Jamming-Resilient Fairness-Oriented Resource Allocation Technique for IRS-Assisted NOMA 6G-Enabled IoT Networks

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***Abstract*—Intelligent Reflecting Surface (IRS) has recently been combined with cutting-edge technologies to meet the demanding requirements of six-generation (6G)-based IoT consumer electronics (CE) communication systems. This paper considers IRS-assisted hybrid orthogonal frequency division multiple access (OFDMA) and non-orthogonal multiple access (NOMA) systems under proactive jamming attacks. Jamming severely affects the performance of CE devices, reducing data rates, increasing packet loss, and significantly reducing communication reliability. A jamming-aware fairness-oriented design is proposed to overcome such attacks and maintain fairness between CE devices. Specifically, the fairness index (FI) is maximized under relevant constraints, including secure transmission requirements and transmission power constraints. However, due to the non-convex and fractional nature of the proposed jamming-aware FI optimization framework, an iterative algorithm is developed to solve the problem and evaluate the optimization parameters, namely the IRS phase reflection coefficients and the per-user allocated power level (i.e., CE device). To validate the effectiveness of the proposed jamming-aware FI maximization framework, its performance is compared with a set of benchmarks. The simulation results demonstrate its superiority in ensuring fairness among users and providing secure jamming-resistant communication in IRS-assisted OFDMA-NOMA CE-based systems.**

***Index Terms*—Consumer electronics, intelligent reflecting surface (IRS), jamming, NOMA, OFDMA, fairness.**

I. Introduction

DUE TO the progressive adoption of Internet-of-Things (IoT) technology in our daily activities, there has been an explosive demand for consumer electronics devices (CEDs), such as smartphones, laptops, and other IoT-based devices [1]. In particular, traditional CEDs have been used to perform unique functions and operate without connections to other CEDs. However, next-generation CEDs can connect to other CEDs and the Internet [2] and thus perform multiple tasks. However, the tremendous proliferation of modern CEDs poses serious challenges in the manufacture of intelligent multi-functional CEs and in the availability of potential network solutions to support the paradigm shift towards next-generation CEDs [3], [4]. In particular, potential solutions should be able to support the massive connectivity requirements of CEDs while providing a reliable, secure, energy-efficient, and fair quality of service (QoS) [5]. Specifically, the diversity of channel conditions poses serious challenges in offering reasonable QoS to users (i.e., CEDs) who have poor channel conditions (i.e., cell-edge CEDs) [6]. In particular, there is no unique definition of fairness. Such a definition varies depending on whether the targeted or resultant fairness is considered [6]. On the other hand, due to the open nature of wireless communication systems, jammers can attack legitimate channels by transmitting jamming signals, thus blocking the transmission of legitimate users [7]. Jamming attacks have the potential to significantly disrupt and degrade the performance of wireless networks [8]. Such attacks can lead to extensive disruptions, reduced data transmission rates, increased packet loss, compromised signal quality, and overall deterioration in the network's ability to efficiently and reliably transmit data. Depending on their transmission functionality, jamming attacks can be classified as proactive and reactive jammers [9]. As CEDs are expected to perform critical tasks such as fintech and healthcare [2], ensuring their security against jammers (i.e., threats) while maintaining reliable QoS becomes an essential requirement. Consequently, extensive research efforts have been conducted to provide secure and fair services in recent CE-based communication systems. In particular, the widespread use of consumer electronics cannot be achieved without initiating multiple access techniques that can support the massive connectivity of CEDs while securing them for different jamming attacks [2]. Consequently, non-orthogonal multiple access (NOMA) has recently been considered a promising candidate for the deployment of CEDs [10]. On the other hand, intelligent reflecting surface (IRS) technology can play a crucial role in helping communications in consumer electronics applications [11].

IRS has been recently identified as cutting-edge technology that can achieve fairness between users and provide secure communication. Specifically, an IRS unit consists of a set of passive reflecting elements connected to a set of controllers that can intelligently steer the radio frequency signal in the intended direction [12]. This enables the use of IRS technology as a potential solution to support

Manuscript received 5 January 2024; revised 29 January 2024, 21 February 2024, and 30 June 2024; accepted 24 July 2024. Date of publication 29 July 2024; date of current version 11 December 2024. *(Corresponding author: Haitham Al-Obiedollah.)*

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Digital Object Identifier 10.1109/TCE.2024.3434596

communication with CEDs (i.e., IoT devices) at the cell edge, which, as a result, improves fairness between CEDs [10]. Furthermore, IRS technology is passive, lightweight, and compatible with existing communication infrastructure [13]. With such potential capabilities, several emerging multiple-access (MA) techniques have recently been investigated with the support of IRS technology. For example, IRS-assisted multiple antenna techniques [14], IRS-assisted orthogonal MA (OMA) techniques [15], and IRS-assisted non-orthogonal MA (NOMA) systems [16]. Although OMA techniques reserve an orthogonal resource block (RB) for each user, NOMA can serve more than one user in each RB through power domain superposition coding (SC). Due to its advantages, NOMA is considered an enabling MA technique; however, implementing a stand-alone NOMA in dense networks raises several practical challenges, such as the complexity of successive interference cancellation (SIC) [17]. Consequently, integrating NOMA with other MA techniques was identified as a potential solution to overcome these challenges while improving spectral efficiency. Such integrated systems include NOMA with multiple antennas, NOMA with orthogonal division MA (OFDMA) [17], and NOMA with time division MA (TDMA) [18]. In OFDMA-NOMA systems, the available bandwidth is divided into sub-bands, and the users are grouped in clusters; as such, a sub-band is reserved to serve a group of NOMA users.

A. Related Work and Motivation

Recent studies have explored different methods to tackle design challenges in IRS-assisted OFDMA-NOMA systems, leveraging the potential of hybrid OFDMA-NOMA and IRS technologies. In these systems, an IRS unit is assigned to enhance transmission for each group of users within each sub-band. Various resource allocation techniques for IRS-assisted hybrid OMA-NOMA systems (such as TDMA-NOMA and OFDMA-NOMA) were previously explored. In [19], a simple IRS-assisted NOMA-based system was considered, in which an IRS unit was dedicated to support users' transmissions. Specifically, a power minimization framework was developed to minimize transmit power in the system. The work in [20] proposed a Sum Rate Maximization (SRM) resource allocation technique, which incorporates the assumption that users can harvest energy and decode information. Consequently, an alternative optimization (AO) algorithm was adopted to solve the problem. In [21], an IRS-assisted hybrid TDMA-NOMA system was considered. Specifically, users were assumed to be self-empowered, and a resource allocation framework was formulated to maximize throughput. In [22], an energy-efficient resource allocation technique was proposed for an IRS-assisted hybrid TDMA-NOMA system. In [23], the authors proposed a power minimization framework under QoS constraints assuming that each cluster is served by one IRS unit. The work in [3] considered a set of IRS units to support a set of CEDs, where the sum rate is maximized under QoS constraints. A power minimization framework for the IRS-assisted CE system in [11] was considered. Furthermore, in [24], a secure framework was investigated for an IRS-assisted IoT CE system.

Although several resource allocation techniques were developed in the literature for IRS-assisted hybrid OFDMA-NOMA systems, the fairness of such systems under jamming attacks has not been considered. However, with the progressive utilization of IoT networks, providing a secure and fair QoS becomes vital, which cannot be achieved with conventional resource allocation techniques. In particular, this paper investigates proactive jamming attacks due to their potential to compromise the security of the communication system and their relatively simple and dynamic nature. Proactive jammers can easily switch between periods of inactivity and jamming, often without synchronization with IoT transmissions. This straightforward approach to launch such attacks increases their relevance in the context of security mitigation. This motivates the need to propose a jamming-aware, fairness-oriented resource allocation technique for IRS-assisted hybrid OFDMA-NOMA systems under proactive jamming attacks.

B. Contribution

The main contributions of this paper can be summarized as:

- An IRS-assisted hybrid OFDMA-NOMA system is presented in a proactive jamming environment. In particular, users are divided into groups, and the available bandwidth is split into sub-bands (i.e., channels). Consequently, an IRS unit is dedicated to serving each group of users while offering a secure mechanism against a proactive jammer.
- To maintain fairness between CEDs, quantified by the Fairness Index (FI), a jamming-aware resource allocation framework, namely the secure FI maximization (FIM), is developed with the main objective of improving system fairness while mitigating the impact of proactive jamming.
- However, the FIM problem is non-convex with joint optimization parameters: power allocations and the IRS units' phase-shift coefficients. The objective function of FIM is fractional, which presents additional difficulty in solving the problem. Hence, an iterative algorithm based on sequential convex approximation (SCA) is proposed to handle the non-convexity and fractional nature of the problem.
- Furthermore, a set of simulation results is provided to validate the effectiveness of the proposed jamming-aware FIM resource allocation technique. Furthermore, the performance of the proposed resource allocation technique is compared with a set of unaware and aware benchmarks [24], [25].

The remainder of the paper is organized as follows. Section II introduces the IRS-assisted hybrid OFDMA-NOMA system model under jamming attacks and presents the secure FIM resource allocation framework. The proposed SCA is provided in Section III. Performance evaluation is discussed in Section IV and conclusions are given in Section V.

II. System Model and Problem Formulation

A. System Model

This paper assumes that a single-antenna base station (BS) communicates with N single-antenna users through a bandwidth of B. Furthermore, the bandwidth, B, is equally

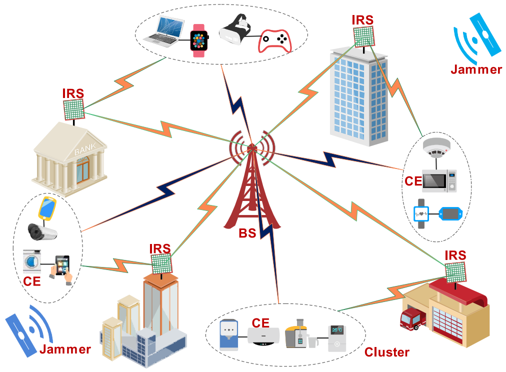

Fig. 1. Example of an IRS-assisted OFDMA-NOMA-based CE network.

divided into $M = \frac{N}{2}$ sub-bands, where each sub-band is referred to as B_m, i.e., $B_m = \frac{B}{M}, \forall m \in \mathcal{M} = \{1, 2, \ldots, M\}$, and it is dedicated to serving a cluster of two CEDs in the presence of a proactive jammer. Figure 1 shows the network model with various types of CE devices. In particular, a proactive jammer attacks the transmission in each sub-band by transmitting a random signal within a period called $T_j^{(m)}$. Then, the jammer turns to sleep mode, where such jamming and sleep modes can be modeled as a Markov process [9]. To facilitate downlink transmission between the BS and the clusters, as well as deal with jamming attacks, a set of IRS units is deployed, where the m^{th} IRS unit is referred to as $\mathfrak{I}_m$ $\forall m \in \mathcal{M}$. In fact, $\mathfrak{I}_m$ is equipped with L reflecting elements and is located at $(x_{\mathfrak{I}_m}, y_{\mathfrak{I}_m})$. Specifically, in the m^{th} sub-band, i.e., B_m, the power domain NOMA is deployed to serve CEDs with support $\mathfrak{I}_m$. Consequently, selecting the users in each sub-band (i.e., clustering) and assigning an IRS unit for each cluster have a considerable impact on the overall performance of the system. Therefore, an efficient clustering and IRS assignment algorithm that considers the system's requirements is proposed. Since NOMA transmission is considered in each sub-band, the BS transmits the following superposed signal within each B_m: $x_m = \sum_{i=1}^{2} \sqrt{p_{i,m}} s_{i,m}, \forall m \in \mathcal{M} = \{1, 2, \ldots, M\}$, where $p_{i,m}$ and $s_{i,m}$ are the power assigned to the i^{th} user, i.e., CED in the m^{th} sub-band ($\mathrm{u}_{i,m}$) and the corresponding symbol, respectively. Hence, the total allocated transmit power is given as $P_t = \sum_{m=1}^{M} \sum_{i=1}^{2} p_{i,m}$. In particular, since $\mathfrak{I}_m$ is dedicated to transmit in B_m; then, the received signal from the users in B_m can be written as:

$$r_{i,m} = \left(h_{i,m} + \mathbf{h}_{m,i}^H \Theta_m \mathbf{g}_m\right) x_m + n_{i,m}, \forall i \in \{1, 2\}, \forall m \in \mathcal{M}, \quad (1)$$

where $h_{i,m}$ denotes the channel between the BS and $u_{i,m}$, $\mathbf{h}_{m,i}^H \in \mathbb{C}^{1\times L}$ represents the channel between $\mathfrak{I}_m$ and $u_{i,m}$. Specifically, $h_{i,m}$ and $\mathbf{h}_{m,i}^H$ are assumed to be Rayleigh fading and are modeled as $h_{i,m} = \sqrt{d_{i,m}^{-\mathfrak{p}}} \tilde{h}_{i,m}$, and $\mathbf{h}_{m,i}^H = \sqrt{d_{m,i}^{-\mathfrak{p}}} \tilde{\mathbf{h}}_{m,i}^H$, respectively. Furthermore, $\mathbf{g}_m \in \mathbb{C}^{L\times 1}$ is the channel between BS and $\mathfrak{I}_m$. In particular, the channel between BS and $\mathfrak{I}_m$ is assumed to be a Rician fading channel and can be modeled as follows [26]:

$$\mathbf{g}_m = \sqrt{d_m^{-\mathfrak{p}}} \left(\sqrt{\frac{\mathfrak{c}}{\mathfrak{c}+1}} \mathbf{g}_m^{\mathrm{LOS}} + \sqrt{\frac{1}{\mathfrak{c}+1}} \mathbf{g}_m^{\mathrm{NLOS}} \right), \quad (2)$$

where d_m, $\mathfrak{p}$, $\mathbf{g}_m^{\mathrm{LOS}}$, and $\mathbf{g}_m^{\mathrm{LOS}}$ are the distance between BS and $\mathfrak{I}_m$, the path loss exponent, the line-of-sight (LOS) component, and the none-LOS (NLOS) component, respectively. Furthermore, $\mathfrak{c}$ is the Rician factor, $\Theta_m = \mathrm{diag}[e^{j\theta_{m,1}}, \ldots, e^{j\theta_{m,L}}]$ is the diagonal phase reflection matrix of $\mathfrak{I}_m$, where $\theta_{m,l} \in [0, 2\pi]$ is the phase shift of the l^{th} reflecting element of $\mathfrak{I}_m$. With this, it is assumed that the first user in each cluster, i.e., $u_{1,m}$, has the strongest equivalent channel conditions, i.e.,

$$\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2 \geq \left|h_{2,m} + \mathbf{h}_{m,2}^H \Theta_m \mathbf{g}_m\right|^2. \quad (3)$$

The channel ordering in (3) implies that $u_{1,m}$ should be able to decode the packet intended for $u_{2,m}$ before decoding its desired packet with signal-to-interference plus noise ratio (SINR), which is given as:

$$\mathrm{SINR}_{2,m}^{1} = \frac{p_{2,m}\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2}{\left(p_{1,m}\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2 + \sigma_{1,m}^2\right)}, \forall m \in \mathcal{M}. \quad (4)$$

Then, $u_{1,m}$ decodes its own message with the following SINR:

$$\mathrm{SINR}_{1,m}^{1} = \frac{p_{1,m}\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2}{\sigma_{1,m}^2}, \forall m \in \mathcal{M}. \quad (5)$$

Unlike the strongest user, the weakest user only decodes its message without performing any SIC with the following SINR:

$$\mathrm{SINR}_{2,m}^{2} = \frac{p_{2,m}\left|h_{2,m} + \mathbf{h}_{m,2}^H \Theta_m \mathbf{g}_m\right|^2}{\left(p_{1,m}\left|h_{2,m} + \mathbf{h}_{m,2}^H \Theta_m \mathbf{g}_m\right|^2 + \sigma_{2,m}^2\right)}, \forall m \in \mathcal{M}. \quad (6)$$

Thus, the SINR of the weakest user can be written as:

$$\mathrm{SINR}_{2,m} = \mathrm{Min.}\{\mathrm{SINR}_{2,m}^{1}, \mathrm{SINR}_{2,m}^{2}\}, \forall m \in \mathcal{M}. \quad (7)$$

With this, the achieved rate at each user can be written as:

$$R_{i,m} = B_m \log\left(1 + \mathrm{SINR}_{i,m}\right), \forall i \in \{1, 2\}, \forall m \in \mathcal{M}. \quad (8)$$

The sum rate (throughput) of the system can be written as:

$$R_{\mathrm{sum}} = \sum_{m=1}^{M} \sum_{i=1}^{2} R_{i,m}. \quad (9)$$

To quantify the achieved fairness, Jain's FI is considered, which can be written in terms of the achieved rate as:

$$\mathrm{FI} = \frac{\left(\sum_{m=1}^{M} \sum_{i=1}^{2} R_{i,m}\right)^2}{K\left(\sum_{m=1}^{M} \sum_{i=1}^{2} R_{i,m}^2\right)}. \quad (10)$$

Optimal fairness based on FI is attained when $R_{i,m}$ is identical for all i, resulting in $\mathrm{FI} = 1$.

B. Jamming and Success Probability Analysis

The proactive jamming strategy can be characterized by the time intervals between consecutive jamming signals on a given channel m,[1] denoted as $T_J^{(m)}$. To successfully deliver a packet of size D for transmission i on channel m, the transmission time $t_x^{(m)} = \frac{D}{R_{i,m}}$ must be shorter than the interval between the jamming signals on channel m, $T_J^{(m)}$, where $R_{i,m}$

[1] Channel and sub-band carry the same meaning in this paper.

is the transmission rate over m for transmission i. The success probability over m for transmission i is computed as:

$$P_{i,m}^{succ} = \Pr\left(t_x^{(m)} < T_J^{(m)}\right). \tag{11}$$

For a memory-less jamming, where $T_J^{(m)}$ follows a statistically independent exponentially distributed random variable with an average of $\bar{T}_J^{(m)}$, the expression for $P^{succ}{}_{m,i}$ is stated as:

$$P_{i,m}^{succ} = e^{-\frac{D}{R_{i,m}\bar{T}_J^{(m)}}}. \tag{12}$$

The expression of the probability of success in (12) over channel m is a function of the achieved rate on m. To ensure a QoS requirement in terms of a minimum probability of success threshold γ for each transmission i on channel m, the transmission rate should be chosen so that $P^{succ}m, i \geq \gamma$. Using (12) and after some algebraic manipulations, the success probability constraint can be expressed in terms of $R_{i,m}$ as:

$$R_{i,m} \geq -\frac{D}{ln(\gamma)\bar{T}_J^{(m)}}. \tag{13}$$

C. Problem Formulation

Traditional SRM frameworks for IRS-assisted NOMA systems were typically designed solely to maximize the achieved sum rate, overlooking the presence of jamming attacks and fairness considerations. This paper introduces a novel approach that considers fairness while being aware of potential jamming attacks. The primary objective is to maximize FI within an IRS-assisted OFDMA-NOMA network that operates in the presence of proactive jamming attacks and adheres to predefined constraints. This resource allocation technique is termed secure FIM (S-FIM), which is formulated as:

$$\mathbf{P}_1 : \max_{p_{i,m},\theta_b} \quad \text{FI} \tag{14a}$$

$$\text{subject to} \quad R_{i,m} \geq -\frac{D}{ln(\gamma)\bar{T}_J^{(m)}}, \tag{14b}$$

$$\sum_{m=1}^{M}\sum_{i=1}^{2} p_{i,m} \leq P_{\max}, \tag{14c}$$

$$\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2 \geq \left|h_{2,m} + \mathbf{h}_{m,2}^H \Theta_m \mathbf{g}_m\right|^2, \tag{14d}$$

$$p_{2,m} \geq p_{1,m}, \tag{14e}$$

where $P_{\max}$ is the maximum available power budget at the BS. Note that the constraints in (14d) and (14e) ensure the successful implementation of SIC. Furthermore, the constraint in (14c) maintains the transmit power less than the total available power budget in the BS, that is, $P_{\max}$. In particular, solving the S-FIM optimization problem $\mathbf{P}_1$ cannot be achieved without addressing critical aspects. First, as every two users (i.e., CEDs) are selected in a cluster, the clustering should be determined before solving the problem. In addition, an appropriate IRS unit should be chosen for each cluster. Worse still, conventional approaches cannot be used to solve problem $\mathbf{P}_1$ for several reasons. First, the problem $\mathbf{P}_1$ is nonconvex, and its objective function is fractional. Furthermore, the optimization parameters (the power allocation and reflection coefficient matrix of each IRS unit) are of a joint nature. Together, these aspects introduce additional complexity to solve $\mathbf{P}_1$.

While the optimization framework in (14) is tailored for proactive jamming, it can be modified to accommodate various types of jamming attacks by deriving the success probability specific to each attack and considering its jamming strategy and parameters. Integrating the derived success probability into (14) enables extending the proposed resource allocation technique to accommodate the considered jamming attack.

III. The Proposed Solution

This section provides a detailed approach to solve the S-FIM optimization framework $\mathbf{P}_1$. Specifically, an efficient grouping strategy is first presented. Then, an iterative method is proposed to solve the problem $\mathbf{P}_1$.

A. Clustering Approach and IRS-Assignment

While an exhaustive search can select the best users in each sub-band (i.e., clustering), such a search is unaffordable in a dense network, where the computational complexity exponentially increases with the number of users. Additionally, since there is a set of available IRS units, assigning the best IRS to each cluster of users is a complicated task that should also consider the unique characteristics of IRS units. Accordingly, a clustering strategy and IRS-assignment are proposed that capture the realistic conditions of the system. To be specific, the following critical facts about IRS-assisted NOMA-based systems are provided to shed more insight into the proposed clustering approach. First, since the users at each sub-band receive the reflected signal from the IRS unit, selecting users with higher correlation improves the quality of the received signal. Second, SIC is successfully implemented when the gain difference between user channels in each cluster is high [27]. Therefore, the proposed clustering takes into account the above key facts. With this, the correlation between users i and j with respect to $\mathfrak{I}_m$ can be defined as follows [28]:

$$\mathfrak{C}_{i,j,m} = \frac{|\mathbf{h}_{i,m}^H \mathbf{h}_{j,m}|}{||\mathbf{h}_{i,m}||\ ||\mathbf{h}_{j,m}||}. \tag{15}$$

The channel gain difference between users is given as [27]:

$$\mathfrak{D}_{i,j,m} = |10 \log |\mathbf{h}_{m,i}^H|^2 - 10 \log |\mathbf{h}_{m,j}^H|^2|. \tag{16}$$

Our clustering and IRS assignment searches for the users with the highest correlation in channel gains based on $\mathfrak{I}_m$ [16].

B. The Proposed Solution for $\mathbf{P}_1$

Considering the clustering strategy in the previous discussion, a comprehensive approach to solve $\mathbf{P}_1$ is now provided. In fact, most existing work uses AO to deal with the joint nature of the optimization parameters where the optimization parameters are alternatively evaluated until convergence. However, such an approach requires a longer computational time. Consequently, a single-stage iterative algorithm is proposed to solve the problem. Specifically, SCA is used to handle the non-convexity and joint nature of the problem, thus simultaneously evaluating the optimization parameters. In particular, each non-convex term (i.e., objective function or constraints) is approximated with a linear (i.e., convex-concave) term. The problem is then addressed using an iterative approach to obtain a sub-optimal solution with reasonable convergence. With this, a non-negative slack variable, namely λ, is inserted to approximate the objective function. Consequently, the optimization problem $\mathbf{P}_1$ can be formulated as follows:

$$\mathbf{P}_2 : \max_{\lambda, p_{i,m}, \theta_b} \quad \lambda \tag{17a}$$

$$\text{subject to} \quad R_{i,m} \geq -\frac{D}{ln(\gamma)\bar{T}_J^{(m)}}, \tag{17b}$$

$$\frac{\left(\sum_{m=1}^{M}\sum_{i=1}^{2} R_{i,m}\right)^2}{K\left(\sum_{m=1}^{M}\sum_{i=1}^{2} R_{i,m}^2\right)} \leq \lambda, \tag{17c}$$

$$\sum_{m=1}^{M}\sum_{i=1}^{2} p_{i,m} \leq P_t \tag{17d}$$

$$\left|h_{1,m} + \mathbf{h}_{m,1}^H \Theta_m \mathbf{g}_m\right|^2 \geq \left|h_{2,m} + \mathbf{h}_{m,2}^H \Theta_m \mathbf{g}_m\right|^2, \tag{17e}$$

$$p_{2,m} \geq p_{1,m}. \tag{17f}$$

Although the objective function of $\mathbf{P}_2$ is linear, the constraints (17b), (17c), and (17e) are non-convex. For the sake of simplicity of notation, it is assumed that $\mathbf{z}_{i,m} = [\mathbf{h}_{i,m}{}^H \text{diag}\ (\mathbf{g_m}), \quad h_{i,m}]$ [26]. Accordingly,

$$|h_{i,m} + \mathbf{h}_{m,i}{}^H \Theta_m \mathbf{g}_m|^2 = |\mathbf{z}_{i,m}\mathbf{r}_m|^2, \tag{18}$$

where $\mathbf{r}_m = [\beta_{m,1}e^{j\theta_{m,1}}, \ldots, \beta_{m,L}e^{j\theta_{m,L}}, 1]^T$.

To handle the non-convexity of (17b) and (17c), a set of slack variables is incorporated such as

$$R_{i,m} = B_m \log\left(1 + \text{SINR}_{i,m}\right) \geq \delta_{i,m}, \tag{19}$$

$${\delta_{i,m}}^2 \geq x_{i,m}, \tag{20}$$

$$\frac{\left(\sum_{m=1}^{M}\sum_{i=1}^{2} \delta_{i,m}\right)^2}{K\left(\sum_{m=1}^{M}\sum_{i=1}^{2} x_{i,m}\right)} \geq \lambda. \tag{21}$$

Accordingly, the non-convex constraint in (17b) can be replaced with the following convex constraint:

$$\delta_{i,m} \geq -\frac{D}{ln(\gamma)\bar{T}_J^{(m)}}. \tag{22}$$

Now, the slack variable $\zeta_{i,m}$ is introduced to deal with the non-convexity of (19), as follows:

$$\left(1 + \text{SINR}_{i,m}\right) \geq \zeta_{i,m}, \quad \zeta_{i,m} \geq 2^{\frac{\delta_{i,m}}{B_m}}. \tag{23}$$

Considering the assumption in (18), (23) can be rewritten as

$$\frac{p_{i,m}\left|\mathbf{z}_{j,m}\mathbf{r}_m\right|^2}{\sum_{k=1}^{i-1} p_{k,m}\left|\mathbf{z}_{j,m}\mathbf{r}_m\right|^2 + \sigma_{j,m}^2} \geq \zeta_{j,m} - 1, \quad i \in \{1,2\}, \forall m \in \mathcal{M}, j \leq i. \tag{24}$$

To address the non-convexity of the constraint (24), a set of slack variables is introduced as follows:

$$\left|\mathbf{z}_{j,m}\mathbf{r}_m\right|^2 \geq q_{j,m}^2, \ i \in \{1,2\}, \forall m \in \mathcal{M}, j \leq i, \tag{25}$$

$$p_{i,m}q_{i,m}^2 \geq \alpha_{j,i,m}, \ i \in \{1,2\}, \forall m \in \mathcal{M}, j \leq i, \tag{26}$$

$$\frac{\alpha_{j,i,m}}{\sum_{k=1}^{i-1}\alpha_{j,i,m} + \sigma_{j,m}^2} \geq \frac{\left(\zeta_{j,m} - 1\right)\beta_{j,m}^2}{\beta_{j,m}^2}. \tag{27}$$

The constraint in (27) can be divided into two parts as:

$$\alpha_{j,i,m} \geq \left(\zeta_{j,m} - 1\right)\beta_{j,m}^2, \forall m \in \mathcal{M}, j \leq i, \tag{28}$$

$$\sum_{k=1}^{i-1}\alpha_{j,i,m} + \sigma_{j,m}^2 \leq \beta_{j,m}^2, \forall m \in \mathcal{M}, j \leq i. \tag{29}$$

The constraints (28) and (29) are non-convex because of the non-convexity of the right-hand side for each of them. Accordingly, the first-order Taylor expansion is exploited to approximate the non-convex terms by lower linear (convex-concave) approximations. Specifically, the convex approximations of (28) and (29) can be, respectively, written as

$$\alpha_{j,i,m} \geq \left(\zeta_{j,m}^{(t)} - 1\right){\beta_{j,m}^{(t)}}^2 + 2\beta_{j,m}^{(t)}\left(\zeta_{j,m}^{(t)} - 1\right)\left(\beta_{j,m} - \beta_{j,m}^{(t)}\right) + {\beta_{j,m}^{(t)}}^2\left(\zeta_{j,m} - \zeta_{j,m}^{(t)}\right), \forall m \in \mathcal{M}, j \leq i, \tag{30}$$

$$\sum_{k=1}^{i-1}\alpha_{j,i,m} + \sigma_{j,m}^2 \leq {\beta_{j,m}^{(t)}}^2 + 2\beta_{j,m}^{(t)}\left(\beta_{j,m} - \beta_{j,m}^{(t)}\right), \quad \forall m \in \mathcal{M}, j \leq i, \tag{31}$$

where $\alpha_{j,i,m}^{(t)}$ is the t^{th} approximation of $\alpha_{j,i,m}$. Similarly, the non-convexity of the constraints (25) and (26) can approximated by the following convex constraints:

$$|\mathbf{z}_{i,m}\mathbf{r}_m^{(t)}|^2 + 2|\mathbf{z}_{i,m}\mathbf{r}_m^{(t)}| \left[\Re\left(\mathbf{z}_{i,m}\mathbf{r}_m\right) - \Re\left(\mathbf{z}_{i,m}\mathbf{r}_m^{(t)}\right), \ \Im\left(\mathbf{z}_{i,m}\mathbf{r}_m\right) - \Im\left(\mathbf{z}_{i,m}\mathbf{r}_m^{(t)}\right)\right] \geq \left(q_{i,m}^{(t)}\right)^2 + 2\left(q_{i,m}^{(t)}\right)q_{i,m} - (q_{i,m}^{(t)}), \tag{32}$$

$$p_{j,m}^{(t)}\left(q_{i,m}^{(t)}\right)^2 + 2p_{j,m}^{(t)}\left(q_{i,m}^{(t)}\right)q_{i,m} - (q_{i,m}^{(t)}) + \left(q_{i,m}^{(t)}\right)^2(p_{j,m} - (p_{j,m}^{(t)})) \geq l_{j,i,m}. \tag{33}$$

With the multiple slack variables, the non-convex constraints (23) can be replaced with the following convex constraints,

$$(19) \equiv \left\{(30),\ (31),\ (32),\ (33)\right\}. \tag{34}$$

To address the non-convexity of the constraint (20), the left-hand side is approximated with a convex approximation through a first-order Taylor expansion:

$${\delta_{i,m}^{(t)}}^2 + 2\delta_{i,m}^{(t)}\left(\delta_{i,m} - \delta_{i,m}^{(t)}\right) \geq x_{i,m}. \tag{35}$$

Similarly, the non-convexity of (21) is addressed as follows:

$$\frac{\left(\sum_{m=1}^{M}\sum_{i=1}^{2} \delta_{i,m}\right)^2}{K\left(\sum_{m=1}^{M}\sum_{i=1}^{2} x_{i,m}\right)} \geq \frac{\lambda y^2}{y^2}. \tag{36}$$

The constraint (36) can be divided into two inequalities:

$$\left(\sum_{m=1}^{M}\sum_{i=1}^{2} \delta_{i,m}\right)^2 \geq \lambda y^2, \text{ and } K\left(\sum_{m=1}^{M}\sum_{i=1}^{2} x_{i,m}\right) \leq y^2. \tag{37}$$

The first-order Taylor expansion is used to write the lower approximations of the two constraints in (37) as follows:

$$\left(\sum_{m=1}^{M}\sum_{i=1}^{2}\delta_{i,m}\right) \geq \sqrt{\lambda^{(t)}}y^{(t)} + \sqrt{\lambda^{(t)}}\left(y - y^{(t)}\right) + \frac{1}{2\sqrt{\lambda^{(t)}}}y^{(t)}\left(\lambda - \lambda^{(t)}\right), \tag{38}$$

$$K\left(\sum_{m=1}^{M}\sum_{i=1}^{2}x_{i,m}\right) \leq y^{(t)2} + 2y^{(t)}\left(y - y^{(t)}\right). \tag{39}$$

Considering the above multiple slack variables incorporation, the objective function of the original FIM problem, i.e., $\mathbf{P}_1$, can be approximated as follows:

$$\text{(14a)} = \begin{cases} \max.\ \lambda \\ \text{subject to } (30)-(33),\ (35),\ (38),(39). \end{cases} \tag{40}$$

On the other hand, the constraint expressed in (17e) can be accurately represented by a convex constraint as follows:

$$\left(q_{1,m}^{(t)}\right)^2 + 2\left(q_{1,m}^{(t)}\right)\left(q_{1,m} - q_{1,m}^{(t)}\right) \geq \left(q_{2,m}^{(t)}\right)^2 + 2\left(q_{2,m}^{(t)}\right)\left(q_{2,m} - (q_{2,m}^{(t)}\right), \forall m. \tag{41}$$

Considering the above approximations of the objective function and constraints, the non-convex FIM problem $\mathbf{P}_1$ can be approximated by a convex optimization problem as:

$$\mathbf{P}_3 : \max_{\Lambda}.\quad \lambda \tag{42a}$$
$$\text{subject to } (14c),\ (14e), (30),\ (31),\ (33), \tag{42b}$$
$$(22),\ (33),\ (35),\ (38), (39),\ (41), \tag{42c}$$

where Λ represent the set of optimization parameters, i.e., $\Lambda = \{\lambda, p_{i,m}, \theta_m, \zeta_{j,m}, \delta_{i,m}, x_{i,m}, q_{j,m}, \beta_{j,m}, y, l_{j,i,m}\}$. With this, the original S-FIM problem can be solved iteratively by solving the approximate optimization problem $\mathbf{P}_3$. The iterative algorithm is run until convergence, which is achieved when the absolute difference between two successive solutions is less than a predetermined limit, i.e., $|\lambda^{(t+1)} - \lambda^{(t)}| \leq \epsilon$.

C. Initial Values Selection

Since $\mathbf{P}_3$ is solved iteratively, it is crucial to select the appropriate initial values. In particular, selecting arbitrary initial values could affect the convergence and feasibility of the problem. Accordingly, a simple approach is provided to select the initial values. First, transmission power levels are chosen that meet the maximum power budget limitations. This can be achieved by solving the following problem:

$$\mathbf{P}_3 : \underset{p_{i,m}^{(0)}}{\text{Find}}\quad p_{i,m}^{(0)}, \forall i, \forall m \tag{43a}$$
$$\text{subject to } \sum_{m=1}^{M}\sum_{i=1}^{2}p_{i,m}^{(0)} \leq P_t, \tag{43b}$$
$$p_{2,m}^{(0)} \geq p_{1,m}^{(0)}. \tag{43c}$$

The analysis starts by evaluating the initial slack variables by substituting these initial power values into the definitions of the slack variables. For example, $\delta_{i,m}^{(0)} = B_m \log(1 + \text{SINR}_{i,m})$, where $\text{SINR}_{i,m}$ can be evaluated by substituting $p_{i,m}{}^{(0)}$ into (4), (5), and (6). Similarly, $x_{i,m}^{(0)} = \delta_{i,m}^{(0)}2$. The remaining initial slack variables can be found using the same methodology.

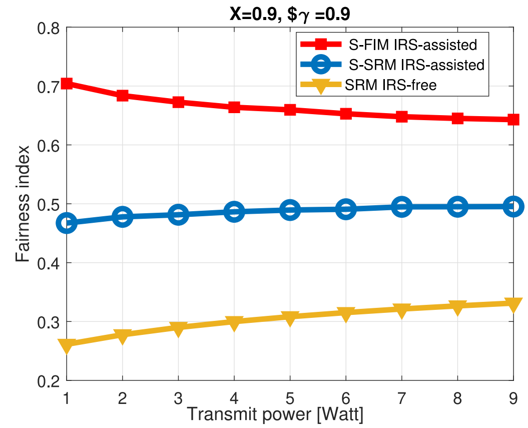

Fig. 2. FI performance versus transmit power for different resource allocations.

IV. Simulation Results

This section illustrates the superior efficacy of the proposed S-FIM resource allocation technique through extensive MATLAB simulation experiments, comparing its performance with two benchmark approaches:

1. A jamming-aware secure SRM (S-SRM) for the IRS-assisted OFDMA-NOMA system: This approach is a variant of S-FIM, but is designed to maximize the achieved sum rate in the IRS-assisted OFDMA-NOMA system. In particular, R_{sum} is maximized under the same constraints.
2. Jamming Unaware Sum-rate Maximization for the IRS-free OFDMA-NOMA system (SRM IRS-free): In this benchmark scenario, a traditional jamming-unaware hybrid OFDMA-NOMA system without any IRS support is considered, where an SRM problem is formulated in this context.

A. Simulation Setup

This simulation assumes that a set of 10 CEDs, $N = 10$, is randomly distributed within a circular field with a diameter of 40 meters. The bandwidth is 10 MHz, i.e., $B = 10$ MHz. Additionally, the IRS units are also located within the network area. Furthermore, the number of IRS elements is set to 16 elements, that is, $L = 16$. On the other hand, the noise variance is assumed to be 10^{-9} watt. The average jamming periods for the various sub-bands are configured as 50, 100, 30, 45, $50\times X$ ms, where $0 \leq X \leq 1$ represents the jamming severity factor. The transmission power is set to $P_{\max}$ and the packet size D to 2-KB. Our main performance metrics are the network sum rate, FI, and the number of dropped users. These metrics are evaluated at different levels of jamming severity and transmit power levels. Simulation experiments are carried out using the MATLAB R2019 programs and the CVX toolbox.

B. Simulation Results

Figure 2 illustrates the FI as a function of transmission power for the S-FIM IRS-assisted, S-SRM IRS-assisted, and SRM IRS-free resource allocation techniques under a jamming severity factor of $X = 0.9$ and a success probability

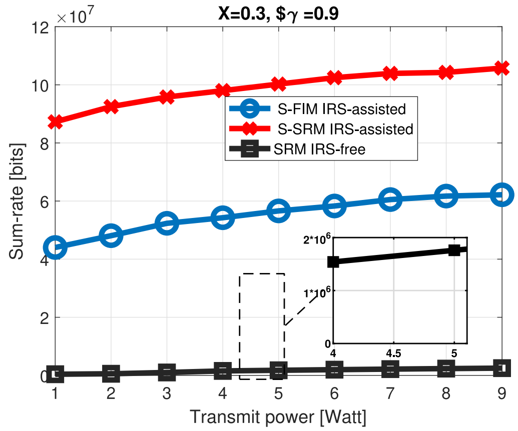

Fig. 3. The achieved sum rate for the proposed FIM against transmit power for different resource allocation techniques.

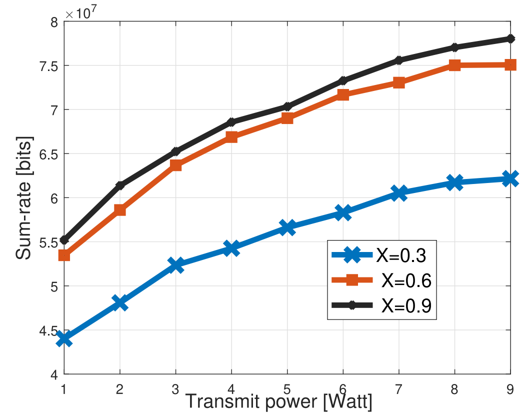

Fig. 4. Sum rate versus the transmit power for various jamming levels X.

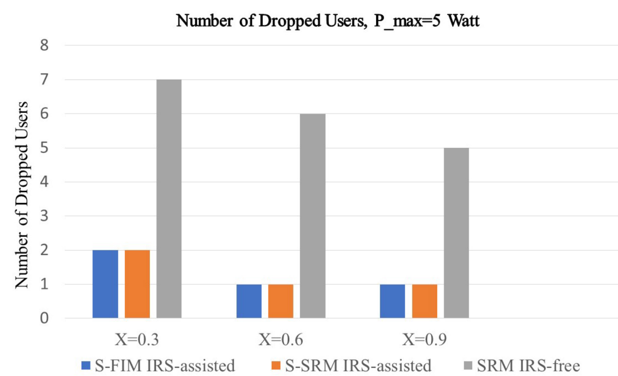

Fig. 5. Number of the dropped users for different designs.

requirement of $\gamma = 0.9$. As demonstrated in Fig. 2, the proposed S-FIM resource allocation method surpasses the other designs in terms of FI, regardless of transmission power. Specifically, an FI of 0.7 is achieved in the proposed S-FIM design, while it is almost 0.2 for the S-SRM IRS-assisted design. This shows that the proposed S-FIM technique is superior when considering fairness as a performance metric.

Figure 3 compares the sum rates achieved using our proposed S-FIM IRS-assisted, S-SRM IRS-assisted, and conventional SRM IRS-free resource allocation techniques. These comparisons are made with a jamming severity factor of $X = 0.3$ and $\gamma = 0.9$. It is evident from the figure that the proposed jamming-aware designs significantly outperform the conventional SRM IRS-free design. This superior performance is because our designs consider the presence of jamming activities and adapt the transmission parameters to ensure compliance with the probability of success requirement. As expected, IRS-assisted S-SRM surpasses the proposed S-FIM and the traditional IRS-assisted SRM design in terms of the total sum rate achieved. This superiority can be attributed to S-SRM, which primarily aims to maximize overall system throughput without considering the rate achieved for individual users. Consequently, the S-SRM resource allocation technique tends to allocate a larger portion of the power budget to users with more favorable channel conditions, leading to a higher overall sum rate. On the other hand, S-FIM prioritizes fairness among users. This objective of fairness is accomplished by allocating higher power levels to users with less favorable channel conditions. Consequently, the overall sum rate of the IRS-assisted S-FIM resource allocation technique is reduced.

Fig. 4 shows the sum rate of the proposed S-FIM design as a function of transmission power for different levels of jamming severity X and $\gamma = 0.9$. Three severity levels of jamming are simulated: $X = 0.3, 0.6$, and 0.9, which have high, moderate, and light jamming activities, respectively. Figure 4 illustrates that the performance of the sum rate is superior at higher values of X, which corresponds to lighter jamming attacks. This outcome aligns with expectations because lower values of X, indicative of more severe jamming attacks, increase the probability of transmission corruption (dropped transmissions) due to jamming. Finally, in Figure 5, the number of dropped transmissions attributed to jamming for the three resource allocation designs is presented under the jamming severity of $X = 0.3, 0.6, 0.9$, and $\gamma = 0.8$. Figure 5 reveals that jamming-aware designs outperform conventional SRM IRS-free design by minimizing the number of dropped transmissions. Specifically, compared to the conventional SRM IRS-free design, the proposed jamming-aware designs significantly reduce the number of dropped transmissions, with reductions of 7 to 2, 6 to 1, and 5 to 1 transmissions for $X = 0.3, 0.6$, and 0.9, respectively. This reduction remains consistent across all types of CE-IoT devices, as they utilize the same proposed jamming-aware communication design and are assumed to be equipped with the same communication capabilities. Therefore, regardless of the device type, the proposed jamming-aware designs consistently improve the system performance in terms of the number of dropped transmissions. This performance improvement can be attributed to the jamming-aware nature of our proposed designs, which seek to meet the specified success probability requirement and reduce the number of failed transmissions. Figure 5 further shows that as the severity of jamming increases (corresponding to lower values of X), the number of packets dropped increases in all designs. However, it is evident that our proposed designs consistently achieve the specified success probability requirements.

V. Conclusion

This paper introduced a resource allocation technique that prioritizes fairness and considers the presence of proactive jamming attacks within an IRS-assisted hybrid

OFDMA-NOMA system. The primary goal of this technique is to maximize the fairness between the simultaneously served users while considering the impact of jamming attacks and satisfying a set of design constraints. The jamming-aware fairness maximization problem was mathematically formulated, which turned out to be a joint non-convex optimization. Therefore, an iterative algorithm was proposed to solve the formulated problem and thus evaluate the optimization parameters. The simulation results revealed that S-FIM IRS-assisted techniques outperformed the conventional SRM IRS-free design in terms of fairness and sum-rate performance at different jamming levels. The results also demonstrated that incorporating jamming awareness into resource allocation designs leads to substantial enhancements in network throughput, fairness, and a reduction in the number of dropped packets. As future work, we intend to expand our investigation to include other jamming types, including reactive, smart, sweep, and selective jamming scenarios. Such expansion will enhance the proposed technique's effectiveness in mitigating various threats in connected CE devices. Additionally, another important research direction involves the development of a testbed comprising a network of CE devices to experimentally verify the efficacy of the proposed jamming-aware resource allocation technique.

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