we focus on channel gains including shadowing and pathloss in an improved range extension (IRE). Without loss of generality, we take account of $w_m = w$ for any device m in the simulation. That means APCDW and APCIW almost have the same association performance. However, they may achieve thinly different results because of algorithm convergence or simulation number. Next, we mainly investigate the impacts of different parameter settings on the association performance including the cumulative distribution functions (CDFs) of downlink long-term rates and uplink transmit power, the

average downlink throughput of all devices, the average downlink throughput of cell-edge devices, and the average uplink transmit power.

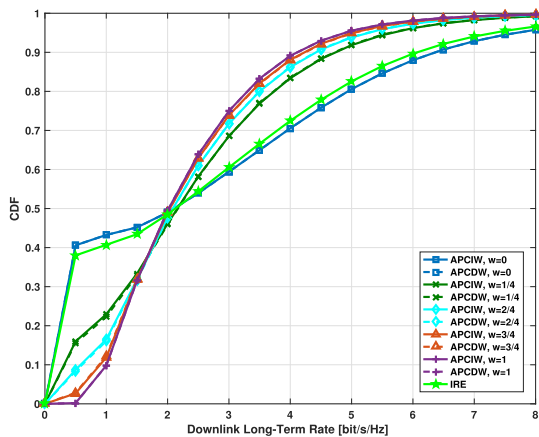


FIGURE 2. The CDFs of downlink long-term rates for different association mechanisms under distinct weighting parameters.

Fig. 2 investigates the impacts of devices' weighting parameters (w) on the CDFs of downlink long-term rates for different association mechanisms. As illustrated in Fig. 2, the downlink long-term rates of devices may be improved with increased w in the designed association mechanisms (i.e., APCDW and APCIW) since the increased w enhances the rate utility in our association objective of (4). When the weighting parameters of all devices are equal to 0, the designed association mechanisms mainly focus on the channel gains (including pathloss and shadowing) and uplink transmit power. However, the mechanism IRE just considers the channel gains. Because the uplink transmit power may take a maximal allowed value that is irrelevant to channel conditions, and such a value may have a high influence on association metrics, IRE may have a relatively better downlink SE experience (i.e., fewer downlink low-rate devices) than the proposed mechanisms with $w=0$.

Fig. 3 shows the impacts of devices' weighting parameters on the CDFs of uplink power for different association mechanisms. Seen from our association objective in (4), we can easily find that our mechanism is heavily weighted in favour of the uplink power optimization if w decreases. That is to say, the number of devices having low power may increase with increased w in APCDW and APCIW. In addition, the IRE and the proposed mechanisms with $w=0$ may achieve almost the same uplink power distribution since they just be dependent on channel gains.

Fig. 4 investigates the impacts of number of MBS antennas (A) on the CDFs of downlink long-term rates for different association mechanisms. As illustrated in Fig. 4, the downlink long-term rates of devices may be improved with increased A in APCDW and APCIW. The reason for this may be that a larger A often means a higher downlink long-term rate.

Fig. 5 shows the impacts of number of MBS antennas on the CDFs of uplink power for different association

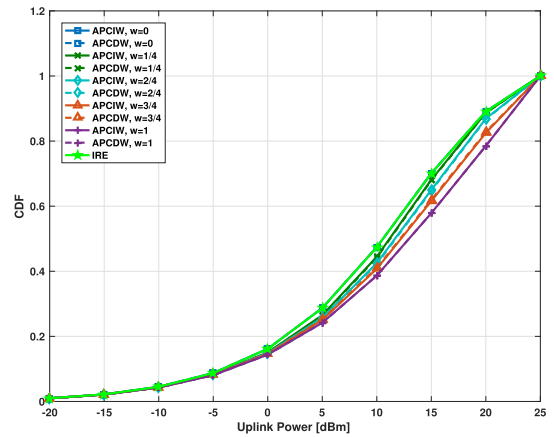


FIGURE 3. The CDFs of uplink power for different association mechanisms under distinct weighting parameters.

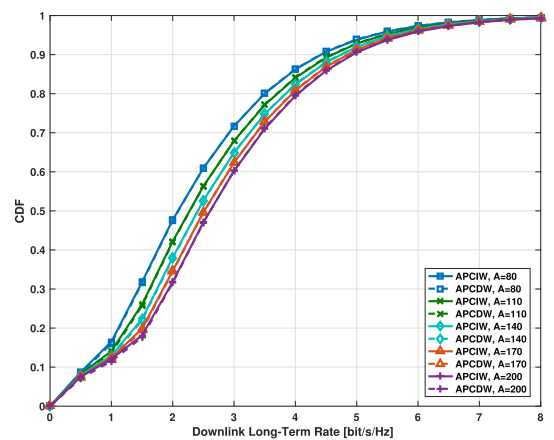


FIGURE 4. The CDFs of downlink long-term rates for different association mechanisms under distinct numbers of MBS antennas.

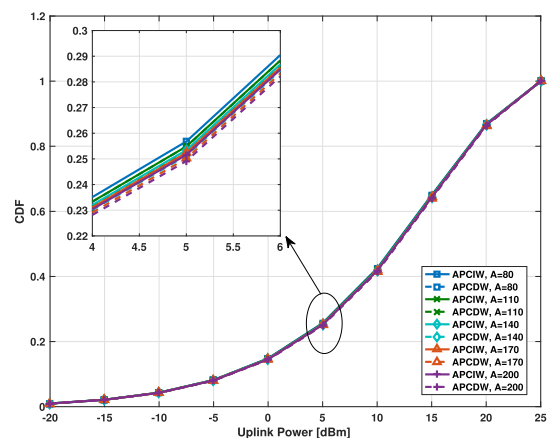


FIGURE 5. The CDFs of uplink power for different association mechanisms under distinct numbers of MBS antennas.

mechanisms. It is easy to find that the CDFs of uplink power may be improved with increased A . As revealed in Fig. 4, the downlink long-term rates of devices are enhanced by increasing A . Therefore, the designed mechanisms may pay

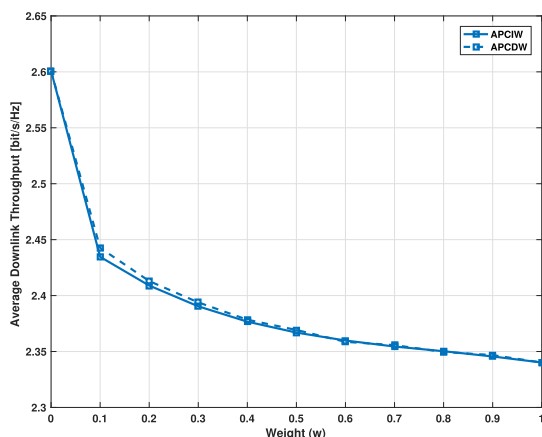


FIGURE 6. The average downlink throughput for different association mechanisms under distinct weighting parameters.

less and less attention to the rate utility optimization when A decreases. In other words, they may pay more and more attention to the uplink power optimization when A decreases. That means the number of devices having low power may increase with decreased A .

Fig. 6 shows the impacts of devices' weighting parameters on the average downlink throughput for different association mechanisms, where the throughput refers to the sum of devices' downlink long-term rates. It is easy to know that a larger w means a higher preference on the rate utility but not rate. That is to say, a larger w often means a higher rate fairness among devices. To guarantee the fairness, the average downlink throughput may decrease with increased w .

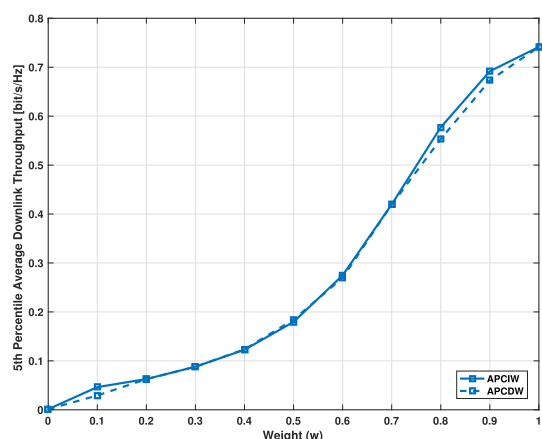


FIGURE 7. The 5th percentile average downlink throughput for different association mechanisms under distinct weighting parameters.

Fig. 7 shows the impacts of devices' weighting parameters on the 5th percentile average downlink throughput (5P-ADT) for different association mechanisms, where 5P-ADT refers to the average of lowest 5% downlink data rates among all devices, and it can also be seen as the one of downlink data rates of downlink cell-edge devices. As shown in Fig. 7, 5P-ADT increases with increased w generally. That's because

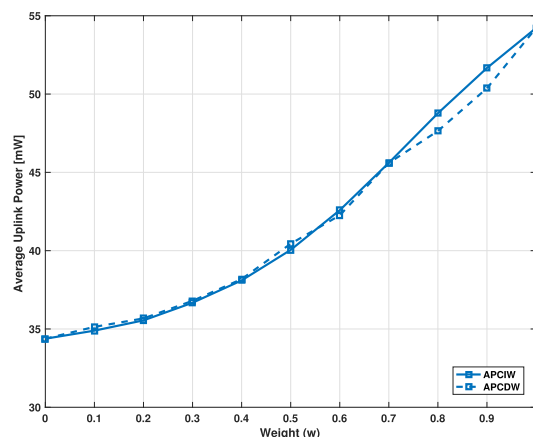


FIGURE 8. The average uplink power for different association mechanisms under distinct weighting parameters.

the increased w enhances rate fairness, and may result in fewer and fewer low-rate devices.

Fig. 8 investigates the impacts of devices' weighting parameters on the average uplink power for different association mechanisms. According to the association rules of these mechanisms, we can easily know that they may be heavily weighted in favour of uplink power minimization when w decreases. Evidently, it should be in accord with the general trend of Fig. 8.

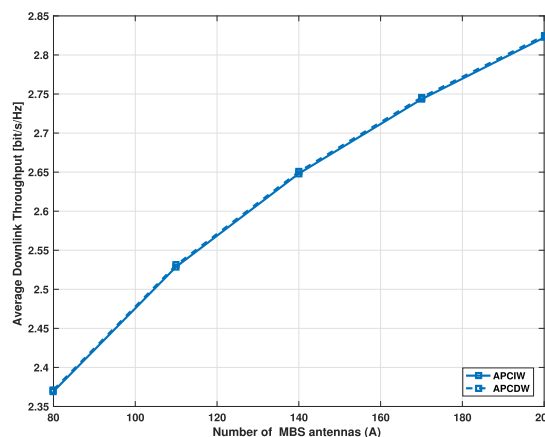


FIGURE 9. The average downlink throughput for different association mechanisms under distinct numbers of MBS antennas.

Fig. 9 investigates the impacts of number of MBS antennas (A) on the average downlink throughput for different association mechanisms. According to the throughput expression, it is evident that devices' downlink rates should increase with the increased A . It means that the average downlink throughput should also have such a trend.

Fig. 10 shows the impacts of number of MBS antennas on 5P-ADT for different association mechanisms. Since the increased A enhances devices' downlink rates, 5P-ADT also increases with it.

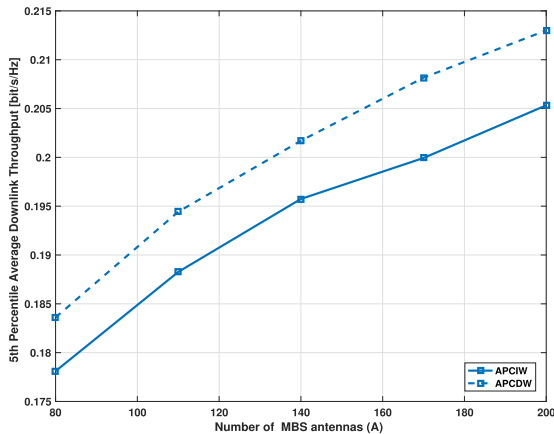


FIGURE 10. The 5th percentile average downlink throughput for different association mechanisms under distinct numbers of MBS antennas.

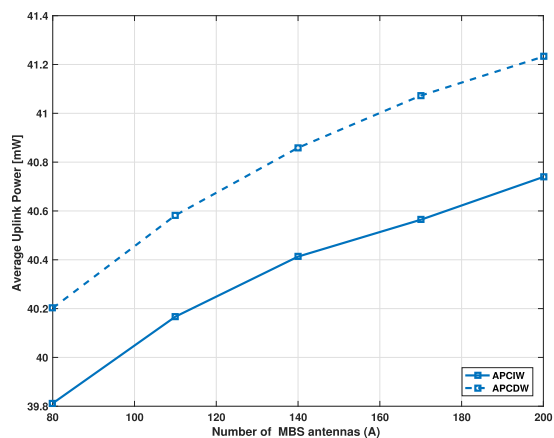


FIGURE 11. The average uplink power for different association mechanisms under distinct numbers of MBS antennas.

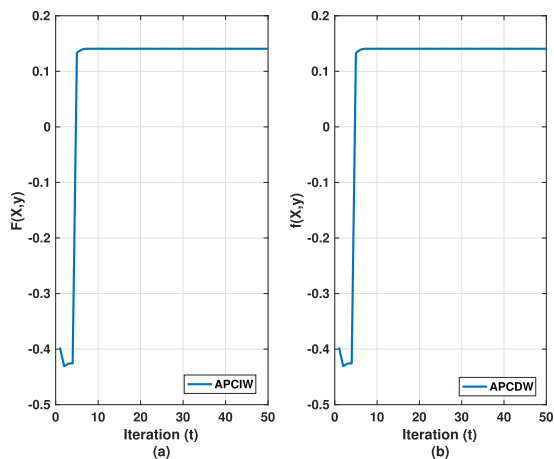


FIGURE 12. The convergence of proposed algorithms including APCIW and APCDW.

Fig. 11 shows the impacts of number of MBS antennas on the average uplink power for different association mechanisms. In Fig. 9 and Fig. 10, we have revealed that a larger A often means a higher downlink throughput. In other words,

when A increases, the designed association mechanisms may be heavily weighted in favour of average downlink throughput maximization, but not the uplink power minimization. Therefore, the average uplink power may increase with A.

Fig. 12 illustrates the convergence of proposed algorithms, where Fig. 8 (a) and Fig. 8 (b) show the one of Algorithms APCIW and APCDW respectively. As shown in Fig. 12, Algorithms APCIW and APCDW converge after very few iterations.

VII. CONCLUSION

In this paper, we design a device association scheme to meet different association requirements of IoT and H2H devices in the massive MIMO enabled HCNs, and formulate it as a network-wide weighted utility maximization problem. According to a distinct treatment of weighting parameters, we develop two types of algorithms, and give some convergence and complexity analyses for them. After that we investigate the impacts of different network parameters on the association performance of designed algorithms and another introduced algorithm. At last, we find that the designed mechanisms (algorithms) can meet different association requirements by properly adjusting weighting parameters. Future work can include the implement of mobility, resource partitioning, and so on.

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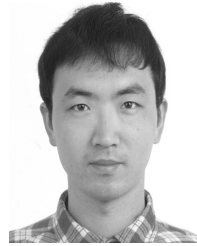
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