Energy-Efficient Resource Allocation for NOMA-Based Heterogeneous 5G Mine Internet of Things

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This work was supported by the National Natural Science Foundation of China under Grant 51874299.

ABSTRACT The Mine Internet of Things (MIoT), as an application paradigm of the IoT in mine environment, realizes the state perception and information interaction by connecting massive smart sensing devices deployed in mine, plays an important role in coal mine production. The fifth-generation (5G) is a key enabling technology to provide an efficient and reliable communication link guarantee for MIoT networks. To meet the increasing demand for huge amounts of data transmission, a NOMA-based heterogeneous MIoT communication system is proposed. In this paper, different types of mine smart devices can occupy the same subchannel resources for data transmission by the NOMA technology, which improves the device access and spectrum utilization of the MIoT system. We aim to maximize the energy efficiency (EE) of all small cell networks via power allocation and subchannel assignment. Under the imperfect channel state information (CSI), a joint power allocation and subchannel assignment iterative algorithm is proposed. Specifically, firstly, by considering the cross-layer interference power constraints, maximum power constraints and QoS constraints, the EE optimization problem is formulated as a mixed integer nonlinear fractional programming problem. Secondly, the uncertain CSI is modeled as an elliptical uncertainty set, and the original problem is transformed into an equivalent convex optimization form by using the Dinkelbach method. Finally, an approximate solution is obtained by using the Lagrangian dual approach. The numerical results validate the effectiveness of the proposed algorithm and significantly show its superior performance as compared with the baseline algorithms.

INDEX TERMS Coal mine, 5G, Internet of Things (IoT), non-orthogonal multiple access (NOMA), heterogeneous network (HetNet), energy efficient, imperfect channel state information.

I. INTRODUCTION
The Mine Internet of Things (MIoT) is an application of the internet of things (IoT) in coal mine industry, constitutes powerful technology for achieving smart mine. In the actual production process, a large number of intelligent communication devices equipped with sensing units are deployed in the entire mine. All these intelligent devices are interconnected by the MIoT, which can continuously monitor the environmental information, equipment fault information, miners’ vital signs parameters and location information, etc. Finally, different smart devices are scheduled to perform various operations according to the instructions of the mine safety monitoring center, so as to ensure the safety and effectiveness of mine production [1], [2].

The arrival of 5G technology not only catalyzes the integrated development of science and technology such as cloud computing, big data and artificial intelligence (AI), but also provides key infrastructure for the development of smart mine communication systems [4]. According to data released by the Ministry of industry and information technology of China, 175 mines have realized 5G commercial applications [5]. There are more than 30 sets of safety mark certifications of 5G communication systems for coal mine, including 3 intrinsically safe 5G base stations. Through the application of special 5G modules for coal mines, a variety of terminal devices...
such as mine cameras, mine gyroscopes, and mine ranging sensors with 5G communication capabilities have been developed, which enriches the form of 5G terminal devices in coal mines [6]. In addition, the ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC) in the three major application scenarios of 5G, fully meet the needs of the safe production business scenario of the MiOT. It can provide an ideal technology platform for MiOT network communications [7]. Meng [8] analyzed the 5G network transmission mode in coal mine, and proposed a non-standalone (NSA)-based network architecture of the integration of 4G and 5G in the mine. In order to achieve the coverage of underground mine 5G wireless signals, Zhang [9] proposed to form a 5G coverage network for mines by using 5G base station controllers, 5G base stations and CPEs. In addition, Sun [10] proposed a method of remote control between mining face and unmanned 5G ground to reduce the number of operators underground mining face. To ensure the safe access of various terminal equipment in the 5G coal mine communication system, the authors designed an antenna isolation circuit to realize that the signal output by the 5G base station is intrinsically safe [11]. Jiang et al. [12] proposed a smart mine 5G network uplink rate enhancement algorithm to solve the problem of insufficient uplink rate of the current 5G network, and the network uplink rate was improved by frequency domain resource allocation and time domain resource scheduling. The reliability of 5G communication system can be improved by the deployment of redundant base stations in the mine [13]. Zhang et al. [14] proposed an unmanned intelligent transportation scheduling system based on 5G and big data for open-pit vehicles, and optimized the vehicle paths by using the vast data from many sensors.

Now, a typical standalone (SA)-based networking architecture of the 5G MiOT system is mainly composed of three layers, as shown in Figure 1. In this 5G MiOT system, the bottom layer is the 5G smart device layer, which contains a large number of various smart mine communication devices equipped with 5G sensors, such as mine 5G cameras, 5G mine mobile phones, smart miner’s lamps, smart mining equipment and smart mine robots, etc. The middle layer is 5G base stations layer, which consists of multiple mine 5G base stations to provide services for all 5G smart device in the mine area. The top layer is the 5G core network layer, including mobile edge computing (MEC) devices, 5G core network devices and the coal mine safety monitoring center, which is used to process amount of monitoring data and schedule various production and execution tasks. However, there exist some problems in this 5G MiOT architecture. On the one hand, with more and more 5G intelligent devices accessed in MiOT, the amount of business data generated also increases rapidly, resulting in the network capacity of the MiOT being unable to meet the communication needs of all devices. In addition, the communication performance of the MiOT system will be severely restricted under the limited spectrum resources. On the other hand, the mine production space is extremely narrow and long, and the traditional homogeneous networking architecture cannot guarantee the communication coverage of the entire mine.

In order to improve the network capacity in the 5G MiOT system, non-orthogonal multiple access (NOMA) transmission technology can be adopted. Different from the traditional orthogonal multiple access (OMA), NOMA allows multiple smart devices to multiplex the same spectrum resource for data transmission by using different power levels, thereby effectively improve the spectrum efficiency (SE) [15]. Specifically, NOMA technology adopts superposition coded signals at the transmitting device, and actively introduces interference information to the signal. Then, the successive interference cancellation (SIC) technology was adopted at the receiving device. The correct demodulation was finally achieved by utilizing the difference of signal strength [16]. There has been proved that multi-carrier power domain NOMA can provide more connection opportunities and higher spectrum efficiency than traditional OMA in downlink transmission [17]. Therefore, by applying NOMA technology to the MiOT system, more smart devices will access to the network under the limited spectrum resources, thus the transmission capacity of the entire system can be increased. However, the connection scale and transmission performance in NOMA systems largely depends on the resource allocation scheme [18]. Moreover, heterogeneous network (HetNet) [19], as a promising network infrastructure in 5G, cannot only enhance the network capacity and user experience of the edge cell, but also reduce coverage blind spots and improve the transmission performance of communication systems. The traditional HetNet is mainly composed of two types of base stations (BSs), namely macro base station (MBS) and small base station (SBS) [20]. Therefore, it is necessary to discuss the performance of the NOMA-based HetNet in the MiOT.

However, the NOMA-based HetNet faces the following challenges, firstly, the generated cross-layer interference and co-channel interference of the HetNet will seriously affect the communication quality [21]. Then, the first decoded devices will be interfered by all other undecoded devices, which will cause the transmission performance of some devices unable to meet the QoS requirements. Zhang et al. [22] investigated
the resource optimization problem of NOMA heterogeneous small cell networks with simultaneous wireless information and power transfer (SWIPT), and proposed a subchannel matching algorithm and a power optimization algorithm based on the Lagrangian duality method. In [23], the authors proposed optimal user-pairing and power allocation solutions towards achieving fair energy-efficient resource allocation in downlink femtocell NOMA-HetNet. To maximize the energy efficiency (EE) subject to the minimum SE requirements and maximum transmission powers, an iterative algorithm with fast convergence speed and a reduced complexity search-based algorithm are respectively presented to solve the power control and user selection problems [24]. Rezwan and Choi [25] formulated an optimal power allocation scheme under Karush–Kuhn-Tucker (KKT) optimality conditions, and a priority-based channel assignment with a deep Q-learning algorithm to maximize the efficiency of NOMA systems. In [26], the authors explored the feasibility of a hybrid power domain sparse code non-orthogonal multiple access (PD-SCMA) algorithm and a power optimization algorithm based on the Langrangian duality method. In [27], the authors considered the problem of joint user association and uplink power allocation in 5G NOMA wireless HetNet, and introduced a Contract Theory (CT) and Reinforcement Learning (RL) based approach.

Nowadays, green communication and energy-saving communication are widely advocated in IoT applications. With the frequent access of massive smart devices to the Internet, energy efficiency optimization is an effective way to improve the resource utilization and energy-saving of the IoT system [28]. Under imperfect channel state information (CSI), the authors investigated joint optimization of user selection, power allocation, and the number of activated base station (BS) antennas of multiple IoT devices to maximize EE [29]. To achieve an improved EE performance in IoT networks under channel uncertainty, a novel resource allocation algorithm of joint power allocation and user selection was presented in [30]. Under the architecture of cell-free IoT, a novel heuristic algorithm is designed for resource allocation to ensure quality data transmission [31]. A power and time allocation algorithm was developed to maximize the EE of the Industrial Internet of Things (IIoT) system [32]. However, unlike the ground IoT application scenarios, the mine space is extremely narrow and long, which often leads to a long distance for signal transmission. In fact, data transmission will be affected in the process of communication by the estimation error, feedback delay and quantization error of the physical channel. Therefore, it is difficult to obtain the perfect CSI in the MIoT communication system. Inspired by this, our aim is to design a NOMA-based heterogeneous MIoT resource allocation scheme with the imperfect CSI to maximize the EE, which can reasonably allocate resources to smart device in mine under the QoS requirements required by mine safety production.

In this paper, we propose a NOMA-based heterogeneous MIoT system framework, which is composed of one MBS and multiple SBSs with different hardware capabilities and QoS requirements. For simplicity, we define the smart devices connected to MBS and SBS as mobile user equipment (MUE) and IoT device (IoTD), respectively. By applying the NOMA technology, MUEs and IoTDs can reuse the same subchannel resources for data transmission, which improves the network capacity and spectrum utilization of the MIoT system. To maximize the total EE of IoTDs in SBSs, a joint power allocation and subchannel assignment iterative algorithm under imperfect CSI is presented. The main contributions of this article are summarized as follows.

- A NOMA-based heterogeneous MIoT communication system is proposed. In this system, each MUE occupies one subchannel resource block for transmitting data to MBS in the uplink. While all SBSs transmit data to pre-connected IoTDs in the downlink by multiplexing the same subchannel resource.
- By considering the QoS requirement of IoTDs, maximum transmit power and maximum cross-layer interference, we formulate the EE optimization in the MIoT system as a resource allocation problem via joint power allocation and subchannel assignment. However, the problem is a generalized mixed integer nonlinear programming problem (MINLP) and it is hard to obtain the exact optimal solution.
- A joint power and subchannel iterative allocation (JPSIA) algorithm under the imperfect CSI with a lower computational complexity is proposed. Firstly, the subchannel assignment factor is converted into a continuous real variable by using the convex relaxation method, and an auxiliary variable is introduced to simplify the original optimization problem; Secondly, the ellipsoid bounded uncertainty set is used to model the channel uncertainty in the cross-layer interference constraint and the data rate constraint, respectively. Finally, the original problem is transformed into an equivalent convex optimization form by using the Dinkelbach method and the successive convex approximation method, then the approximate solution is obtained by using the Lagrangian dual approach. Extensive simulations results show that the proposed algorithm has better EE as compared with benchmark algorithms.

The rest of this article is organized as follows. In Section II, we introduce the model of NOMA-based heterogeneous MIoT system, and the resource allocation problem of maximizing EE of all IoTDs is formulated in details. A joint power and subchannel iterative allocation scheme under the imperfect CSI is described in Section III. Section IV gives the simulation results and analysis. Finally, Section V concludes this article.

II. NETWORK MODEL AND PROBLEM FORMULATION
A. SYSTEM MODEL
We consider a NOMA-based heterogeneous MIoT system with two-tier networks, as shown in Figure 2. There are two
types of BSs in the MIoT system, i.e., MBS and SBS. The MBS is used to providing services to \( N \) MUEs with a set denoted by \( \mathcal{N} = \{1, \ldots, n, \ldots, N\} \), and \( U \) SBSs denoted by \( \mathcal{U} = \{1, \ldots, u, \ldots, U\} \) are responsible for serving IoTDs.

In Figure 2, MBS is deployed at the edge of the mine, and all SBSs are randomly deployed inside the mine. As the data center and resource management center of the network, MBS has divided the available spectrum resources into orthogonal subcarriers. Assumed that they have been pre-allocated to all MUEs, which means the subchannel assignment of MUEs is known in this paper. In the NOMA transmission uplink, MUEs with different power levels transmit their signals to MBS by occupying \( K \) subchannel resource denoted by a set \( \mathcal{K} = \{1, \ldots, k, \ldots, K\} \) and the subchannel bandwidth is denoted \( B, B = 1\ Hz \). In the NOMA transmission downlink, each SBS transmits the operation signal from the monitoring center to \( M \) IoTDs with a set denoted by \( \mathcal{M} = \{1, \ldots, m, \ldots, M\} \), one SBS only occupies one subchannel block for data transmission. Therefore, MUEs and IoTDs can multiplex the same subchannel resource through NOMA transmission, which improves the SE of MIoT system. The maximum transmit power of SBSs is denoted by \( P_{\text{max}} \), the channel gain from SBS \( u \) to MUE \( n \) is denoted by \( G_{u,n} \), \( \delta \) is zero-mean additive white gaussian noise with variance \( \sigma^2 \).

It is assumed that each subchannel experiences block fading, which means the channel gain is constant within a resource block and varies between different subchannels. To ensure the communication quality of MUEs, we assume that a subchannel can only be allocated to one MUE, so there is no mutual interference between MUEs. In the NOMA downlink, IoTDs will receive cross-layer interference from MUEs occupying the same subchannel. Moreover, the first decoded IoTD also receive co-layer interference from other IoTDs with lower channel gain in the same SBS. Due to the low power of SBSs in mine, the interference between SBSs is ignored in this paper [33]. Assumed that each MUE and IoTD is equipped with an antenna and only one BS is connected. In addition, MUEs and IoTDs have completed user association before resource allocation, which means MUEs are connected to MBS and IoTDs are connected to SBS.

**B. CHANNEL MODEL**

Without loss of generality, we suppose that there are SBS \( u \) and MUE \( n \) occupy a subchannel \( k \). In this scenario, all interferences in the network is shown in Figure 3. Let the \( i \) th IoTD connected to SBS \( u \) denotes as \((u, i), \forall i \in M, i \neq j \). We assume that the channel gain of \( M \) IoTDs in SBS \( u \) is satisfied \( h_{u,1} > h_{u,2} > \cdots > h_{u,M} \). According to the downlink domain NOMA criterion, IoTD \((u, 1)\) will be allocated the maximum transmission power. Hence, IoTD \((u, 1)\) receives interference signals from all other IoTDs in SBS \( u \). Therefore, the signal-to-interference-plus-noise ratio (SINR) of IoTD \((u, i)\) when occupying subchannel \( k \) can be expressed as

\[
\gamma_{i,k}^{u} = \frac{P_{i,k}^{u}h_{i,k}^{u}}{\sum_{j=i+1}^{M} P_{j,k}^{u}h_{j,k}^{u} + P_{k,n}G_{n,k}^{n} + \delta^2}
\]

where \( P_{i,k}^{u} \) is the transmit power allocated for IoTD \((u, i)\) on subchannel \( k \), \( h_{i,k}^{u} \) represents the channel gain between SBS \( u \) and IoTD \( i \) on subchannel \( k \). The first term of denominator is the co-interference generated by other IoTDs in SBS \( u \). The second term is cross-layer interference generated by MUE \( n \) on subchannel \( k \), \( P_{k,n}^{n} \) is the transmit power allocated for MUE \( n \) on subchannel \( k \), \( G_{n,k}^{n} \) represents the channel gain between MUE \( n \) and IoTD \( i \) on subchannel \( k \). The third term represents zero-mean additive white gaussian noise with variance \( \delta^2 \).

Thus, the achievable rate of IoTD \((u, i)\) on subchannel \( k \) is expressed as

\[
R_{i,k}^{u} = \log_2(1 + \gamma_{i,k}^{u}) = \log_2(1 + \frac{P_{i,k}^{u}h_{i,k}^{u}}{\sum_{j=i+1}^{M} P_{j,k}^{u}h_{j,k}^{u} + P_{k,n}G_{n,k}^{n} + \delta^2})
\]

Let \( x_{i,k}^{u} \) denotes the subchannel assignment indicator for IoTD, \( x_{i,k}^{u} = 1 \) if IoTD \((u, i)\) is assigned with subchannel \( k \), otherwise \( x_{i,k}^{u} = 0 \). According to the information theory, the total data rate \( R_{\text{tot}} \) of IoTDs in downlink transmission can be given by

\[
R_{\text{tot}} = \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} R_{i,k}^{u}
\]
C. POWER CONSUMPTION MODEL

In MIoT networks, the total power consumption $P_{tot}$ of data transmission from SBS to IoTDs consists of RF transmit power consumption $P_t$ and circuit power consumption $P_c$ [34]. Therefore, the total power consumption of all IoTDs is defined as

$$P_{tot} = P_t + P_c$$

and the RF transmit power consumption $P_t$ is expressed as

$$P_t = \frac{1}{\varepsilon} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u}$$

where $\varepsilon$ is the power amplification factor.

D. THE EE PROBLEM FORMULATION

To achieve the goal of green communication, the optimization of energy efficiency (EE) is critical to improve the performance of MIoT systems. In this paper, EE is defined as the ratio of the total achievable data rate $R_{tot}$ to the total power consumption $P_{tot}$ in bits/joules. It can be stated as

$$EE = \frac{R_{tot}}{P_{tot}} = \frac{\sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} R_{i,k}^{u}}{\frac{1}{\varepsilon} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u} + P_c}$$

In order to meet the different communication requirements, the following optimization constraints are considered in the proposed system.

1) SUBCHANNEL ASSIGNMENT CONSTRAINT

One SBS can only occupy one subchannel block at most. Hence, the subchannel assignment constraint is expressed as

$$\sum_{k=1}^{K} x_{i,k}^{u} = 1, \ x_{i,k}^{u} \in \{0, 1\}, \forall k \in \mathcal{K}, \forall i \in \mathcal{M}$$

2) TRANSMIT POWER CONSTRAINT

Mine smart devices are limited by the explosion-proof power, which is set as

$$\sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u} \leq P_{max}$$

3) CROSS-TIER INTERFERENCE CONSTRAINTS

In order to ensure the communication quality of MUEs, the cross-tier interference from the SBS to the MUE should not be higher than an interference threshold $I_{thr}$, which is expressed as

$$\sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u} G_n^{u} \leq I_{thr}$$

4) QoS CONSTRAINT

To guarantee the basic communication of IoTDs on each subchannel, the QoS requirement is set as

$$\sum_{k=1}^{K} x_{i,k}^{u} R_{i,k}^{u} \geq R_{min}$$

In this paper, the focus is to maximize the EE satisfying the QoS and power constraints. The formulated problem to joint optimize the power allocation $P$ and subchannel assignment $X$ is given as follows:

$$P1: \max_{X,P} EE$$

s.t. : $C1: \sum_{k=1}^{K} x_{i,k}^{u} = 1, \ x_{i,k}^{u} \{0, 1\}, \forall k \in \mathcal{K}, \forall i \in \mathcal{M}$

$C2: \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u} \leq P_{max}$

$C3: \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^{u} P_{i,k}^{u} G_n^{u} \leq I_{thr}$

$C4: \sum_{k=1}^{K} x_{i,k}^{u} R_{i,k}^{u} \geq R_{min}$

where $X = \{x_{i,k}^{u}|k \in \mathcal{K}, \ i \in \mathcal{M}, \ u \in \mathcal{U}\}$ denotes subchannel assignment indicator vector for IoTDs. $P = \{P_{i,k}^{u}|k \in \mathcal{K}, \ i \in \mathcal{M}, \ u \in \mathcal{U}\}$ is the transmit power vector of IoTDs. $C1$ ensures that one SBS can only be assigned at most one subchannel. $C2$ indicates the transmit power boundary at SBSs and the maximum transmit power is denoted by $P_{max}$. $C3$ represents the maximum cross-tier interference from SBSs to MUEs and the maximum interference value is denoted by $I_{thr}$. $C4$ guarantees that all IoTDs meet the minimum QoS requirements, determined by the rate threshold $R_{min}$.

III. PROPOSED RESOURCE ALLOCATION SCHEME FOR EE MAXIMIZATION

In this section, we propose a joint power allocation and sub-channel assignment iterative algorithm under the imperfect CSI to solve the original nonconvex and NP-hard optimization problem. Firstly, an auxiliary variable is introduced to simplify the optimization problem in P1, and the uncertain channel constraints in the transmission links of IoTDs are considered in P1; Then, based on ellipsoid bounded uncertainty model, we formulate the uncertain channel function. Finally, the original problem is transformed into an equivalent convex optimization form by using the Dinkelbach method and the successive convex approximation method, and the approximate solution is obtained by Lagrangian dual approach.

A. AN AUXILIARY VARIABLE

In this paper, we introduce an auxiliary variable $Z_{i,k}^{u}$ into P1 for reducing the variable symbols. It is expressed as

$$Z_{i,k}^{u} = x_{i,k}^{u} P_{i,k}^{u}$$
Noted that $x_{i,k}^u$ is a binary discrete variable in C1, which is not convenient to solve. We use the convex relaxation method to transform $x_{i,k}^u$ into a continuous real variable in this article, which varies in the range $[0, 1]$. Thus, C1 can be converted to C5, i.e.,

$$C5: 0 \leq x_{i,k}^u \leq 1$$ (13)

where $x_{i,k}^u$ represents the proportion of time that the subchannel $k$ occupied by IoTD $(u, i)$, which is within one resource block transmission time. Then, P1 can be stated as

$$\text{P2: } \max \frac{EE}{x_{i,k}^u Z_{i,k}^u} = \max \left( \frac{1}{\frac{1}{r} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u + P_c \right)$$

s.t. : C5, C6, C7, C4,

where C8 contains the set of channel uncertainty parameters, $\mathcal{R}_h$, $\mathcal{R}_r$ and $\mathcal{R}_G$ are the channel uncertainty sets of the link between IoTD and SBS, the link between MUE and IoTD, and the link between SBS and MUE, respectively.

B. CHANNEL UNCERTAINTY IN CROSS-LAYER INTERFERENCE

According to the robust optimization theory, the bounded channel error is considered in this paper. By using an ellipsoid bounded uncertainty set, the channel uncertainty parameter $\mathcal{R}_G$ can be expressed as

$$\mathcal{R}_G = \left\{ \Delta G_n^u | G_n = \bar{G}_n^u + \Delta G_n^u : \sum_{u=1}^{U} |\Delta G_n^u|^2 \leq (\alpha_n)^2 \right\}$$ (16)

where the value of $\mathcal{R}_G$ depends on the accuracy of the channel estimation, $\alpha_n \geq 0$ is the upper bound of error, $\bar{G}_n^u$ and $\Delta G_n^u$ are the channel estimation value and the corresponding estimation error value, respectively.

Based on the worst-case criterion, C7 can be guaranteed under worst-case of channel uncertainty, which means maximizing the worst-case estimation error. According to the Cauchy-Schwartz inequality, the cross-layer interference maximization is presented as

$$\max \Delta \bar{G}_n^u \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u G_n^u$$

$$= \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u \bar{G}_n^u + \max \Delta \bar{G}_n^u \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u (G_n^u - \bar{G}_n^u)$$

$$= \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u \bar{G}_n^u + \sum_{u=1}^{U} \max \Delta \bar{G}_n^u \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u (G_n^u - \bar{G}_n^u) + \sum_{u=1}^{U} \Delta \bar{G}_n^u \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u$$

$$\leq \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u \bar{G}_n^u + \sum_{u=1}^{U} \Delta \bar{G}_n^u \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u$$

$$+ \sum_{u=1}^{U} \max \Delta \bar{G}_n^u \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u G_n^u$$

$$= \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u (\bar{G}_n^u + \alpha_n)$$ (17)

where $\sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u \bar{G}_n^u$ is certain.

$$\max \Delta \bar{G}_n^u \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u (G_n^u - \bar{G}_n^u)$$ is the perturbation part, and it is a protection function to balances the relationship between robustness and optimality, which is affected by the shape and size of $\mathcal{R}_G$.

Therefore, C7 is transformed into a convex constraint, which is expressed as

$$\text{C9: } \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u (\bar{G}_n^u + \alpha_n) \leq I_{thr}$$ (18)

C. CHANNEL UNCERTAINTY IN TRANSMISSION RATE

In order to guarantee the QoS requirement of IoTDs, the channel uncertainty in the data rate is taken into account. Similarly, based on the bounded uncertainty set, the channel uncertainty set $\mathcal{R}_h$ and $\mathcal{R}_r$ can be expressed as
\[ R_h = \left\{ \Delta h^n_{i,k} \mid h^n_{i,k} = \tilde{h}^n_{i,k} + \Delta h^n_{i,k} : |\Delta h^n_{i,k}| \leq \delta^n_{i,k} \right\} \] (19)
and
\[ R_h = \left\{ \Delta g^n_{i,k} \mid g^n_{i,k} = \tilde{g}^n_{i,k} + \Delta g^n_{i,k} : |\Delta g^n_{i,k}| \leq \nu^n_{i,k} \right\}, \] (20)
respectively.
where \( \delta^n_{i,k} \geq 0 \) and \( \nu^n_{i,k} \geq 0 \) represent upper bound of errors. Thus, C4 can be equivalent to
\[
\begin{align*}
\sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} + \min_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} (\Delta h^n_{i,k}, \Delta g^n_{i,k}) \\
\geq R_{\min}
\end{align*}
\] (21)
where the first part on the left side is the certain function, \( \tilde{R}^n_{i,k} = \log_2 \left( 1 + \frac{p^n_{i,k} h^n_{i,k} g^n_{i,k} \bar{g}^n_{i,k} \bar{h}^n_{i,k}}{\sum_{n=1}^M p^n_{i,k} h^n_{i,k} g^n_{i,k} \bar{g}^n_{i,k} \bar{h}^n_{i,k} + \delta^2} \right) \), the second part on the left side is the protection function.

Due to the transmission rate \( R^n_{i,k} \) is a monotonically increasing function with respect to \( \gamma^n_{i,k} \), it can be obtained that
\[
\begin{align*}
\min_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} & \iff \min_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \gamma^n_{i,k} \\
& = \sum_{j=i+1}^M p^n_{j,k} + \max_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \left( \frac{p^n_{i,k} (\bar{g}^n_{i,k} + \Delta g^n_{i,k})}{(\bar{g}^n_{i,k} + \Delta g^n_{i,k}) (\bar{h}^n_{i,k} + \Delta h^n_{i,k})} \right)
\end{align*}
\] (22)

Based on formular 19, there exists \( \max_{\Delta h^n_{i,k} \in R_h} \frac{\delta^2}{(\bar{h}^n_{i,k} - \delta^n_{i,k})} = \frac{(\delta^2 \bar{h}^n_{i,k})(\bar{g}^n_{i,k} + \Delta g^n_{i,k})}{(\bar{g}^n_{i,k} + \Delta g^n_{i,k})(\bar{h}^n_{i,k} + \Delta h^n_{i,k})} \), and the Taylor expansion of binary function is used to solve the function, which is expressed as
\[
\begin{align*}
F = \frac{\tilde{g}^n_{i,k}}{\bar{h}^n_{i,k}} + (\Delta g^n_{i,k}) (\frac{\partial F}{\partial g^n_{i,k}}) \\
+ (\Delta h^n_{i,k}) (\frac{\partial F}{\partial h^n_{i,k}}) \\
+ \alpha(\Delta g^n_{i,k}, \Delta h^n_{i,k}) \\
\approx \frac{\tilde{g}^n_{i,k}}{\bar{h}^n_{i,k}} + \frac{\Delta g^n_{i,k}}{\bar{h}^n_{i,k}} - \frac{\Delta h^n_{i,k}}{\bar{h}^n_{i,k}}^2
\end{align*}
\] (23)
where \( \alpha(\Delta g^n_{i,k}, \Delta h^n_{i,k}) \) represents a higher-order infinitesimal.

Hence, \( \max_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \left( \frac{p^n_{i,k} \bar{g}^n_{i,k} + \Delta g^n_{i,k}}{(\bar{h}^n_{i,k} + \Delta h^n_{i,k})} \right) \) can be converted to
\[
\begin{align*}
\max_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \left( \frac{p^n_{i,k} \bar{g}^n_{i,k} + \Delta g^n_{i,k}}{(\bar{h}^n_{i,k} + \Delta h^n_{i,k})} \right) \\
\leq \frac{1}{\bar{h}^n_{i,k} p^n_{i,k} \bar{h}^n_{i,k}} \bar{g}^n_{i,k}
\end{align*}
\]

As a result, C4 can be restated as
\[ C_{10} : \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} \geq R_{\min} \] (25)
and \( \tilde{R}^n_{i,k} \) is expressed as
\[ \tilde{R}^n_{i,k} = \log_2 \left( 1 + \frac{p^n_{i,k} \bar{g}^n_{i,k} \bar{h}^n_{i,k}}{\left( \sum_{n=1}^M p^n_{i,k} \bar{g}^n_{i,k} \bar{h}^n_{i,k} + \delta^2 \right)} \right) + l^n_{i,k} \] (26)
where \( l^n_{i,k} = \sum_{j=i+1}^M p^n_{j,k} \bar{g}^n_{i,k} \) and \( \tilde{R}^n_{i,k} + P_c \) represents the determined interference power.

Considering formular 18 and formular 25, P3 can be reformed as P4, which is given as
\[ P_{\max} : \sum_{i=1}^U \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} + \sum_{i=1}^U \sum_{k=1}^K Z^n_{i,k} (G^n + \alpha_n) \leq I_{th} \]
\[ C_{10} : \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} \geq R_{\min} \]
\[ C_{5,6} \] (27)

D. JOINT POWER ALLOCATION AND SUBCHANNEL ALLOCATION ITERATIVE ALGORITHM

The objective function in P4 is a fractional function which is too complex to solve directly. Here, we can use the Dinkelbach method to transform P4 into a convex equivalent function [35]. In this article, the optimal value of P4 is defined as \( q^* \), which is expressed as
\[ q^* = \min_{x, z, \tilde{R}_{i,k}} \left( \sum_{i=1}^U \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} \right) \]
\[ + \frac{1}{\bar{h}^n_{i,k}} \max_{\Delta h^n_{i,k} \in R_h, \Delta g^n_{i,k} \in R_g} \left( \frac{p^n_{i,k} \bar{g}^n_{i,k}}{(\bar{h}^n_{i,k} + \Delta h^n_{i,k})} \right) \] (28)
where \( x^n_{i,k} \) and \( Z^n_{i,k} \) represent the optimal solution of subchannel assignment and power allocation of P4, respectively.

According to the proof in [36], we can obtain such a conclusion, which is stated as
\[ \sum_{i=1}^U \sum_{k=1}^K x^n_{i,k} \tilde{R}^n_{i,k} - q^* \left( \sum_{i=1}^U \sum_{k=1}^K Z^n_{i,k} + P_c \right) = 0 \] (29)
Then, P4 can be rewritten as

$$\text{P5}: \max_{x_{i,k}^u, Z_{i,k}^u} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u - q(t) \left( \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u + P_c \right)$$

s.t.: C5, C6, C9, C10

(30)

where \( q \geq 0 \) represents the total EE of SBS networks.

In this paper, we take two steps to tackle the problem P5. Firstly, we apply the successive convex approximation method to transform P5 into a convex optimization problem. Then, the Lagrangian dual approach is used to obtain the optimal solution. It can be expressed as

$$\log_2 Q + b \leq \log_2 (1 + Q)$$

(31)

where \( a \) and \( b \) satisfy \( a = \frac{Q_0}{1 + Q_0} \) and \( b = \log_2 (1 + Q_0) - \frac{Q_0}{1 + Q_0} \log_2 Q_0 \), respectively. When \( Q = Q_0 \), the equation in formual 31 is true, i.e., \( \log_2 Q + b = \log_2 (1 + Q) \).

Based on formular 26, the SINR of IoTTD \((u, i)\) when reusing subchannel \( k \) can be rewritten as

$$\tilde{R}_{i,k}^u = \frac{P_e^u}{\gamma_{i,k}^u - \frac{a_{i,k}^u}{b_{i,k}^u}} + P_b^u$$

(32)

Therefore, the achievable rate of IoTTD \((u, i)\) on subchannel \( k \) can be approximately obtained by

$$\tilde{R}_{i,k}^u = a_{i,k}^u \log_2 (1 + \tilde{R}_{i,k}^u) + b_{i,k}^u$$

(33)

where \( a_{i,k}^u \) and \( b_{i,k}^u \) can be estimated as \( a_{i,k}^u = \frac{\tilde{R}_{i,k}^u}{1 + \tilde{R}_{i,k}^u} \) and \( b_{i,k}^u = \log_2 (1 + \tilde{R}_{i,k}^u) - \frac{\tilde{R}_{i,k}^u}{1 + \tilde{R}_{i,k}^u} \log_2 \tilde{R}_{i,k}^u \), respectively, where \( \tilde{R}_{i,k}^u \) is the SINR of IoTTD \((u, i)\) obtained by the previous iteration when using subchannel \( k \).

Thus, the question P5 can be converted as P6, which is expressed as

$$\text{P6}: \max_{x_{i,k}^u, Z_{i,k}^u} \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u - q(t-1) \left( \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u + P_c \right)$$

s.t.: C11: \( \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u \geq R_{\text{min}} \)

C5, C6, C9

(34)

From formular 34, we can observe that the maximization problem P6 is a definite convex optimization problem which has a unique optimal solution.

In this paper, we use the Lagrangian dual approach to solve convex optimization problem P6. The iteration factor of Dinkelbach method is denoted by \( t, t \in \{1, 2, \ldots, I_{\text{outer}}\} \), where \( I_{\text{outer}} \) is the external maximum number of iterations. We assume that \( x_{i,k}^u, Z_{i,k}^u \) and \( q(t) \) are calculated in the \( t \)th iteration, then the enhanced Lagrange function of the optimization problem P6 can be defined as

$$L(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u)$$

\( = \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u - q(t-1) \left( \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u + P_c \right) \)

s.t.: C11: \( \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} x_{i,k}^u R_{i,k}^u \geq R_{\text{min}} \)

C5, C6, C9

(35)

where \( \lambda_u \geq 0, \omega_n \geq 0, \psi_u \geq 0 \) and \( \phi_{i,k}^u \geq 0 \) are the Lagrange multipliers corresponding to the four constraints in P6, respectively.

Therefore, the Lagrange function of P6 can be expressed as

$$L(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u)$$

\( = \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} L_k(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u) \)

\( = \sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} \bigg[ q(t-1)P_c + \sum_{n=1}^{N} \omega_n(t)(\sum_{u=1}^{U} \sum_{i=1}^{M} \sum_{k=1}^{K} Z_{i,k}^u) - \lambda_u(t) \bigg] \)

(36)

where \( L_k(\bullet) \) is calculated as follows

$$L_k(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u)$$

\( = [1 + \psi_u(t)]x_{i,k}^u(t)R_{i,k}^u - [q(t-1) + \lambda_u(t)]Z_{i,k}^u(n) \)

\( - \sum_{n=1}^{N} \omega_n(t)Z_{i,k}^u(n)(G_{u,n} + \alpha_u) - \phi_{i,k}^u(t)x_{i,k}^u(t) \)

(37)

By using the Lagrangian dual approach, P6 can be decomposed into a min-max problem, which is expressed as

$$\min_{\lambda_u, \omega_n, \psi_u, \phi_{i,k}^u} \max_{L(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u)} L(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \omega_n, \psi_u, \phi_{i,k}^u)$$

s.t.: \( \lambda_u \geq 0, \omega_n \geq 0, \psi_u \geq 0, \phi_{i,k}^u \geq 0 \)

(38)

According to the Karush-Kuhn-Tucker (KKT) conditions [37], the optimal power allocation for IoTTDs can be given by

$$P_{i,k}^u(t) = \left[ \begin{array}{c} \frac{Z_{i,k}^u(t)}{x_{i,k}^u(t)} \\
(1 + \psi_u(t))d_{i,k}^u(t) \\
\ln (2 [(q(t-1) + \lambda_u(t)] + \sum_{n=1}^{N} \omega_n(t)(G_{u,n} + \alpha_u)) \end{array} \right]^{+}$$

(39)

where

$$[x]^+ = \max\{0, x\}.$$
assignment \( x_{i,k}^u \), which is achieved by
\[
\frac{\partial L_k(x_{i,k}^u, Z_{i,k}^u, q, \lambda_u, \alpha_n, \psi_i^u, \phi_{i,k}^u)}{\partial x_{i,k}^u} = G_{i,k}^u(t) - \phi_{i,k}^u(t) = \begin{cases} 
< 0, & x_{i,k}^u = 0 \\
= 0, & 0 < x_{i,k}^u < 1 \\
> 0, & x_{i,k}^u = 1 
\end{cases} 
\]
where \( G_{i,k}^u(t) \) is expressed as
\[
G_{i,k}^u(t) = [1 + \psi_i^u(t)]\hat{R}_{i,k}^u - [q(t - 1) + \lambda_u]P_{i,k}^u(t) - \sum_{n=1}^N \alpha_n(t)P_{i,k}^u(t)(G_n^u + \alpha_n) \tag{40} 
\]
where we can conclude that the IoTD \((u, i)\) with the largest \( G_{i,k}^u \) value will reuse the subchannel resource \( k \) in downlink transmission.

Furthermore, the subchannel assignment vector \( X \) can be obtained by
\[
X = \{x_{i,k}^u(t) = 1\} = \max \limits_k G_{i,k}^u(t), \forall i \in M, \forall u \in U \tag{42} 
\]

In this paper, we use the subgradient method to update Lagrange multipliers, which are stated as
\[
\begin{align*}
\lambda_u(t, \tau + 1) &= \left[ \lambda_u(t, \tau) - \mu_1(t, \tau) \left( P_{\text{max}} - \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u \right) \right]^{+} \\
\omega_n(t, \tau + 1) &= \left[ \omega_n(t, \tau) - \mu_2(t, \tau) \left( I_{\text{thr}} - \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u (G_n^u + \alpha_n) \right) \right]^{+} \\
\psi_i^u(t, \tau + 1) &= \left[ \psi_i^u(t, \tau) - \mu_3(t, \tau) \left( \sum_{k=1}^K x_{i,k}^u \hat{R}_{i,k}^u - R_{\text{min}} \right) \right]^{+} \\
\phi_{i,k}^u(t, \tau + 1) &= \left[ \phi_{i,k}^u(t, \tau) - \mu_4(t, \tau) (1 - x_{i,k}^u) \right]^{+} 
\end{align*} \tag{43, 44, 45, 46} 
\]
where \( \tau \in \{1, 2, \ldots, I_{\text{inner}}\} \) denotes the iteration index for updating Lagrange multipliers, \( I_{\text{inner}} \) is the convergence number of Lagrange dual decomposition, \( \mu_1, \mu_2, \mu_3 \) and \( \mu_4 \) are step sizes.

Therefore, the proposed JPSIA resource allocation algorithm for NOAM-based heterogeneous MlIoT networks is presented in Algorithm 1.

### Algorithm 1 Proposed JPSIA Algorithm

**Input:** \( N, U, M, K, \bar{K}, P_{\text{thr}}, \alpha_n, G_n, P_c, I_{\text{thr}} \), \( R_{\text{min}}, \alpha_n, \delta_{i,k}^u, \psi_{i,k}^u \)

**Initialise:**
1. \( i = 1, \tau = 0, q(0), \psi_{i,k}^u(1, 0), \lambda_u(1, 0), \alpha_n(1, 0), \psi_{i,k}^u(1), I_{\text{outer}}, I_{\text{inner}}, \Delta_1, \Delta_2 \)
2. While \( \tau < I_{\text{outer}} \) do
3. Obtain \( P_{i,k}^u(t), G_{i,k}^u(t) \) and \( x_{i,k}^u(t) \) by using (39), (41) and (42)
4. If \( \left| \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u(t) + P_c \right| < \Delta_1 \)
5. \( q^* = \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M x_{i,k}^u(t) \hat{R}_{i,k}^u \left/ \left( \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u(t) + P_c \right) \right. \), \( P_{i,k}^u = P_{i,k}^u(t) \) and \( x_{i,k}^u = x_{i,k}^u(t) \)
6. break
7. else
8. \( t \to t + 1 \)
9. While \( \tau < I_{\text{inner}} \) do
10. Set \( \lambda_u(t) = \lambda_u(t - 1), \alpha_n(t) = \alpha_n(t - 1) \), \( \psi_{i,k}^u(1, t - 1), \phi_{i,k}^u(1, t - 1) \), \( P_{i,k}^u(t) = P_{i,k}^u(t - 1) \) and \( x_{i,k}^u(t) = x_{i,k}^u(t - 1) \)
11. Update \( \omega_n(t, \tau + 1), \lambda_u(t, \tau + 1), \alpha_n(t, \tau + 1), \psi_{i,k}^u(t, \tau + 1), \) and \( \phi_{i,k}^u(t, \tau + 1) \) by using (43) ~ (46)
12. If \( |\lambda_u(t, \tau + 1) - \lambda_u(t, \tau)| \), \( |\alpha_n(t, \tau + 1) - \alpha_n(t, \tau)| \), \( |\psi_{i,k}^u(t, \tau + 1) - \psi_{i,k}^u(t, \tau)| \), \( |\phi_{i,k}^u(t, \tau + 1) - \phi_{i,k}^u(t, \tau)| \) < \( \Delta_2 \),
13. Update \( P_{i,k}^u(t), G_{i,k}^u(t) \) and \( x_{i,k}^u(t) \) by using (39), (41) and (42)
14. \( q^* = \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M x_{i,k}^u(t) \hat{R}_{i,k}^u \left/ \left( \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u(t) + P_c \right) \right. \), \( q(t - 1) = \sum_{u=1}^U \sum_{k=1}^K x_{i,k}^u(t - 1) \hat{R}_{i,k}^u \left/ \left( \sum_{u=1}^U \sum_{k=1}^K \sum_{i=1}^M Z_{i,k}^u(t) + P_c \right) \right. \)
15. break
16. end if
17. \( \tau \to \tau + 1 \)
18. end while
19. end if
20. end while
21. end for

### E. Complexity Analysis

The complexity of the proposed JPSIA algorithm mainly caused by two factors, i.e., the Dinkelbach method and the Lagrangian dual approach. In the outer layer, we use the Dinkelbach method to achieve the optimal \( q^* \) value. Then, the Lagrangian dual approach is used to update the \( q^* \) value in the inner layer. The maximum of outer iteration denoted as \( I_{\text{outer}} \), \( I_{\text{inner}} \) represents the inner iteration maximum that converged to the optimal EE. The computational complexity of the Dinkelbach method is a super-linear time complexity \( O(I_{\text{outer}}) \). For each subchannel block \( k \), the complexity of performing the proposed algorithm is assumed to be \( O(UM) \). According to (43) ~ (46), the complexity of iteratively updating Lagrangian multiplier is \( O(UMKN) \), where \( K \) and \( N \) are the number of subchannels and MUEs, respectively. Due to \( I_{\text{inner}} \) is a polynomial that depends on the iteration index, the complexity of the inner iteration calculated as \( O(I_{\text{inner}}U^2M^2NK) \). As a result, the total computational complexity of the proposed JPSIA algorithm is \( O(I_{\text{outer}}I_{\text{inner}}U^2M^2NK) \).
IV. SIMULATION AND RESULTS ANALYSIS

In this section, we evaluate the effectiveness of the proposed resource allocation algorithm in the NOMA-based heterogeneous MIoT system through extensive simulations. In addition, we also compare the performance of the proposed algorithm with benchmark algorithms in terms of the energy efficiency.

A. SIMULATION PARAMETERS

In our simulations, we consider a NOMA system with one MBS and multiple SBSs, where each SBS is placed at the middle of the respective cell. The radius of MBS is 500m, while the radius of SBS is 20m. All the MUEs and IoTDs are randomly distributed in their respective networks. We assume all SBSs serve the same number of IoTDs. To ensure the coverage of entire network, the minimum distance between MBS and SBS is set to 50m, the minimum distance between SBSs is set to 40m. In addition, the minimum distance between IoTDs is set to 40m. The channel fading model includes Rayleigh fading, shadow fading and path loss, where the path loss index is set to 3 and the standard deviation of the shadow from the BS to user is 10dBm [38]. The fixed power allocated for MUEs on each subchannel is 21dBm. The noise power is $\delta^2 = B N_0$, where $N_0 = 174$ dBm / Hz. The maximum error tolerance for the algorithm is set to $10^{-6}$. Other simulation parameters are summarized in Table 1.

| Parameter                        | Values |
|----------------------------------|--------|
| subchannel resources             | 10     |
| Number of SBSs                   | 2      |
| Number of MUEs                   | 2      |
| Number of IoTDs in each SBS      | 2      |
| Power amplifier efficiency       | 0.27   |
| Circuit power consumption        | 0.3W   |
| Subchannel bandwidth             | 1Hz    |
| Minimum data rate of IoTDs       | 1bps/Hz|
| Maximum transmit power of IoTDs  | 25dBm  |
| Maximum transmit power of MUEs   | 35dBm  |
| The maximum number of iterations | 10^6   |
| Interference threshold of MUEs   | 0.22mW |

B. BASELINE ALGORITHMS

At first, we compare the proposed NOMA-based system with the traditional OMA system in terms of energy efficiency. In the OMA-based system, we assume that each user can occupy only one subchannel [39]. Each user will be assigned the channel with the highest channel gain under the resource allocation scheme. Then, we compare the proposed JPSIA algorithm with exhaustive search (ES) method and Random allocation (RA) algorithm [40], [41]. The ES method is used to solve the three-dimensional matching problem, searching all possible solutions in the constructed graph to obtain the optimal result. The RA algorithm randomly allocates transmission power and subchannel for all users. In order to ensure fairness, we assume that all users occupying the same subchannel constitute a vertex. Meanwhile, all algorithms have the same simulation parameters.

C. RESULTS ANALYSIS

The convergence of Algorithm 1 is analyzed by simulating the number of iterations. Figure 4 shows the number of iterations against the total energy efficiency of IoTDs under different number of SBSs. In the simulation, the maximum accessing pair of SBS and MUE on each subchannel is 2, the maximum transmit power of SBS is 30dBm. From Figure 4, we can observe that the proposed JPSIA algorithm can converge within 10 iterations under different $U$, after that, the EE of IoTDs is a fixed constant approximately. In addition, as the number of SBSs $U$ increases, the EE of IoTDs also increases. Due to the number of IoTDs $M$ connected in each SBS is fixed, the total number of IoTDs accessed to the NOMA-based MIoT system will increase while $U$ increases. In this paper, each subchannel resource occupies unit bandwidth, therefore the system with more IoTDs will acquire higher EE than the system with less IoTDs. Hence, the proposed JPSIA algorithm achieves the optimal solution of power allocation and subchannel assignment with low computational complexity, and obtains better network performance in terms of convergence and energy efficiency.

Figure 5 demonstrates the total energy efficiency of IoTDs versus the number of IoTDs. The proposed NOMA-based system is compared with traditional OMA-based system in terms of energy efficiency. In this simulation, the parameters are set as $U = 5 \sim 30$, ‘OMA’ represents the traditional OMA-based scheme, and ‘NOMA’ indicates that the proposed NOMA-based scheme. It can be observed from Figure 4 that under the same $P_c$, the EE of all schemes increases with the increase of the total number of IoTDs connected in the system. Meanwhile, we can also observe that the EE of IoTDs obtained in NOMA-based scheme is higher than in the OMA-based scheme. This is because in the proposed NOMA-based system, the SIC technology is
applied in the receiving terminal of IoTDs. By utilizing SIC technology, the co-channel interference from other IoTDs with weaker channels gain can be eliminated when receiving the signals, thus the EE of IoTDs is improved. In addition, it is observed from Figure 5 that the proposed NOMA-based scheme has higher energy efficiency in the system of $P_c = 10\, \text{dBm}$ than of $P_c = 20\, \text{dBm}$ in case of the same number of IoTDs. From the energy efficiency model formulated in this paper, we can observe that $EE$ is a decreasing function with respect to $P_c$, which means that the value of $EE$ will decrease with the increase of the $P_c$. On the contrary, the smaller the $P_c$, the higher the $EE$. Therefore, the proposed NOMA-based scheme can achieve higher energy efficiency as compared with the existing schemes.

Figure 6 shows the impact of various cross-layer interference threshold $I_{thr}$ and minimum data rate $R_{min}$ on the total energy efficiency of IoTDs. In this simulation, we set the parameters as $M = 2$, $U = 2$. From Figure 5, we can observe that when the minimum data rate $R_{min}$ is fixed, the EE of IoTDs will increases as the cross-layer interference threshold $I_{thr}$ increases. It’s obvious that the EE of IoTDs increases slowly when $I_{thr}$ is lower than 20dBm in Figure 6. This is because when $I_{thr}$ increases, the required transmit power allocation range of IoTDs will increase. According to the definition of energy efficiency, the larger the transmit power allocated for IoTDs, the higher the total energy efficiency can be achieved. In Figure 6, the EE of IoTDs will decrease with the increase of $R_{min}$ under the same $I_{thr}$. It’s necessary to satisfy the requirements of minimum data rate of IoTDs, so IoTDs must increase the transmit power $P_{u,k}$. Thus, the total power consumption of IoTDs $P_{tot}$ will increase, which will further lead to the reduction of $EE$. Therefore, we assume that the parameter in other simulations sets $R_{min} = 1\, \text{bps/Hz}$ in this article to ensure energy efficiency performance.

Figure 7 illustrates the total energy efficiency of IoTDs compared with the transmit power of SBSs with varying $U$ and $P_c$, respectively. In the simulation, we assume that the transmit power of SBSs ranges from 0dBm to 30dBm. From Figure 7, it is observed that when the transmit power of SBSs increases, the EE of IoTDs also increases. Remarkably, the EE of IoTDs will approximately keep stable after the SBS transmit power reaches a certain value, i.e., 15dBm. At the same time, it is can be seen that compared with other schemes, the EE of IoTDs is the highest under the condition $U = 20$ and $P_c = 15\, \text{dBm}$. This indicates the proposed algorithm can guarantee more IoT devices access to MiIoT networks. Meanwhile, it can achieve the optimal transmit power allocation for IoT devices under different SBSs transmit powers. In Figure 6, we can observe that the higher EE can be achieved by $U = 20$ than $U = 10$ under the same $P_c$. This is because the former scheme connects to more IoTDs. Based on the definition of energy efficiency in this article, it can be seen that compared with the system of fewer IoTDs, the more IoTDs transmit on each subchannel that occupies a unit bandwidth, the higher the EE will be obtained. Therefore, the proposed algorithm can make good performance of robustness and energy efficiency with diverse SBSs’ transmit powers.
Figure 8 shows the influence of the different channel uncertainty parameter $\alpha_n$ in cross-layer interference constraint on the total energy efficiency of IoTDs. In the simulation, we assume that the cross-layer interference threshold $I_{thr}$ ranges from 0.1mW to 0.6mW. As it can be proved from Figure 8, when $I_{thr}$ is fixed, the EE of IoTDs increases as the value of $\alpha_n$ increases. This is because, according to formula 17, when the channel uncertainty parameter $\alpha_n$ increases, the transmit power of IoTDs will decrease, so the power consumption of IoTDs will decrease, resulting in the increase of the EE of IoTDs.

Figure 9 shows the influence of the different channel uncertainty parameters $\delta_{i,k}^u$ and $\nu_{i,k}^n$ in data rate constraint on the total energy efficiency of IoTDs. As can be seen from Figure 8, on the one hand, when $I_{thr}$ and $\delta_{i,k}^u$ are fixed, the EE of IoTDs increases with the increase of $\nu_{i,k}^n$. This is because the increase of the channel uncertain parameter $\nu_{i,k}^n$ will lead to the decrease of SINR. According to formula 33, the value of $a_{i,k}^n$ will reduce, thus the transmit power of IoTDs will decrease, and the power consumption of IoTDs decrease, so the EE of IoTDs will increase. On the other hand, when $I_{thr}$ and $\nu_{i,k}^n$ are fixed, it can be seen from Figure 8 that with the increase of $\delta_{i,k}^u$, the EE of IoTDs will decrease. This is because when $\delta_{i,k}^u$ becomes larger, it means that the channel environment of the transmission downlink between SBS and IoTDs is worse. In order to ensure reliable communication links, the transmit power required by IoTDs increases, resulting in lower EE of IoTDs.

Figure 10 examines the total energy efficiency of IoTDs versus $P_{\text{max}}$ with different $U$ taking into account. The simulation parameters are set as $M = 2$, $R_{\text{min}} = 1$bps/Hz, the maximum number of links allowed on each subchannel is 2. In this paper, we compare the energy efficiency performance of the JPSIA algorithm with ES algorithm and RA algorithm, all simulations are performed in the same NOMA-based system. From Figure 10, we can observe that compared with the other two algorithms, the JPSIA algorithm greatly improves the EE of IoTDs. This is because the joint power allocation and subchannel assignment algorithm can obtain the optimal subchannel and transmit power for IoTDs, which can more effectively eliminate co-channel interference and improve the transmit rate, so as to maximize the EE of IoTDs. Meanwhile, it can be observed that when $U$ is same, the value of EE obtained by three algorithms all decrease with the increase of $P_{\text{max}}$. This is because when the number of IoTDs is fixed, the total communication power consumption will increase as the allocated transmit power of IoTDs increase, which leads to the reduction of the EE of IoTDs. Hence, compared with the baseline algorithms, the proposed JPSIA algorithm has better performance in terms of effectiveness and energy efficiency.

**V. CONCLUSION**

In this paper, a NOMA-based heterogeneous MIoT network was proposed to support the large-scale communications between different types of BSs and smart sensing devices.
in 5G coal mine scenario. The NOMA technology was applied in data transmission to improve the access ratio and spectrum utilization of 5G MIoT system. In order to maximize the total energy efficiency of IoTDs, a resource allocation optimization problem has been formulated, which is NP-hard and nonconvex. A joint power allocation and subchannel assignment iterative algorithm under the imperfect CSI was proposed while the maximum transmits power, maximum cross-layer interference and QoS requirement of IoTDs were satisfied. Then, the suboptimal solution to optimization problem was obtained by using the Dinkelbach method and Lagrangian dual decomposition approach with guaranteed convergence and low computational complexity. Simulation results showed that the proposed algorithm can significantly improves energy efficiency performance compared with baseline algorithms. In the future, we will investigate the energy-efficient resource allocation problem for user association, power allocation and subchannel assignment in NOMA-based heterogeneous MIoT networks, to achieve an improved energy efficiency performance in MIoT networks under imperfect CSI.

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