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Adaptive Resource Allocation and Mode Switching for D2D Networks With Imperfect CSI in AGV-Based Factory Automation

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ABSTRACT In industrial factory automation and control system, reliable communication for automated guided vehicles (AGVs) in dynamic, interference laden factory settings are essential particularly for real-time operations. Device-to-device (D2D) technology can enhance industrial network performance by offloading traffic and improving resource utilization. However, deploying D2D-enabled networks presents challenges such as interference control and imperfect channel state information (ICSI). In this paper, we investigate an adaptive resource allocation and mode switching strategy (ARAMS) in D2D-enabled industrial small cell (SC) networks with ICSI to maximize the system throughput and address reuse interference for AGVs. The ARAMS scheme integrates mode switching (MS), channel-quality factor (CQF), and power control (PC) within a bi-phasic resource-sharing (RS) algorithm to lower the computational complexity. In the initial phase, the operational mode for each D2D user (DU) per cell is adaptively selected based on the channel gain ratio (CGR). Subsequently, it computes the CQF for each cell with a reuse DU to identify an optimal reuse partner. The final phase employs the Lagrangian dual decomposition method to decide the DU's and industrial cellular users (CUs) optimum distributed power to maximize the system throughput under the interference constraints. The numerical results show that as channel estimation error variance (CEEV) increases, the ARAMS scheme consistently outperforms other approaches in maximizing system throughput, except for the AIMS scheme.

INDEX TERMS Channel quality factor (CQF), D2D users, interference-control (IC), imperfect channel state information (ICSI), mode switching (MS), channel estimation error variance (CEEV).

I. INTRODUCTION

The rapid advancement of Industry 4.0 and industrial Internet of Things (IIoT) networks has led to an exponential increase in automated guided vehicle (AGV) and connected devices within factory environments. AGV enhance productivity and efficiency by automating material handling and transportation tasks. However, ensuring reliable, low latency communication for AGVs is essential for seamless operation in dynamic, and interference-prone industrial settings. One solution that has shown promise is the deployment of device-to-device (D2D)-enabled networks. These networks offer an effective and reliable means to enhance network capacity, efficiency, and user experience in industrial settings. Smart devices, including sensors and actuators, have proven highly beneficial in closed-loop control systems. In industrial warehouses, sensors are integral to AGVs for route optimization, collision avoidance, and task coordination. These sensors enable AGVs to collect real-time data, facilitating informed decisions and dynamic responses to environmental changes. As a result, AGVs equipped with proximity sensors can share real-time data on their movements while navigating through the warehouse. Thus, enhancing efficiency, safety, and adaptability in industrial applications.

Direct data transmission to a central controller via D2D communication, especially in dynamic and fluctuating network environments, enhances efficiency and reliability by bypassing traditional network infrastructure. Dedicated small cells, such as femtocells, can support AGV communication via D2D links, effectively managing the challenges posed by a high density of connected smart devices [1]. Integrating small cell (SC) networks within the 5G framework further enhances AGV operations, ensuring both efficiency and reliability. However, practical challenges, like interference, suboptimal resource allocation and imprecise channel state information (CSI), can adversely affect D2D communication and system performance. Consequently, we investigate system performance using the adaptive resource allocation and mode switching (ARAMS) scheme, taking into account the optimal reuse resources, operational modes (i.e., cellular or D2D mode) of all potential D2D users (DUs), and improved quality of service (QoS) for cellular users (CUs) and DUs under channel uncertainty.

Current research on D2D-enabled SC networks predominantly addresses scenarios either perfect CSI [2] or imperfect CSI (ICSI) including estimation error [3] to mitigate interference. For instance, [3] employs a stochastic single-cell network model to optimize coverage probability and cellular user rate while maximizing the number of scheduled D2D links. The research goal is achieved through the use of centralized and distributed power control strategies under the condition of channel uncertainty. [4] investigates two D2D communications strategies: probabilistic and partial feedback schemes including channel uncertainty. The goal is to examine the equilibrium between signaling overhead and performance while optimizing the system sum rate of CUs and permissible DUs. [5] considers a D2D-enabled heterogeneous network (HetNets) including ICSI to manage interference challenges among different tiers sharing the same spectrum. To improve the system performance under ICSI conditions, the authors evaluated the performance impact of channel estimation error variance (CEEV) on both CUs and DUs within the networks without considering mode switching (MS) or channel quality factor (CQF) (a fundamental feedback principle required for reliable and efficient D2D links. In [6], energy-aware schemes for joint power and mode selection (MS) are implemented for D2D and cellular links to reduce transmission power and optimize mode operation, thereby improving overall system performance. In [7], a D2D downlink power control scheme using geometric analysis and convex optimization is proposed to enhance system sum rate under ICSI. [8] examines power reliability control issues within cellular networks, considering two channel uncertainty sets-ellipsoidal and column-wise for user and network-centric approaches. The work aimed to maximize energy efficiency for both CUs and DUs through a Stackelberg game approach. However, most existing schemes lack real-time adaptability and primarily focus on power control (PC) without incorporating joint interference constraints, MS, and CQF [9], which limits potential improvements in data transmission. Integrating joint interference constraints, MS, and CQF could lead to optimized resource allocation, adaptive system configuration, enhanced interference management, improved QoS, and maximized system throughput. Failing to account for these factors may result in suboptimal performance, higher interference, and inefficient resource utilization, ultimately compromising the reliability and communication quality of D2D-enabled networks.

Building on insights from previous studies [3] and [5], this paper presents ARAMS as a solution to enhance resource allocation, increase network throughput, and address interference challenges in industrial D2D-enabled small cell networks with ICSI. The ARAMS scheme is specifically designed to adapt to the dynamic nature of the network environment such as channel variability and limited feedback, which is highly relevant to industrial factory automation, where real-time communication, ultra-reliable low-latency (URLLC) performance, and high-density device connectivity are crucial. Unlike [3] and [5], which primarily focused on PC and interference management, respectively, ARAMS integrates joint interference constraints, MS, and CQF to optimize resource allocation. In industrial environments, stable communication is critical for ensuring uninterrupted operations of automated production lines and real-time monitoring systems. The MS allows the network to dynamically switch between D2D and cellular modes based on real-time channel conditions, ensuring optimal throughput and latency for common time-sensitive tasks in factory settings. The CQF plays a crucial role in selecting the most appropriate reuse channel link, particularly in reuse mode (RM), where multiple devices share spectrum resources. CQF continuously monitors channel impairments and makes necessary adjustments to transmission parameters, enhancing data rate and reliability. The CQF adaptive mechanism is crucial in industrial settings where environmental factors, such as interference from heavy machinery, can disrupt communication. Maintaining a high CQF helps ensure uninterrupted, low-latency communication, crucial for factory automation processes (where delays could lead to costly downtimes), data rate and reliability by adjusting parameters based on current channel conditions. The distributed power allocation mechanism, based on Lagrangian decomposition, further optimizes network sum rate and reduces interference, making ARAMS ideal for industrial applications.

The ARAMS scheme facilitates communication between potential DUs and the small cell base stations (SMBSs), adapting to network conditions either through D2D mode or via SMBS. The scheme operates under a distributed architecture, where the macro eNode base station (MeNB) plays a coordinating role in interference control and spectrum reuse among the SMBSs. The distributed approach ensures efficient system performance by allowing the MeNB to manage interference power coordination and resource allocation (RA) across the network. Each SMBS estimates neighboring SMBSs' ICSI through transmitted pilot signals under channel uncertainty and feedback from users. The MeNB leverages this information to perform interference coordination and resource allocation among SMBSs, ensuring that each SMBS receives its allocated resource blocks. Subsequently, the SMBS uses these resources to perform MS and allocate resources and power to associated users, ensuring fairness and efficient spectrum utilization.

In addition, the proposed ARAMS approach is adaptive, aiming to optimize frequency orthogonality and spectrum reuse among SMBSs. This adaptability is vital in industrial factory automation where multiple wireless sensors, machine-to-machine (M2M) communication, and even vehicular ad-hoc networks (VANETs) are increasingly integrated for applications like safety monitoring, traffic management, and infotainment services. Our scheme differs from the traditional centralized technique, hindered by high overhead and latency. ARAMS is a purely distributed scheme with decentralized decision-making, specifically designed for adaptive, distributed environments such as smart factories and automated production lines. The decentralized structure enables ARAMS to manage interference, efficiently allocate resources, and switch modes seamlessly, effectively meeting the real-time, reliable communication demands of industrial systems.

The article's contributions are outlined as follows:

1) We designed a distributed 5G-based architecture for industrial D2D-enabled SMBSs, incorporating the ARAMS scheme under imperfect channel state information to maximize system throughput while enabling communication with the MeNB for RA and interference coordination.
2) We classified the problem as NP-hard due to resource sharing (RS) and decomposed the optimization into bi-phasic segments to reduce the computational complexity of the system. The initial phase computes the DU's operation mode per SMBS based on the channel gain ratio (CGR) in both cellular mode (CM) and reuse mode. The CQF is then calculated for DUs in the RM to choose a prospective reuse partner with improved QoS management. The final phase achieves an optimal distributed power by iteratively solving PC using the Lagrangian decomposition-dual method.
3) We extensively evaluated the proposed ARAMS approach against existing schemes via simulations. The simulation results reveal that as the channel estimation error variance increases, the proposed ARAMS surpasses existing methods to maximize the system throughput, except for the AIMS scheme.

The paper's organization is as follows: In Section II, the system model and problem formulation are introduced. Section III outlines the procedures of the ARAMS scheme. In Section IV, the numerical results are presented, and the paper is concluded in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

Fig. 1 shows a 5G D2D-enabled SCs uplink transmission for an industrial network, where $\mathcal{N}$ SMBSs are deployed with the MeNB in HetNet. The SMBSs share a frequency bandwidth, $\mathcal{F}_s$, that is distinct from the frequency bandwidth $\mathcal{F}_m$ allocated

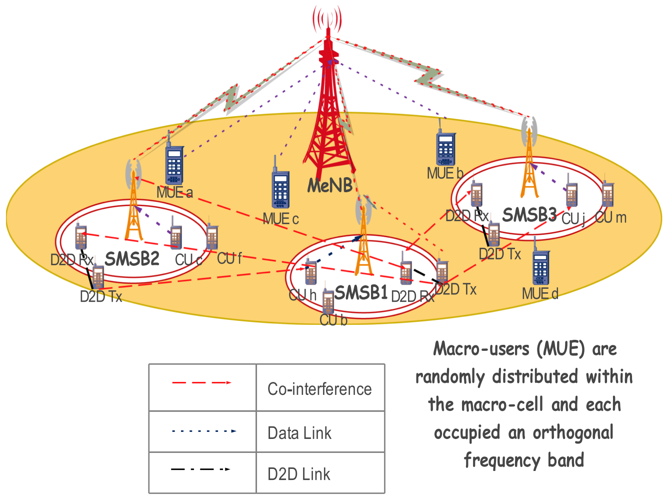


FIGURE 1. System model [2].

to the MeNB. For control information sharing, each SMBS establishes a connection with the centralized MeNB through the $\mathcal{X}2$ interface. We assume that each DU and CU is equipped with multiple antenna technologies to support advanced applications. This aligns with the current state-of-the-art in 5G and beyond networks, and reflects the potential benefits of leveraging multiple antennas to enhance overall system performance. To ensure fairness among all users, multiple interference sources (i.e., cross-tier and co-tier) are mitigated adaptively to limit the adverse effect on the DU's reuse channel condition. Denote $\mathcal{N} = \{1, 2, .., n\}$ as the SMBSs' set, and each SMBS $i \in \mathcal{N}$ is associated with a subchannel set $\mathcal{S}_i$ containing $|\mathcal{S}_i| = \ell$ orthogonal frequencies chosen from the total subchannel set $(\mathcal{L}(\mathcal{S}_i \subseteq \mathcal{L}))$ in a frequency division duplexing (FDD) access mode. Each SMBS $i \in \mathcal{N}$ subchannel $(r \in \mathcal{S}_i)$ supports $\mathcal{Y}_i$ orthogonal CUs and a D2D pair[1], u. Let $\mathcal{Y} = \{\mathcal{Y}_i | i = 1, 2, \ldots, yi\}$ and $u_i = 4\mathcal{Y}_i$ per SMBS. The CUs are limited to cellular communication mode only and the D2D user supports dual operation as: cellular mode or D2D mode relative to mode variable, Ψ_j value. Denote $\mathcal{K}_c$ and $\mathcal{K}_d$ as the CUs set and D2D pairs set, respectively, where $\mathcal{K}_d = \{u_j | j = 1, 2, \ldots, \mathrm{u}\}$ and $\mathcal{K}_d = \mathcal{N}$. In the cellular mode (CM), D2D transmitters receive extra orthogonal spectrum resources from the base station to establish communication with their receivers, thereby preventing interference with conventional CUs. Conversely, in the RM, DU transmitters transmit directly to the receivers, sharing spectrum resources with CUs to improve spectral efficiency. However, this approach causes more interference with reuse partners.

To minimize interference and optimize RS, a CQF Ω is introduced to achieve an optimum reuse partner for the D2D pair. Ψ_j is the mode decision variable, where $\Psi_j = 1$ indicates the RM and $\Psi_j = 0$ indicates the CM. Assume $\mathcal{K}_d^j$ and $\mathcal{K}_c^i$ represents D2D sets in the RMs and CMs, respectively. Additionally, a resource decision variable, $\rho_{i,j}$ is introduced to

[1] The D2D pair comprises a transmitter and a receiver.

signify if resources are shared between the CU i and D2D pair j or not, with $\rho_{i,j} = 1$ indicating reuse and $\rho_{i,j} = 0$ indicating non-reuse. Independent block fading is assumed for all links, and the channel power gain, $g_{i,\mathcal{N}}$, between CU i and the SMBS is modeled under ICSI due to the dynamic nature of wireless channel as:

$$g_{i,N} = \left|h_{i,N}\right|^2 \beta_{i,N} \tag{1}$$

where $h_{i,\mathcal{N}}$ is the small fading coefficient, assumed to be identically distributed and independent (i.i.d) as $\mathcal{CN}(0, 1)$, and $\beta_{i,\mathcal{N}}$ determines the large fading effect including the pathloss and shadowing. We assume imperfect CSI at the transmitter and utilize a minimum mean square error (MMSE) estimation to acquire the estimate $\hat{h}$. Thus, the fading model is expressed as:

$$h_{i,N} = \sqrt{1-\alpha}\hat{\mathrm{h}}_{i,N} + \sqrt{\alpha}\tilde{\mathrm{h}}_{i,N} \tag{2}$$

where $\hat{h}_{i,\mathcal{N}}$ is the estimate of $h_{i,\mathcal{N}}$, and $\widetilde{h}_{i,\mathcal{N}}$ denotes the estimation error, which is independent of $\hat{h}_{i,\mathcal{N}}$. We assumed both followed a $\mathcal{CN}(0, 1)$. The parameter α, takes a value between 0 and 1, and represents the variance of the CEEV. The case $\alpha = 0$ implies that the CSI is perfect and when $\alpha = 1$, it indicates that the estimated channel is incorrect. In the latter scenario, the receiver must decode the received signal in a non-coherent manner, and the anticipated power is exclusively influenced by the pathloss.[2] Table 1 list all the notations used. We define the channel links $g_{i,j}$, $g_{j,\mathcal{N}}$, and g_j as the channel link between the CU i and the D2D pair j, the D2D pair j and SMBS, and between the D2D's transmitter and its receiver, respectively. For SMBS $i \in \mathcal{N}$, the signal-to-interference-plus-noise ratio (SINR), Υ_i^y for CU on subchannel ($r \in \mathcal{S}_i$) is expressed as [2]:

$$\Upsilon_i^y = \frac{P_i^c \mu_{i,N}^c}{\underbrace{P_i^c \nu_{i,N}^c + N_0}_{N_1} + \sum_{j\in K_d^j} \rho_{i,j} P_j^d \theta_{j,N}^d}, \forall i \in y_i \tag{3}$$

Knowing $|\tilde{h}_{i,\mathcal{N}}|^2 = 1$, Let $\mu_{i,\mathcal{N}}^c = (1-\alpha)|\hat{h}_{i,\mathcal{N}}|^2 \beta_{i,\mathcal{N}}$, $\nu_{i,\mathcal{N}}^c = \alpha\beta_{i,\mathcal{N}}$ and $\theta_{i,\mathcal{N}}^c = \mu_{i,\mathcal{N}+}^c \nu_{i,\mathcal{N}}^c$. Approximating $|\tilde{h}_{i,\mathcal{N}}|^2 = 1$ helps average out channel uncertainties by normalizing the error magnitude, thereby neglecting random variations in channel uncertainty. This assumption simplifies the analysis of adaptive resource allocation and interference management.

Consequently, if the DU utilizes the D2D pairs' resources in the CM, the SINR of the D2D pair in both the cellular mode, $\Upsilon_{j,0}^d$, and reuse mode $\Upsilon_{j,1}^d$, is expressed as:

$$\Upsilon_{j,0}^d = \frac{P_{j,0}^d \mu_{j,N}^d}{\underbrace{P_{j,0}^d \nu_{j,N}^d + N_0}_{N_0} + \sum_{i\in K_d^j, i\neq j} \rho_{i,j} P_i^d \theta_{i,N}^d}, \forall j \in K_c^i \tag{4a}$$

$$\Upsilon_{j,1}^d = \frac{P_{j,1}^d \mu_{j,1}^d}{\underbrace{P_{j,1}^d \nu_{j,N}^d + N_0}_{N_2} + \sum_{i\in K} \rho_{i,j} P_i^d \theta_{i,j}^c + \sum_{i\in K_c} \rho_{i,j} P_i^c \theta_{i,j}^c},$$
$$\forall j \in K_d^j \tag{4b}$$

TABLE 1. Notations

$\mathcal{N}$	Number of SMBSs
$\mathcal{F}_s$	Allocated frequency bandwidth of all SMBSs
$\mathcal{F}_m$	Frequency bandwidth of MeNB
$\mathcal{X}2$	Interface used for information coordination and control between SMBSs and MeNB
$\mathcal{S}_i$	Subchannel resource set for each SMBS
L	Total subchannel resource sets allocated to all SMBSs
r	Subchannel assigned to a CU
$\mathcal{Y}_i$	Number of CUs per SMBS
u	D2D pair per SMBS
$\mathcal{K}_d$	Total number of D2D pairs
$\mathcal{K}_c$	Total number of CUs
Ω	Channel-quality factor
Ψ_j	Mode decision variable
$\mathcal{K}_d^j$, $\mathcal{K}_c^i$	D2D pair sets in reuse mode (RM) and cellular mode (CM), respectively
$\rho_{i,j}$	Resource decision variable that indicates if resources are shared between the CU and D2D pair or not
$g_{i,\mathcal{N}}$	Channel power gain from the CU to SMBS
$h_{i,\mathcal{N}}$, $\hat{h}_{i,\mathcal{N}}$	Small fading coefficient and its' estimate from the CU to the SMBS
$\beta_{i,\mathcal{N}}$	Large fading effect including the pathloss and shadowing.
α	Channel estimation error variance (CEEV)
N_o	Gaussian white noise power
r_{max}	Maximum distance between D2D's transmitter and its receiver
P_j^d, P_i^c	D2D pair and CU transmit powers, respectively
I_o, I_1	Cross-tier and Co-tier interference Thresholds
Φ_i^c	D2D mode decision variable for cellular mode
Φ_j^d	D2D mode decision variable for reuse mode
$\pi_i^c, \pi_{j,0}^d, \pi_{j,1}^d$,	Channel-to-interference-plus-noise ratio

[2]NB: $P_i^c \nu_{i,\mathcal{N}}^c$, $P_{j,0}^d \nu_{j,\mathcal{N}}^d$, and $P_{j,1}^d \nu_{j,1}^d$ are the received noisy signals from the respective received signals and as such, the receiver decodes as background noise (AWGN) as presented in (8). Again, Both the transmitter and receiver are presumed to possess knowledge of the estimate $\hat{h}_{i,\mathcal{N}}$, and $|\hat{h}_{i,\mathcal{N}}|^2 \sim \mathcal{CN}(0, 1)$.

Therefore, the combined SINR, $\Upsilon^d_{j,\Phi_{j\epsilon(0,1)}}$ of the D2D pair is reformulated as follows:

$$\Upsilon^d_{j,\Phi_{j\epsilon(0,1)}} = \Phi_j \Upsilon^d_{j,\Phi_j} + \left(1 - \Phi_j\right) \Upsilon^d_{j,\Phi_j}, \forall j \in K^j_d \cup K^i_c \quad (5)$$

where P^d_j and $\mathrm{P}^c_{\mathrm{i}}$ denotes the D2D pair j and CU i transmit powers, respectively, and N_o is the Gaussian white noise power. To mitigate reuse interference, the system assumes that the distance between the DU's transmitter and receiver is no more than $r_{\max}$, and that the uncertainty in the channel $(\tilde{h}_{i,\mathcal{N}})$ is averaged out.

The ARAMS scheme also addresses the AGV's mobility and the dynamic nature of the communication environment by incorporating ICSI, real-time mode switching, channel gain factor for proximity-based communication, interference management, and iterative optimization. These features enable dynamic updates to resource allocation and power control decisions, ensuring reliable communication even under changing conditions.

B. PROBLEM FORMULATION

In industrial SMBS networks, we maximize the system throughput by formulating an optimization problem that jointly optimizes the reuse channel quality selection (RCQS), MS, and power control based on the QoS satisfaction of users (i.e., both CUs and DUs) under interference (cross-tier and co-tier) constraints and ICSI. As such, the optimization problem (P1) is expressed as follows:

$$\begin{aligned} &P1{:}\, max \left[\mathrm{Z}_{\Phi_j, \rho_{i,j}, P^d_{j,0}, P^d_{j,1}, P^c_i} \right] \\ &= \sum_{i\in N} \sum_{r\in S_i} \sum_{u_j \in K^i_c \cup K^j_d} \log_2 \left(1 + \Upsilon^d_{j\Phi_j}\right) \\ &\quad + \sum_{i\in N} \sum_{y_i \in K_c} \log_2 \left(1 + \Upsilon^y_i\right) \end{aligned} \quad (6)$$

$$\text{s.t.} \begin{cases} D1: \Upsilon^y_i \geq \Upsilon^y_{\mathrm{imin}}, \forall i \in y_i, \\ D2: \Upsilon^d_{j,1} \geq \Upsilon^d_{\mathrm{jmin}}, \forall j \in K^j_d, \\ D3: \Upsilon^d_{j,0} \geq \Upsilon^y_{\mathrm{imin}}, \forall j \in K^i_c \\ D4: \sum_{i\in N} \sum_{j\in K^j_d} \rho_{i,j} \leq 1, \forall i \in \left\{K_c \cup K^i_c\right\} \\ D5: \sum_{i\in N} \sum_{i\in(K_c \cup K^i_c)} \rho_{i,j} \leq 1, \forall j \in K^j_d \\ D6: P^d_{j,1} \theta^d_{j,N} \leq \sum_{i\in y_i} I_o, \forall r \in S_i, \\ D7: \sum_i \in N \sum_{j\in K^j_d} P^d_{j,1} \theta^d_{j,N} \leq \sum_{i\in N} \sum_{i\in K_c \cup K^i_c} I_1, \forall i \in N \\ D8: \sum_{S_i \in L} P^c_i \leq P^c_{\max}, \forall i \in y_i, \\ D9: \sum_{S_i\in L} P^d_{j,1} \leq P^d_{\max} \forall j \in K^j_d \\ D10: \sum_{S_i\in L} P^d_{j,0} \leq P^c_{\max} \forall j \in K^i_c, \\ D11: \sum_{j\in K_d} \Psi_j \leq Q, \\ D12: \rho_{i,j} \in \{0, 1\}, \forall i \in K_c, \forall j \in K^j_d \end{cases} \quad (7)$$

$$I_o = \frac{P^c_i \mu^c_{i,N}}{\Upsilon^y_{\mathrm{imin}}} - N_1, I_1 = \frac{\sum_{i\in K_c \cup K^i_c} \left(P^c_i + P^d_i\right) \mu^c_{i,N}}{\Upsilon^y_{\mathrm{imin}}} - N_1,$$

$$N_1 = P^c_i \nu^c_{i,N} + N_0, N_2 = P^d_j \nu^d_{j,N} + N_0 \quad (8)$$

The objective function Z seeks to maximize system throughput. The first set of three summations represents the logarithmic sum of achievable data rates for the D2D pairs across various small cells in the network. The other two summations correspond to the logarithmic sum of achievable data rates for all CUs within the small cells in the network.

To ensure frequency reuse and maintain a minimum SINR requirement for D2D pairs and each pair link, it is necessary to consider the received SINR at each SMBS and the overall network, as well as limit the interference by I_o (cross-tier) and I_1 (co-tier) thresholds caused by D2D users to CUs. This is achieved via adaptable computation processes and the applications of QoS conditions defined in constraints (D1)–(D3) for each CU and D2D pair. D1 guarantees a minimum SINR (data rate) for all CUs, addressing the QoS requirement of reliable and adequate bandwidth to maintain uninterrupted communication and performance. D2 ensures that D2D links in RM achieve a baseline SINR (data throughput), which is critical for effective D2D communication, especially in real-time industrial applications such as AGV operations. D3 enforces a minimum SINR (data rate) for D2D users in CM, meeting the QoS performance standards necessary for effective communication. As result, D1–D3 ensure bandwidth allocation, reliability, and fairness for all users (CUs and D2D users) with in the network. Constraints (D4), (D5), and (D12) ensure that each CU channel resource is utilized by a single DU and restrict each D2D pair to sharing only one channel. Constraints (D6) and (D7) restrict the interferences within the SMBS networks, while power transmission constraints for the CUs and D2D users are defined in (D8)–(D10). Constraint (D11) specifies a limit on the additional RA to D2D pairs in cellular mode. However, solving the optimization problem in (6) is challenging within polynomial time due to its NP-hard, combinatorial (due to the channels and optimal power selection for multiple users in an interference-limited environment), and non-convex characteristics [10].

III. ADAPTIVE RESOURCE ALLOCATION AND MODE SWITCHING SCHEME (ARAMS)

To simplify the system computations, the optimization problem is segmented into bi-phasic

A. INITIAL PHASE: REUSE CHANNEL QUALITY SELECTION (RCQS) AND MODE SWITCHING (MS)

In this phase, the channel for each reuse DU $j \in \mathcal{K}^j_d$ is calculated. The algorithm prioritizes the reuse partner with the utmost CQF among the CUs in each SMBS, which reduces complexity as the count of reusable channels declines. The CQF, denoted as Ω, is defined as an estimation of the quality of the link channel between the reuse partner (CUs) and the D2D users, as expressed in (9a):

$$\Omega = \frac{\mu^c_{i,N}}{\theta^d_{j,N}} * \frac{\mu^d_{j,1}}{\theta^c_{i,j}} \text{ (9a) and } \Phi^c_i = \frac{\mu^d_{j,N}}{\mu^d_{j,1}}, \Phi^d_j = \frac{\mu^d_{j,1}}{\mu^d_{j,N}} \quad (9b)$$

The y_i^{th} CU with the lowest Ω value is selected during RCQS, as this choice can optimize the throughput compared to most other CUs under the power transmission constraints for the CUs and D2D users [11]. Conversely, selecting the u_j^{th} D2D pair with a higher Ω value can result in maximum throughput. However, before RCQS, it is optimal to satisfy the constraint (D11) with equality by setting $Q = \Phi_i^c >> \Phi_j^d$ for each SMBS $i \in \mathcal{N}$ to decide the D2D users that would operate in cellular mode via the MS computed in 9(b), while the remaining $\mathcal{K}_d - Q$ D2D pairs operate in RM, and vice versa.[3] As the value of Q increases, the probability of DU operating in CM also rises. Under these conditions, we define the mode-switching criteria as:

$$\begin{cases} \Psi_j^d = 1, if \Phi_j^d > \Phi_i^c \forall j \in K_d \\ \Psi_j^d = 0, if \Phi_j^d < \Phi_i^c \forall j \in K_d \end{cases} \tag{10}$$

Based on the values of Φ_j^d (i.e., ascending order), the DUs with higher Ω values are assigned to RM and the lower ones to CM. Thus, for each DU per SMBS $i \in \mathcal{N}$, we evaluate Q to categorize each DU per SMBS into RMs and CMs accordingly. The DUs in the RM and CMs are denoted as $\mathcal{K}_d^j = \{j|\Psi_j = 1, \quad j\epsilon\mathcal{K}_d\}$ and $\mathcal{K}_c^i = \{j|\Psi_j = 0, \quad j\epsilon\mathcal{K}_d\}$, respectively.

B. FINAL PHASE: OPTIMAL DISTRIBUTED POWER ALLOCATION

To simplify the optimization problem, P1, the variable $\rho_{i,j}$ in (D4) and (D5) is transformed into a continuous real variable with a range of [0,1]. As a result, a convex problem (i.e., a concave objective function and convex constraints) is obtained as P2:

$$P1: max\left[Z_{\Phi_j, P_{j,0}^d, P_{j,1}^d, P_i^c}\right] = \sum_{i\in N}\sum_{r\in S_i}\sum_{u_j\in K_c^i\cup K_d^j}\log_2\left(1+\Upsilon_{j\Phi_j}^d\right) + \sum_{i\in N}\sum_{y_i\in K_c}\log_2\left(1+\Upsilon_i^y\right) \tag{11}$$

$$\text{s.t.}\begin{cases} D1: \Upsilon_i^y \geq \Upsilon_{imin}^y, \forall i \in y_i, \\ D2: \Upsilon_{j,1}^d \geq \Upsilon_{jmin}^d, \forall j \in K_d^j, \\ D3: \Upsilon_{j,0}^d \geq \Upsilon_{imin}^y, \forall j \in K_c^i \\ D4: P_{j,1}^d\theta_{j,N}^d \leq \sum_{i\in y_i} I_o, \forall r \in S_i, \\ D5: \sum_{i\in N}\sum_{j\in K_d^j} P_{j,1}^d\theta_{j,N}^d \leq \sum_{i\in N}\sum_{i\in K_c\cup K_c^i} I_1, \forall i\in N \\ D6: \sum_{S_i\in L} P_i^c \leq P_{\max}^c, \forall i \in y_i, \\ D7: \sum_{S_i\in L} P_{j,1}^d \leq P_{\max}^d \forall j \in K_d^j \\ D8: \sum_{S_i\in L} P_{j,0}^d \leq P_{\max}^c \forall j \in K_c^i, \\ D9: \sum_{j\in K_d}\Psi_j \leq Q, \\ D10: \rho_{i,j} \in \{0,1\}, \forall i \in K_c, \forall j \in K_d^j \end{cases} \tag{12}$$

Due to the close correlation between the user's minimum SINR requirement in the SMBS networks and the D2D user's cross-tier interference, we compute a distributed optimal transmit power allocation policies by applying the Lagrangian multipliers approach to the optimization problem P2 to achieve the maximum network throughput using Theorem 1.

Theorem 1: The optimal transmission power for the CUs and DUs in CM and RM with imperfect CSI, as proven in the appenndix, satisfies the Karush-Kuhn-Tucker (KKT) conditions, which hold for P2, and is expressed as follows:

$$\begin{aligned} P_i^{c*} &= \left\{\min\left(\left(\frac{1}{\ln 2(\lambda_1 - a_3\pi_i^c)} - \frac{1}{\pi_i^c}\right)^+, \frac{\Upsilon_{i\min}^y}{\pi_i^c}\right)\right\} \geq P_{\max}^c, \\ P_{j,0}^{d*} &= \left\{\min\left(\left(\frac{1}{\ln 2\left(\lambda_2 - a_1\pi_{j,0}^d\right)} - \frac{1}{\pi_{j,0}^d}\right)^+, \frac{\Upsilon_{i\min}^y}{\pi_{j,0}^d}\right)\right\} \geq P_{\max}^c \\ P_{j,1}^{d*} &= \left\{\min\left(\left(\frac{1}{\ln 2\left(\lambda_3 - a_2\pi_{j,1}^d\right)} - \frac{1}{\pi_{j,1}^d}\right)^+, \frac{\Upsilon_{j\min}^d}{\pi_{j,1}^d}\right)\right\} \geq P_{\max}^d \end{aligned} \tag{13}$$

where $(x)^+ = max\,(x, 0)$,

$$\pi_{j,0}^d = \sum_{\tau\in S_i}\frac{\mu_{j,N}^d}{N_0 + \sum_{i\in K_d^j, i\neq j} P_i^d\theta_{i,N}^d}, and$$

$$\pi_{j,1}^d = \sum_{\tau\in S_i}\frac{\mu_{j,1}^d}{N_2 + \sum_{i\in K} P_i^c\theta_{i,j}^c + \sum_{i\in K_c^i} P_i^d\theta_{i,j}^c} \tag{14}$$

$\pi_i^c, \pi_{j,0}^d$ and $\pi_{j,1}^d$ denotes the channel-to-interference-plus-noise ratio for the CUs and DUs. The values of $\pi_i^c, \pi_{j,0}^d$ and $\pi_{j,1}^d$ are derived from (3), (4a), and (4b), respectively. $a_1 - a_3$ and $\lambda_1 - \lambda_3$ are the non-negative Lagrangian multipliers. To evaluate the optimal value of the Lagrange dual variables in (13), an algorithmic bisection approach is employed [12]. As a result, P2 in (11) is simplified to (15):

$$\max_{P_{j,0}^d, P_{j,1}^d, P_i^c} Z = \sum_{i\in N}\sum_{r\in S_i}\sum_{u_j\in K_c^i\cup K_d^j}\log_2\left(1+\Upsilon_{\Phi_j}^d\right) + \sum_{i\in N}\sum_{y_i\in K_c}\log_2\left(1+\Upsilon_i^y\right)$$

$$\text{s.t. D4}: P_{j,1}^{d*}\theta_{j,N}^d \leq \sum_{i\in y_i} I_o, \forall r \in S_i \tag{15a}$$

$$\text{D5}: \sum_{i\in N}\sum_{j\in K_d^j} P_{j,1}^{d*}\theta_{j,N}^d \leq \sum_{i\in N}\sum_{i\in y_i\cup K_c^i} I_1, \forall i \in N \tag{15b}$$

To control the D2D pairs' interference power, the constraints (D4) and (D5) in (15) are employed. Constraint (D4) can also be utilized to derive the initial D2D transmit power in reuse mode, which is given by: $P_{jini}^d = \frac{I_0}{\theta_{j,N}^d}$. Algorithm 1 describes the distributed power scheme for the proposed ARAMS.

The small positive value ϵ, has minimal effect on the tolerance of the power selection process. Factors such as

[3] From an intuitive perspective, prioritizing the mode that achieves a higher network throughput via D2D pair implementation is preferred to maximize network spectral efficiency. The CM experiences lower interference compared to the RM, making it more advantageous in this context.

Algorithm 1: The Distributed Power Scheme for the ARAMS

1. *Set-up:* $a_0 = 0, a_{\mathfrak{f}} = \delta\sigma$ $\lambda_0 = 0$, $\lambda_{\mathfrak{f}} = \delta\sigma$
2. *Calculate* $\pi_i^c, \pi_{j,0}^d, \pi_{j,1}^d, P_i^c, P_{j,0}^d$, *and* P_{jini}^d,
3. *For* $i \in \mathcal{N}$ *with reuse D2D pairs*
4. *For* $j \in \mathcal{K}_d^j$ *in RM*
5. *Calculate* $P_{j,1}^{d*}$ *in* (20), *If* $\frac{\Upsilon_{j\,\min}^d}{\pi_{j,1}^d} < P_{\max}$
6. *else*
7. *While* $|\frac{\Upsilon_{j\,\min}^d}{\pi_{j,1}^d} - P_{\max}| \geq \varepsilon$
8. *Use the bisection principle to calculate* $\lambda_i = \frac{\lambda_0 + \lambda_{\mathfrak{f}}}{2}$, $a_i = \frac{a_0 + a_{\mathfrak{f}}}{2}$
9. *Execute the transmit power in* (13) *as:*
10. $P_{j,1}^{d2d} = \left(\left(\frac{1}{Ln2(\lambda_i - a_i * \pi_{j,1}^d)}\right) - \frac{1}{\pi_{j,1}^d}\right)$
11. *If* $P_{j,1}^{d2d} > 0$, $\forall j \epsilon \mathcal{K}_d^j$, $P_{j,1}^{d2d} = P_{j,1}^{d2d}$, $\lambda_* = \lambda_i$ *and* $a_* = a_i$
12. *break*
13. *Else*
14. $P_{j,1}^{d2d} = min(P_{j,1}^{d2d})$
15. *End*
16. *End*
17. *Compute* $P_{j,1}^{d*} = min(P_{j,1}^{d2d}, P_{iini}^d)$.
18. *End*
19. *Do the same for* P_i^{c*}, $P_{j,0}^d$
20. *End*

Algorithm 2: The Proposed ARAMS Algorithm for Industrial D2D-Enabled SCs Networks With Imperfect CSI.

1. *For* $i \in \mathcal{N}$
2. *Calculate (9b) to obtain* $\mathcal{K}_d^j$ *and* $\mathcal{K}_c^i$ *based on* (10)
3. *Setup additional channel for* $\mathcal{K}_c^i$ *based on D9 in* (12)
4. *Calculate* (9a) *for the reuse D2D pair and chose the* $u_j{}^{th}$ *with the highest* Ω *value.*
5. *Compute the powers in* (13), *using* Algorithm 1
6. *Calculate the system throughput in (15) s.t. (15a) and (15b)*
7. *End*

the choice of initial starting point, iteration sequence, and desired accuracy for each user's optimal power allocation have a more significant influence on achieving a local optimum [13]. Determining the exact number of iterations for an optimal solution is challenging, though convergence is reached when power constraints are satisfied. The interference constraints (D4 and D5) dynamically adjust transmission power in response to incoming interferences, enhancing system throughput by reducing interference from both co-tier and cross-tier users. Algorithm 2 provides the optimal solution for the proposed ARAMS scheme in industrial D2D-enabled SC networks with imperfect CSI.

C. COMPLEXITY

The complexity of the ARAMS algorithm involves two main aspects: selection of reuse channel quality and mode switching, and power optimization. If $\boldsymbol{\mathcal{N}}$ is the small cells number and $\mathcal{K}_c$ is the CUs (i.e., $\mathcal{K}_c$, total number), the complexity is express as $O|\boldsymbol{\mathcal{N}}\mathcal{K}_c|$. For DUs in cellular mode and reuse mode, the complexity is $O|\mathcal{K}_c^i|$ and $O|\mathcal{K}_d^j|$, respectively. In reuse mode, each $\mathcal{K}_d^j$ selects an optimal sub-channel with the highest CQF value as $O|\mathcal{K}_d^j * r|$.

Lastly, for the power allocation, a maximum $O|\mathcal{K}_d^j * \mathcal{L}|$ iterations are performed at each round to achieve optimum transmission power. The number of iteration rounds corresponds to the number of network sub-channels. Thus, the expressed system complexity of the proposed ARAMS approach is: $O|(\boldsymbol{\mathcal{N}}\mathcal{K}_c + \mathcal{K}_c^i + \mathcal{K}_d^j * r + \mathcal{K}_d^j * \mathcal{L})|$. With an increasing number of DUs, the scheme's complexity scales linearly. Notably, each SMBS $i \in \boldsymbol{\mathcal{N}}$ identifies the interference and channel gains affecting its users ($\mathcal{Y}_i$ CUs set and a u_i D2D user), as the MeNB lacks precise location information for individual users within SMBS $i \in \boldsymbol{\mathcal{N}}$. In summary, MeNB manages resource management and interference coordination on a coarse time scale, $\mathbb{TH}_{\mathcal{PS}}$, while each SMBSs applies the ARAMS algorithm for RA among its users at each $\mathbb{TH}_{\mathcal{S}}$ [14]. As a result, this design allows the proposed algorithm to operate without imposing strict constraints on latency, overhead, or delay.

IV. NUMERICAL RESULTS

This section presents the numerical results to evaluate the performance of the proposed ARAMS. The simulation was conducted in MATLAB, with six orthogonal small cells randomly distributed within a 500 m macro-cell coverage area. The spatial locations of the SMBSs were modeled using a homogeneous Poisson point process (PPP) with a density of $\vartheta_{\&}$. Cellular and D2D users were randomly positioned within each small cell, with a 25 m radius. The CQF and mode decision for each D2D user per SMBS were calculated based on sub-channel allocation for each independent operation. Cumulative interference from co-tier and cross-tier sources was controlled by I_o and I_1, respectively. Each small cell allocated up to 100 sub-channels per user for data transmission, assuming independent block fading on each sub-channel. Table 2 summarizes the key simulation parameters.

To benchmark the proposed ARAMS algorithm's effectiveness, we employ the cumulative distribution function (CDF) and system throughput metrics, to compare with the following approaches:

- Interference management for D2D-enabled HetNets (IMDeH) [5]: employs a centralized approach to maximize the system performance, focusing on channel estimation error between underlay DUs and CUs in macro-small cell networks that share the same spectral resources under ICSI.
- Adaptive interference and mode selection scheme (AIMS) [16]: considers a semi-centralized approach of

TABLE 2. Simulation Parameters

Parameters	Values
Uplink bandwidth	10 MHz
Carrier Frequency	2 GHz
r_{max}, & Network Topology	14 m, Tree Top. (Star & Bus)
MeNB radius	250 m
SMBS radius	25 m
CUs Pathloss model	128.1+37.6*log10(dis [Km])
D2D pair Pathloss model	LOS in WINNER I
Small Antenna gain/height	8 dBi/25 m [15]
CUs Antenna gain/height	3 dBi/1,5 m
SINR Threshold	5 dB
Noise Power	−174 dBm
D2D pair Maximum Power	20 dBm
CUs Maximum Power	20 dBm, 23 dBm

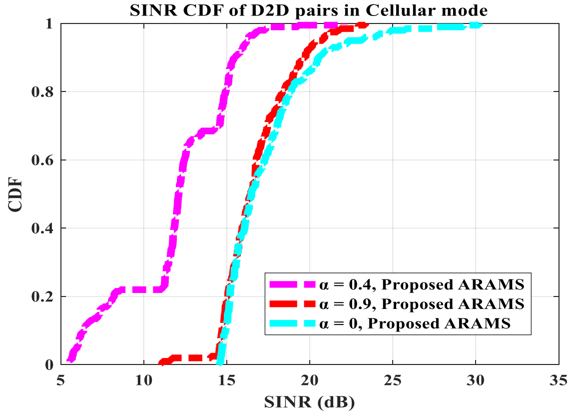
macro-small cell networks with D2D communication under perfect CSI to maximize the system performance.

- Power control (PC) scheme [7]: uses geometric analysis and convex optimization to regulate the transmit power of the DUs and the base station to maximize the system sum rate under imperfect channel state information.
- Random scheme [17]: Similar to the proposed ARAMS in terms of mode switching technique but relies on random partner assignment for reuse DUs under ICSI.

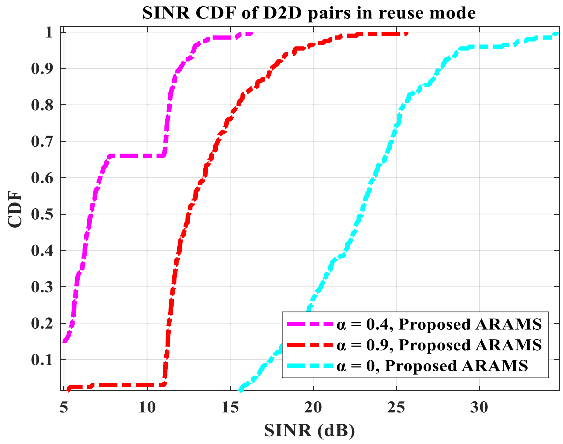
To gain a comprehensive understanding of the operation of the proposed ARAMS algorithm in industrial factory automation, we generated the DU's SINR CDF plot in both CM and RM at three different values of the channel estimation error (i.e., $\alpha = 0,\ 0.4\ \textit{and}\ 0.9$) in Fig. 2. In Fig. 2(a), the DU's SINR CDF plot in CM with $\alpha = 0$ demonstrates superior performance compared to the other two values of $\alpha \in (0.4,\ \textit{and}\ 0.9)$. Specifically, it outperforms $\alpha = 0.9$ (which shows performance nearly identical to $\alpha = 0$) by 5.24% and $\alpha = 0.4$ by 50.03%. In Fig. 2(b), the DU's SINR CDF plot in reuse mode with $\alpha = 0$ surpasses the other two values of α. It outperforms $\alpha = 0.9$ by 22.60% and $\alpha = 0.4$ by 41.11%. As observed from the trend, it indicates that as the channel estimation error (α) increases, D2D pairs tend to increase their transmit power, resulting in improved system performance. This behavior can be attributed to the MS and CQF technique, which enables D2D pairs to leverage imperfections in CSI to their advantage.

In summary, interference control based on perfect CSI leads to better system performance compared to scenarios with imperfect CSI, even when the channel is estimated.

Fig. 3 presents the proposed ARAMS's CDF plot for (a) system SINR and (b) system throughput with four other schemes at $\alpha = 0.4$. In Fig. 3(a), the CDF plot of the system SINR for the AIMS scheme outperforms the proposed ARAMS approach by 16.67%, while the proposed ARAMS outperforms the Random, IMDeH and PC schemes by 23.34%, 69.75%, and 80.87%, respectively. The efficiency of the AIMS scheme is attributed to its precise estimation of CSI and the utilization of appropriate channel gain factors.



(a)



(b)

FIGURE 2. (a) The CDF plot of DU's SINR for the proposed ARAMS scheme in CM with three (3) distinct values of α. (b) The CDF plot of DU's SINR for the proposed ARAMS scheme in RM, with three (3) distinct values of α.

Consequently, the AIMS scheme is a benchmark for evaluating the proposed ARAMS scheme's performance. Conversely, the lower performance of the other schemes is attributed to their inability to select reuse partners with enhanced QoS for DUs in the reuse process.

In Fig. 3(b), the CDF plot of the system throughput for the AIMS approach exceeds the proposed ARAMS by 9.89%. However, the proposed ARAMS surpasses the Random, IMDeH, and PC schemes by 7.14%, 48.57%, and 68.90%, respectively. The proposed ARAMS's effectiveness is associated with its precise estimation of ICSI. As a result of leveraging MS and CQF, the D2D pairs explore the ICSI, allowing the D2D pairs to raise transmit power and fulfill QoS requirements despite channel uncertainty.

Fig. 4 depicts the plot of system throughput vs. the α values for the proposed ARAMS and four other approaches when (a) $P_i^c = P_j^d = 20$ dBm and (b) $P_i^c = 23$ dBm, $P_j^d = 20$ dBm. In both Fig. 4(a) and (b), the AIMS scheme initially rises and then falls and rises again as the α values increase. This behavior is attributed to changes in the α values, which were not explicitly considered in the execution of the system throughput. Nevertheless, the AIMS scheme successfully

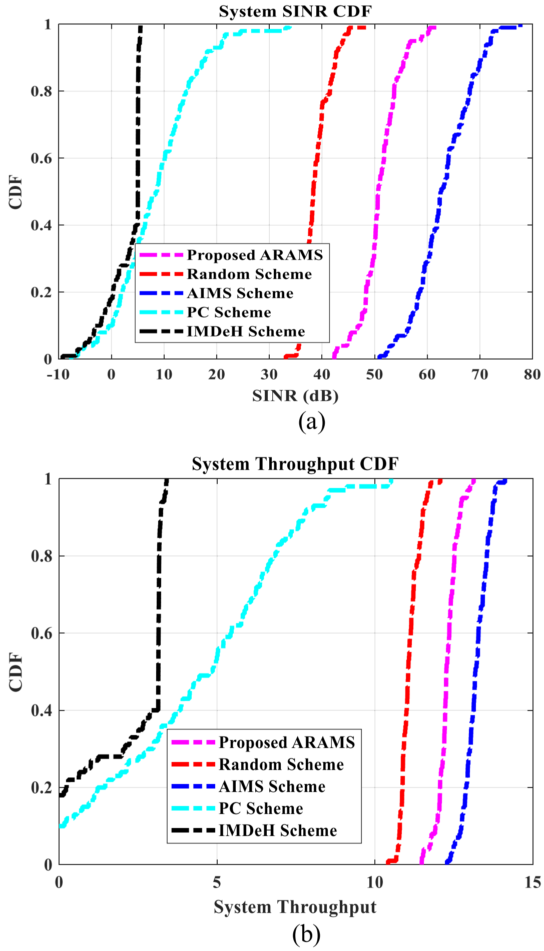


FIGURE 3. (a) The proposed ARAMS's CDF plot for System SINR with four other schemes at $\alpha = 0.4$. (b) The proposed ARAMS's CDF plot for System Throughput with four other schemes at $\alpha = 0.4$.

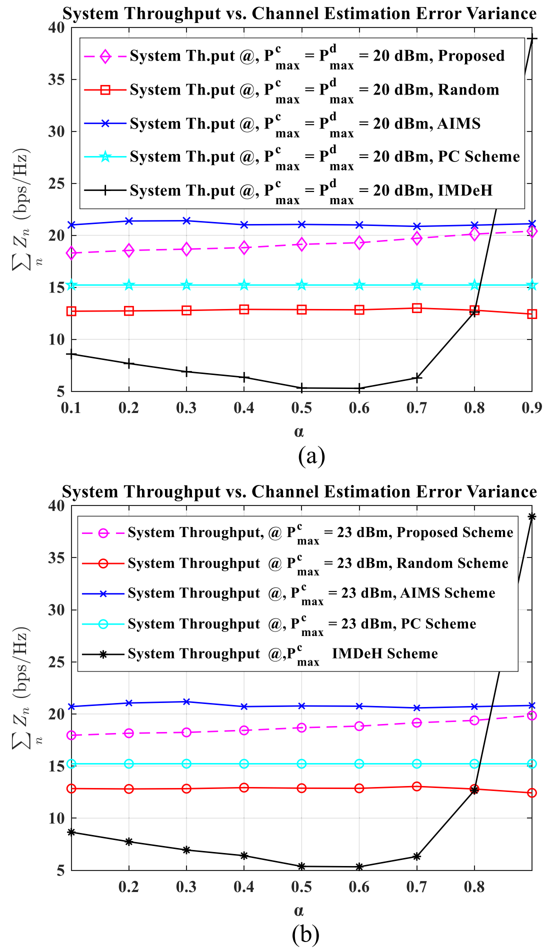


FIGURE 4. (a) The System throughput vs. α values for the proposed ARAMS and four other schemes when $P_i^c = P_j^d = 20$ dBm. (b) The System throughput vs. α values for the proposed ARAMS and four other schemes when $P_i^c = 23$ dBm, $P_j^d = 20$ dBm.

adapts and outperform the other approaches, including the proposed ARAMS. However, observing the reactions of all the schemes to the increase in values, it is evident that each scheme responds differently. The proposed ARAMS scheme demonstrates an increase in performance as α rises. This performance is due to the D2D pairs' ability to utilize MS and CQF techniques to explore ICSI, allowing the D2D pairs to increase transmission powers and fulfill QoS satisfaction under channel uncertainty. Consequently, there is a corresponding increase in system performance for each increment in α value. The PC scheme, on the other hand, maintains stability regardless of the rise in α values. The Random scheme exhibits a decreasing trend as α values rise, highlighting the benefit of the CQF technique in improving the efficiency of the proposed ARAMS scheme. The IMDeH scheme initially decreases as α values increase, but it experiences a geometric increase when α is between 0.7 and 0.9. This behavior may be attributed to the possibility of D2D users encountering reuse partners with enhanced QoS which results in an improved overall D2D users' sum rate and the system performance. A critical observation of Fig. 4(b) compared to Fig. 4(a) when the CUs transmit power is raised from $P_i^c = 20$ dBm – 23 dBm and the DU transmit power is fixed at $P_i^c = 20$ dBm, shows that both the AIMS and the proposed ARAMS scheme experience a decrease of 1.38% and 1.86% in system throughput, respectively. Conversely, the Random and IMDeH schemes exhibit increases of 1.11% and 0.82%, respectively. The PC scheme's performance remains unchanged for both Fig. 4(a) and (b).

Fig. 5 presents the plot of (a) system SINR and (b) system throughput vs. the interference power for the proposed ARAMS and two other approaches at $\alpha = 0.4$. As observed, both figures show that an increase in interference power results in a proportional increase in system SINR and system throughput for all schemes, including the proposed ARAMS scheme. The proposed ARAMS scheme enables D2D users to leverage the MS and CQF techniques to effectively explore imperfect CSI and adjust transmission power in reaction to the increasing interference power that leads to improved system performance. In contrast, the Random scheme solely relies on mode selection to address channel uncertainty. As a result, D2D users randomly select reuse partners without considering appropriate resource block allocation. Consequently,

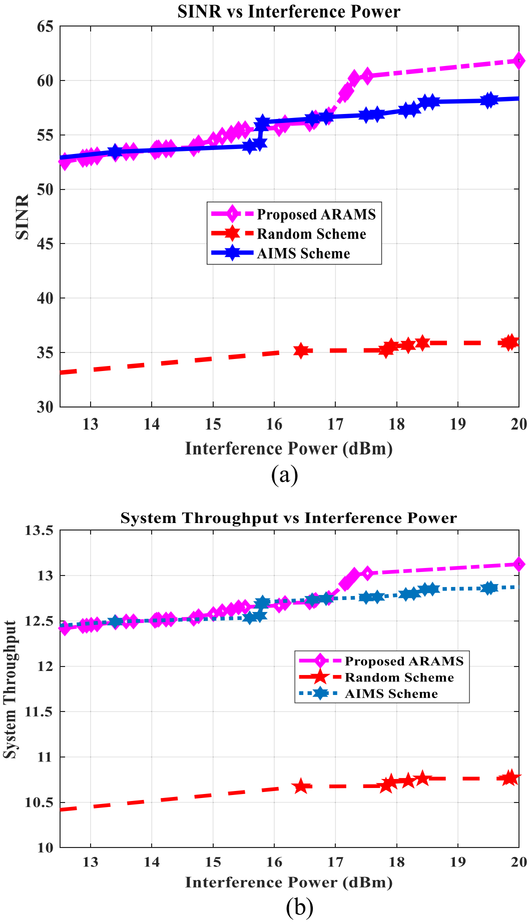


FIGURE 5. **(a) The Proposed ARAMS's plot of System SINR against the Interference power with two other approaches at $\alpha = 0.4$. (b) The Proposed ARAMS's plot of System throughput against the Interference power with two other approaches at $\alpha = 0.4$.**

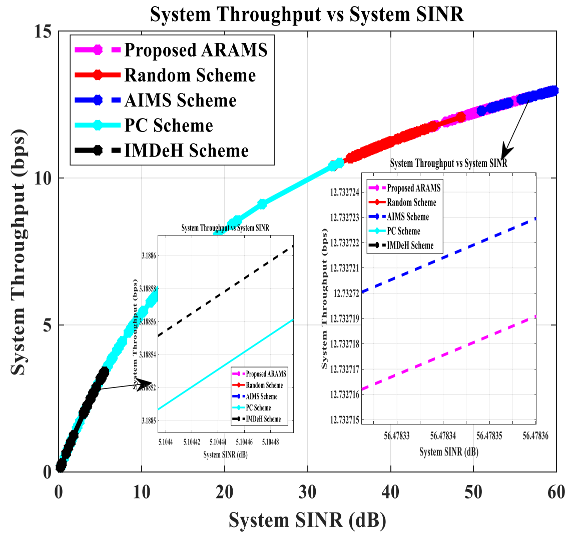


FIGURE 6. **The proposed ARAMS's system throughput vs. system SINR with four other approaches at $\alpha = 0.4$.**

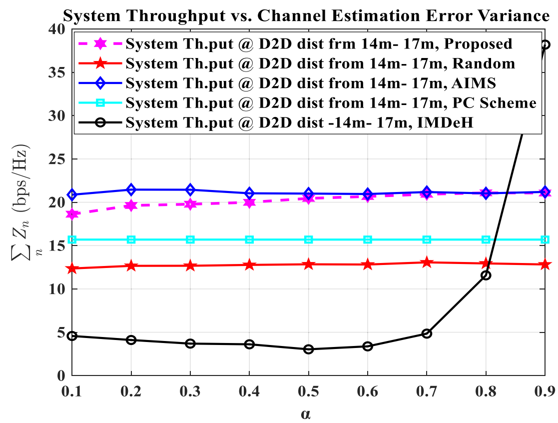
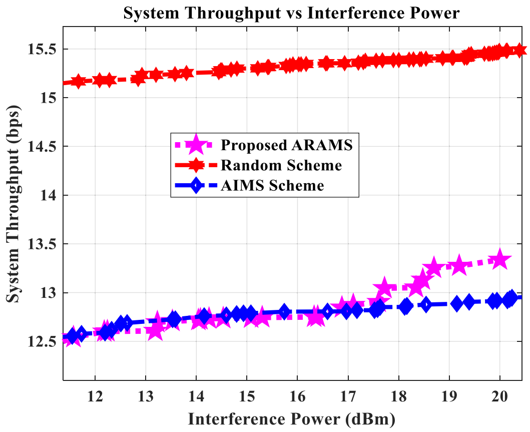


FIGURE 7. **The system throughput vs. α values for the five approaches, including the proposed ARAMS when DU distance is raised from 14 m – 17 m.**

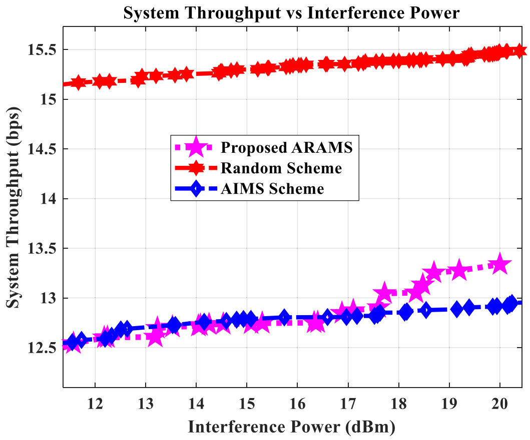
this approach downplays the interference power by transmitting with lower power compared to the AIMS and proposed ARAMS schemes. In summary, the proposed ARAMS and AIMS scheme leverage the MS, channel gain factor, and CQF, allowing the D2D users to adapt to imperfect CSI and adjust their transmit power accordingly in the face of rising interference power. This adaptive behavior contributes to enhanced system performance compared to the Random scheme, which lacks proper resource block allocation and results in suboptimal interference power management.

Fig. 6 presents the proposed ARAMS' s system SINR vs. system throughput with four other schemes at $\alpha = 0.4$. The AIMS scheme outperforms the other schemes, including the proposed ARAMS approach. As observed, the lower section of the plot exhibits the optimal value of SINR for the IMDeH scheme, surpassing the PC scheme by 6.93%. The upper section indicates that the AIMS scheme outperforms the proposed ARAMS approach by 16.67%, effectively bridging the performance gap between ARAMS and the other schemes. Overall, higher SINR values reflect increased user demand and greater spectrum occupancy to meet SINR thresholds [17]. The ARAMS-AIMS MS mechanism and the assignment of reuse partners both significantly enhance SINR performance across all plotted results.

Fig. 7 depicts the relationship between the system throughput and various α values for five schemes including the proposed ARAMS when the DU distance is raised from 14 m – 17 m. Generally, most schemes, including the proposed ARAMS, exhibit an increase in system throughput compared to Fig. 4(a), though the AIMS and IMDeH schemes show a decline in performance. The observed improvements in system throughput for most schemes, including the proposed ARAMS, is attributed to more reuse partners with better QoS becoming available for D2D users, which enhances performance. The proposed ARA-MS, PC, and Random schemes achieve throughput improvements of 1.80%, 3.12%, and 3.22%, respectively, while the AIMS scheme declines by 0.68%, as some D2D pairs are unable to find reuse partners with adequate QoS. For the IMDeH scheme in Fig. 7, there is an initial steep growth in throughput between α values of 0.1 and 0.6, indicating that an increase in DU distance



(a)



(b)

FIGURE 8. (a) The proposed ARAMS's system SINR vs. interference power with other schemes at $\alpha = 0.4$ when DU distance is raised from 14 m – 17 m. (b) The Proposed ARAMS's system throughput vs. Interference power with other schemes at $\alpha = 0.4$ when DU distance is raised from 14 m – 17 m.

accommodates more Dus, contrasting with Fig. 4(a), where throughput initially declines, suggesting fewer D2D pairs between α values of 0.1 and 0.6 before recovering. Although IMDeH experiences a 1.88% decrease in system throughput in Fig. 7, it involves a greater number of participating DUs compared to the IMDeH scheme in Fig. 4(a).

Fig. 8 provides an assessment of (a) system SINR and (b) system throughput vs. the interference power at $\alpha = 0.4$ when the DU distance is increased from 14 m – 17 m for the proposed ARAMS and two other approaches. As observed from the results of both figures, the Random scheme introduces significant interference, leading to channel errors for the cellular users, which contrasts with the findings in Fig. 5(a) and (b). Specifically, the interference power in the Random scheme rose from 46.02% in Fig. 5(a) to 89.30% in Fig. 8(a) while maintaining the same system throughput at 386% in both Figs. 5(b) and 8(b). On the other hand, both the AIMS and the proposed ARAMS scheme maintain consistent system performance, with SINR performance values of 53.73% and 98.14% in Figs. 5(a) and 8(a), and with system throughput performance value of 4.60%, and 9.19% for Figs. 5(b) and 8(b), respectively. It is evident that the Random scheme's reliance on CSI with errors leads D2D transmitters to use unsuitable resource blocks, causing significant interference that degrades individual SINR performance for cellular users.

Conversely, the effectiveness of our algorithm in interference control and mode selection, as evidenced by the AIMS and ARAMS schemes, underscores the importance of MS and CQF for CSI in power control and resource allocation algorithms for industrial factory automation.

V. CONCLUSION

This paper explores the ARAMS for industrial D2D-enabled networks with imperfect CSI within the 5G framework. Our proposed ARAMS scheme utilizes CQF and MS techniques to optimize DU sum rates while applying the Lagrangian dual approach to enhance the system performance and meet the CUs' QoS requirements. The numerical results illustrate that the proposed ARAMS surpasses the other schemes, except the AIMS scheme, in maximizing the system throughput as the estimation error value increases. Future work should examine multiple D2D pairs sharing the resources of a cellular user under channel uncertainty to advance the understanding and optimization of D2D-enabled networks in practical and complex settings.

APPENDIX

Proof of Theorem 1

To simplify the optimization problem, P2, the Lagrangian function based on (11) is formulated as:

$$
\begin{aligned}
L\left(P_{j,0}^{d}, P_{j,1}^{d}, P_{i}^{c}\right) = & \sum_{i\in N} \log_2\left(1 + P_{j,0}^{d}\pi_{j,0}^{d}\right) \\
& + \sum_{i\in N} \log_2\left(1 + P_{j,1}^{d}\pi_{j,1}^{d}\right) \\
& + \sum_{i\in N} \log_2\left(1 + P_{i}^{c}\pi_{i}^{c}\right) \\
& - a_1\left(\Upsilon_{i\,\min}^{c} - P_{j,0}^{d}\pi_{j,0}^{d}\right) \\
& - a_2\left(\Upsilon_{j\,\min}^{d} - P_{j,1}^{d}\pi_{j,1}^{d}\right) \\
& - a_3\left(\Upsilon_{i\,\min}^{c} - P_{i}^{c}\pi_{i}^{c}\right) \\
& + \lambda_1\left(P_{\max}^{c} - \sum_{S_i\in K} P_{i}^{c}\right) \\
& + \lambda_2\left(P_{\max}^{c} - \sum_{S_i\in K} P_{j,0}^{d}\right) \\
& + \lambda_3\left(P_{\max}^{d} - \sum_{S_i\in K} P_{j,1}^{d}\right)
\end{aligned} \tag{16}
$$

$$f_n\left(a_1,a_2,a_3,\lambda_1,\lambda_2,\lambda_3\right)=max\left\{\begin{array}{l}\log_2\left(1+P^d_{j,0}\pi^d_{j,0}\right)+\log_2\left(1+P^d_{j,1}\pi^d_{j,1}\right)+\log_2\left(1+P^c_i\pi^c_i\right)\\-\left(\lambda_2-a_1\pi^d_{j,0}\right)P^d_{j,0}-\left(\lambda_1-a_3\pi^c_i\right)P^c_i-\left(\lambda_3-a_2\pi^d_{j,1}\right)P^d_{j,1}\end{array}\right\} \quad (18)$$

The values of $\pi^c_i, \pi^d_{j,0}$ and $\pi^d_{j,1}$ are expressed in (14). The constraints in the problem are governed by non-negative Lagrangian multipliers $a_1 - a_3$ and $\lambda_1 - \lambda_3$. To find the solution to (16), we introduce the dual function as defined in [13]:

$$\min f\left(a_1,a_2,a_3,\lambda_1,\lambda_2,\lambda_3\right)=max\left\{L\left(P^d_{j,0},P^d_{j,1},P^c_i\right)\right\} \quad (17)$$

Equation (17) is rewritten as;

$$\begin{aligned}f\left(a_1,a_2,a_3,\lambda_1,\lambda_2,\lambda_3\right)=&\sum_{i\in N}f_n\left(a_1,a_2,a_3,\lambda_1,\lambda_2,\lambda_3\right)\\&+\lambda_1\sum_{S_i\in K}P^c_{\max}+\lambda_2\sum_{S_i\in K}P^d_{\max}\\&+\lambda_3\sum_{S_i\in K}P^c_{\max}-a_1\Upsilon^c_{i\min}\\&-a_2\Upsilon^d_{j\min}-a_3\Upsilon^c_{i\min}\end{aligned}$$

and (18) as shown at the top of this page.

Applying the Karush-Kuhn-Tucker (KKT) conditions [19], the optimum possible solution for (18) as follows:

$$\begin{aligned}P^d_{j,0}&=\left(\frac{1}{\ln 2\left(\lambda_2-a_1\pi^d_{j,0}\right)}-\frac{1}{\pi^d_{j,0}}\right)^+,\\P^d_{j,1}&=\left(\frac{1}{\ln 2\left(\lambda_3-a_2\pi^d_{j,1}\right)}-\frac{1}{\pi^d_{j,1}}\right)^+,\\P^c_i&=\left(\frac{1}{\ln 2\left(\lambda_1-a_3\pi^c_i\right)}-\frac{1}{\pi^c_i}\right)^+\end{aligned} \quad (19)$$

Equation (19) provides the possible transmission power of DUs in CM and RM, and the CUs in each SMBS $i \in \mathcal{N}$. The peak transmission power for DUs and CUs in cellular and reuse mode can be determined by considering the limitations specified in constraints (D1–D3) as:

$$\begin{aligned}\Upsilon^c_i&=P^c_i\pi^c_i\geq\Upsilon^c_{i\min}\Rightarrow P^c_i\geq\frac{\Upsilon^c_{i\min}}{\pi^c_i},\\\Upsilon^d_{j,0}&=P^d_{j,0}\pi^d_{j,0}\geq\Upsilon^c_{i\min}\Rightarrow P^d_{j,0}\geq\frac{\Upsilon^c_{i\min}}{\pi^d_{j,0}},\\\Upsilon^d_{j,1}&=P^d_{j,1}\pi^d_{j,1}\geq\Upsilon^d_{j\min}\Rightarrow P^d_{j,1}\geq\frac{\Upsilon^d_{j\min}}{\pi^d_{j,1}}\end{aligned} \quad (20)$$

As a result, the optimum transmission power for the CUs and DUs in CM and RM is expressed in (13).

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