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RESEARCH ARTICLE

IoT Underlying Cellular Uplink Through D2D Communication Principle

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ABSTRACT Device-to-device (D2D) communication is an innovative technique within cellular networks, holding great potential for future wireless communication systems, particularly for the Internet of Things (IoT). One key advantage of D2D communication is its ability to alleviate cellular traffic congestion, as many IoT applications may prefer to use cellular networks due to interoperability and compatibility. In this paper, we propose a novel opportunistic channel access model and adaptive power control strategy for a cluster of IoT transmitter-receiver pairs (referred to as D2D pairs) underlying the cellular uplink. Our objective is to assess the feasibility of leveraging this proposed model for offloading IoT traffic. To this end, we evaluate the model's performance under various parameter settings, considering practical limitations such as total power restrictions and minimum spectral efficiencies. Additionally, we compare the results against two baseline power control strategies. Our findings indicate that instead of constructing a new and dedicated network architecture for IoT applications, it is possible to offload IoT-generated traffic through D2D communication underlying the cellular uplink. This approach not only avoids detrimental effects on the cellular network's traffic but also provides satisfactory performance for IoT users.

INDEX TERMS Internet of Things, D2D assisted offloading, opportunistic channel access, underlying cellular uplink.

I. INTRODUCTION

Despite the huge effort to integrate IoT into various aspects of our daily lives, its practical usage rate is growing rather slowly. The requirement of a new and specific communication infrastructure for IoT is one of the factors that slow down practical usage. Therefore, using existing cellular networks as a communication infrastructure for IoT would ease one of the challenges of the IoT's practical implementation. However, mobile network operators are already facing the challenge of a rapidly increasing data traffic demand because of the increasing number of mobile devices. Although using cellular networks for Internet of Things (IoT) applications is an attractive option, it would result in increased traffic demand and additional issues for mobile operators. To tackle the growth in traffic demand, traffic offloading, which redirects data traffic initially intended for transmission over cellular networks to alternative links or networks, has been inevitable and has received much attention in the literature. In this study, we examined device-to-device (D2D) communication-assisted traffic offloading, where IoT transmitter-receiver pairs act as D2D pairs underlying cellular network.

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A. STATE OF THE ART

D2D communication allows for direct transmission between user devices without the need for communication to pass through a base station (BS) [1]. There are two spectrum sharing models for implementing D2D communication in cellular networks; underlay sharing and overlay sharing models [2]. In the underlay sharing model, D2D users and cellular users (CUs) can share the uplink or downlink channels simultaneously; however, in the overlay sharing model, a dedicated resource for D2D communication exists in either the uplink or downlink channels. In a D2D underlying cellular network, D2D users communicate directly with each other by sharing radio resources with CUs in a non-orthogonal principle, resulting in two types of mutual interference: intra-tier (between D2D pairs) and cross-tier (between CU and D2D pairs) [3]. Therefore, transmission power control is crucial for mitigating interference and maximizing network spectral performance. In the literature, there has been considerable interest in power control for mitigating the interference in underlying D2D communication [4], [5] whereas some recent studies [6], [7], [8], [9], [10] have addressed both delay and power control.

In all existing D2D performance analysis studies, the delay analysis of the used power control approaches has been discussed independently from the supported individual data rates, with the focus being on the sum spectral efficiency [9], [11] or energy efficiency [8], [10]. Furthermore, none of these studies have addressed individual rates for both CU and D2D pairs. However, knowing the achievable rates and the delays of individual users is critical in determining whether a D2D setting is suitable for the aimed offloading scenario for an IoT application. We consider a scenario in which there is a high demand for channel allocation and where the cellular network is exploited for IoT applications. Therefore, we examined the upper bounds on interference-limited rates and the maximum delay to investigate the applicability of a traffic offloading scenario where IoT transmitter-receiver pairs use D2D communication. Throughout this paper, the terms 'D2D pairs' and 'IoT Pairs' (IoT Transmitter-Receiver Pairs) are used interchangeably.

D2D-assisted offloading with opportunistic access for reducing traffic in cellular networks has been shown as an efficient method to improve the cellular network performance [12], [13]. The core concept stands on utilizing the principles of D2D communication to offload traffic whenever the source and destination are in close proximity to each other. Therefore, all the existing studies primarily focus on assessing the extent to which D2D communication enhances cellular network performance through offloading. Some studies also explore how social networks can be utilized for effective offloading for trending streaming. However, our study takes a completely different perspective from these existing works. We consider offloading of traffic generated by IoT pairs through the underlying cellular uplink, rather than solely focusing on how to initiate or organize offloading via D2D communication.

B. MOTIVATION

Using current cellular network infrastructure for IoT communication would accelerate its practical application. This has motivated us to propose offloading traffic generated by IoT pairs via the underlying cellular uplink, rather than using a separate communication protocol. It is important to note that the nature of IoT-generated data differs from regular cellular traffic, as it does not typically require high data rates, and streaming applications are not common for IoT transmitter-receiver pairs. Therefore, we aim to investigate whether IoT Pairs can coexist within the cellular network infrastructure, rather than requiring a separate communication technology. In our proposed scenario, candidate IoT pairs within clusters, formed by the base station (BS), opportunistically share the uplink channel with a single cellular user (CU). Therefore, our concern is meeting the quality of service requirements of the IoT pairs and the cellular uplink when the opportunity for underlying communication arises. This differs from the objective of effectively offloading regular mobile traffic through the D2D principle.

C. CONTRIBUTION

The main contributions of our study are summarized as follows:

(i) Based on traffic offloading motivation, we propose a cluster-based non-orthogonal opportunistic channel access model (NOOA), in which a cluster of N D2D pairs (IoT transmitter and receiver pairs) exists, and each pair shares the uplink radio resource of the CU with non-orthogonal basis. The D2D receiver and BS treat the intra-tier and cross-tier interferences as noise (TIN), and they both directly decode their signals unless the signal-to-interference-plus-noise ratio (SINR) is under the required decoding threshold. In contrast to previous performance analysis studies of D2D communication [2], [7], [9], [14], [15], the proposed NOOA-based model characterizes D2D-enabled cellular networks under a delay-sensitive scenario, considering both the D2D and cellular rates.

(ii) In the proposed NOOA-based D2D access model, emerging resource sharing, power control, and scheduling problems were formulated as a mixed-integer nonlinear programming (MINLP) problem. The power levels of the user devices and the scheduling order of the D2D pairs were taken as decision variables in the MINLP model, and a controlled random search algorithm was developed to solve the problem because it was nonconvex. The optimization model used a queue weighting factor in the objective function to consider the delay sensitivity of the user devices.

(iii) Solution of the formulated MINLP attains maximum sum rate and corresponding adaptive transmission powers under delay consideration, and we name it adaptive power control strategy (NOOA-APC). Then we compare the NOOA-APC with two baseline power control strategies which run NOOA; i) Binary Power Control (BPC) [16] ii) Channel inversion power control (CIPC) [2]. These two baseline schemes were chosen because BPC represents optimum power control for two interfering links, while CIPC serves as a baseline power control mechanism for analytical studies using stochastic geometry for interference modeling. The results show that using NOOA-based D2D communication ensures satisfactory individual rates while maintaining the minimum rate and delay requirements for voice and video traffic. Therefore, the proposed NOOA model can be used to offload IoT traffic when cellular networks are exploited for IoT applications.

The rest of this paper is organized as follows. Section II discusses related works on D2D-assisted offloading and existing power control strategies for D2D communication and review two baseline power control strategies. Section III introduces the system model. Section IV presents the problem formulation and the solution algorithm. Section V introduces the delay calculation algorithm and opportunistic scheduling. Section VI presents the numerical results and discussion. Finally Section VII concludes the paper.

II. RELATED WORKS

We present the literature review in three parts to highlight the different contributions of our study. The first part summarizes existing D2D-assisted data offloading strategies. Given our scenario where IoT devices function as D2D pairs and our focus on individual rate and delay performance, it's crucial to review previous studies on D2D communication that address power control and delay awareness. The second part presents the state-of-the-art performance analysis of delay-aware D2D communication. Finally, we review two power control strategies, BPC and CIPC, chosen as baselines for evaluating our proposed scheme.

A. D2D-ASSISTED DATA OFFLOADING

Data offloading technologies are classified into four types based on network topology and link constructions [17]: i) data offloading (DO) through small cell networks, ii) DO through Wi-Fi networks, iii) DO through opportunistic mobile networks, and iV) DO through heterogeneous networks. Data offloading through D2D links can be classified as opportunistic, and it has been discussed in the literature in three approaches: i) D2D offloading in which nearby devices are used for their computational ability [18], [19], similar to the edge computing approach. ii) D2D offloading in which nearby devices are used to increase the cellular coverage through multi-hop relaying via D2D links [20], [21], [22], [23]. iii) D2D offloading with opportunistic access for reducing traffic in cellular networks when possible [24], [25], [12], [13], [26].

Our study might be considered inline with the third approach, however, all the existing studies under the third approach focus on how D2D communication improves cellular network performance via offloading and, some investigate how social networks can be utilized for an effective offloading. The primary issue in these studies is how to start or plan the D2D communication offloading for an improvement in cellular performance. Instead, our goal is to determine whether it is viable to use cellular networks for IoT applications without negatively impacting cellular users while yet meeting IoT application criteria. Instead of a novel communication structure for IoT system, our focus is on the quality of service that IoT pairs can achieve when all IoT-generated traffic is offloaded via D2D underlying cellular network. Therefore, from the perspective of individual QoS performance, none of the present D2D offloading schemes are appropriate for comparison with ours.

B. POWER CONTROL FOR DELAY-AWARE D2D COMMUNICATION

The delay-aware design of D2D communication is just as important as the spectral efficiency gain generated by integrating it to the cellular networks. To achieve delay sensitivity, the transmission powers of the D2D users and CUs must be adjusted to consider the queue dynamics. The associated power control problem involves selecting a power control policy that maximizes the overall spectral efficiency while integrating a queue-weighting factor into the problem.

Wang and Lau [3] investigated delay-aware resource allocation with dynamic power control while neglecting the cross-tier interference and assuming carrier-sense multiple access (CSMA) like medium access control protocol in the D2D system. Later on authors [6] proposed a dynamic power control algorithm for delay-sensitive D2D communications but only for the overlay implementation model. Xu [7] analyzed the trade-offs between successful transmission probability, delay, and energy consumption for single-hop and multi-hop D2D communications by assuming that the D2D and cellular links are orthogonal to each other (i.e., no cross-tier interference). Sheng et al. [8] investigated the trade-off between energy efficiency and delay by formulating a stochastic optimization problem; however, they only focused on the average delay of the network, which is defined as the ratio of the network's average queue length to the sum traffic arrival rates. Huang et al. [27] designed a distributed delay-aware power allocation and flow control scheme for D2D communication underlaying multiple cells, in which the D2D average throughput is maximized while queue stability and CU coverage probability are guaranteed. In [11], delay-aware power control was studied by integrating a successive interference cancellation mechanism in a D2D communication underlying multiple cells. In [9], the authors used priority transmission mechanisms to satisfy the requirements of diverse traffic types in a D2D heterogeneous network, and the performance of the D2D underlay cellular network was analyzed in terms of overall average throughput and delay. In [10], a joint power control and mode selection scheme for D2D underlying communication was proposed to maximize energy efficiency while meeting the strict delay requirements of a specific type of smart grid communication. However, to satisfy the delay requirement, the overall scheme must consider two other transmission options rather than relying on only D2D communication. In addition, the CU requirements on the shared subchannel were not considered in the study.

The studies listed above concentrated on delay sensitivity while employing power management to reduce interference in D2D communication; however, most of them neglected individual rate performances, and some neglected cross-tier interference. However, in our study, we consider the delay by integrating queue-weighting factor in the objective function of a mixed integer nonlinear programming formulation (MINLP) in a scenario where D2D pairs share the CU's uplink in non-orthogonal principle by treating interference as noise (i.e., taking cross-tier interference into account). The solution of MINLP attains the optimum transmission powers for maximum sum rate and the scheduling of existing D2D pairs on CU's uplink appropriately.

C. SELECTED BASELINE POWER CONTROL STRATEGIES FOR PERFORMANCE EVALUATION

We have selected two baseline power control strategies to compare with our proposed scheme. Although our interest is the achievable individual rates, we formulated the problem that takes the maximum sum rate as an objective function. In our scenario, there are always two interfering users that exist simultaneously in the cellular uplink; the primary user is the regular cellular user which has continuous channel access while the secondary user is one of the IoT transmitter-receiver pairs that are scheduled to underlay the CU's uplink based on its queue length and maximum sum rate target of the network. Therefore, we have selected Binary Power Control (BPC) [16] to compare with the proposed scheme for the overall spectral efficiency of the network. In the BPC strategy, it is demonstrated that transmitting at full power on poor link and at minimum power on strong link is the optimal power allocation for two interfering links.

Channel inversion power control (CIPC) [2] is a power control mechanism that is used as a basis approach for many analytical studies using a stochastic geometry formulation for the interference in shared channels. Therefore, we have selected Channel inversion power control (CIPC) as the second baseline power control strategy to support possible future studies that utilizes stochastic geometry. In CIPC approach transmission power is proportional with distance, i.e., $P_{transmision} = P_{average} * R^{\alpha\varepsilon}$, where R is the link distance, α is path loss exponent, and ε is a parameter which is selected based on the maximum allowed distance for minimum SINR threshold and maximum-minimum transmission power limitations.

III. SYSTEM MODEL

In this study, a resource-sharing scenario was considered for a cellular network with multiple cells. In this scenario, the BS creates a cluster of N IoT pairs (i.e., $2N$ D2D users) that opportunistically use the uplink resource of a CU in a single cell, and the overall network is modeled on a regular hexagonal lattice array that is illustrated in Figure 1. The base station is responsible for assigning an uplink channel to a collection of IoT pairs and forming a cluster with a single cellular user and a collection of IoT in accordance. The formation of these clusters is contingent upon the availability of uplink resources and the number of IoT devices seeking channel access within a given IoT application. For example, a cluster might encompass all IoT devices belonging to a single IoT application, such as a smart home system consisting of appliances such as a refrigerator and TV. Figure 2 depicts the system model in a single cell that was considered in this study. It demonstrates an example clustering structure that include 5 IoT pairs (10 IoT devices) in (a), cross-tier interference among CU, IoT, and BS including other cell interference from neighboring cells in (b), and finally, shows the scheduling of IoT pairs in (c). It is assumed to have ongoing uplink communication and $2N$ IoT devices establish direct connections among themselves in pairs. The IoT pairs are denoted as $K_a = \{1, 2, \ldots N\}$, where a stand for a^{th} cell in the hexagonal cellular array, $A = \{1, 2, 3, 4, 5, 6\}$. The set of user devices is denoted as $U_a = \{1, 2, \ldots (2N + 1)\}$, which consists of $2N$ IoT devices and a CU. Note that $K_a \subset U_a$, and we used the K_a set to indicate that an equation is valid only for IoT devices and use the U_a set to indicate that the equation is valid for both CU and IoT devices in a cell a. For the cell of interest, we use K_o and U_o notations, i.e., the users in this cell are exposed to the interference from the surrounded six cells in the array A, (Refer to Figure 1).

It is assumed that communications occur within a frame period (τ_f) and one IoT pair coexists with the uplink transmission of the CU. It is considered the Rayleigh block fading channel with a block length of τ_f, indicating that the channel gains are time-invariant during each frame and change independently between different frames. Assuming a regular hexagonal lattice, base station and D2D receivers are exposed to other cell interference (OCI) as well. Therefore, when a IoT pair and a CU are simultaneously scheduled in the same channel, the received baseband signal at the BS is written as

$$\begin{aligned} Y &= h_c\sqrt{p_c}m_c + h_d\sqrt{p_d}m_d \\ &\quad + \sum_{j=1}^{6}(h_{\tilde{c}}\sqrt{p_{\tilde{c}}}m_{\tilde{c}} + h_i\sqrt{p_i}m_i) + n \\ &\quad \forall d, c \in U_o, \quad \forall i, \tilde{c} \in U_j \end{aligned} \tag{1}$$

where $m_c(o)$ and $m_i(o)$ are transmitted messages for the CU and the scheduled IoT pair, respectively in the cell of interest; $p_c(o)$ and $p_i(o)$ are the transmission powers for the CU and the scheduled IoT pair,i, respectively, with $E\left\{|m_c|^2\right\} = 1$ and $E\left\{|m_i|^2\right\} = 1$; n denotes a zero-mean additive white Gaussian noise with a variance of σ^2; and h_c and h_i are the channel gains for the link between the BS and CU, and for the link between i^{th} D2D transmitter-receiver pair, respectively. Opportunistic scheduling of the candidate IoT pairs in each frame and selection of the proper transmission powers (p_c, p_i) were achieved to maximize the sum rate of the overall network. The total power on the channel is restricted by p_{total}. The SINR at each receiver and the queue lengths associated with each user device are the main criteria for the scheduling and power-setting decisions. As IoT pairs and CU share the channel in non-orthogonal principle, the SINR at the IoT receiver or BS must be higher than the respective

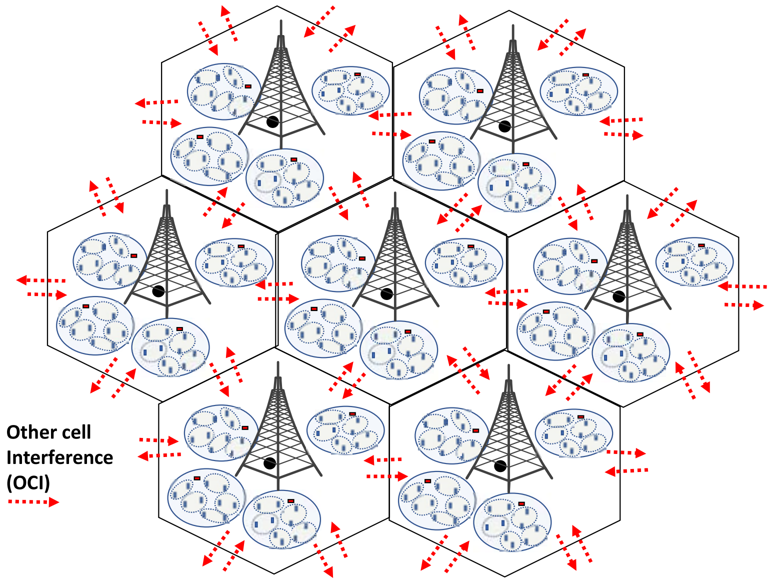

FIGURE 1. Hexagonal cellular array model.

minimum decoding thresholds, Γ_i and Γ_{bs}. This corresponds to a minimum data rate (R_{min}) requirement for the scheduling.

A. QUEUE DYNAMICS AND ITS RELATIONSHIP WITH DATA RATES

All the transmitting devices are assumed to receive data from the application layer at an average rate of λ bits per second (bps). Data are sent to the buffer of the i^{th} active transmitter. At the f^{th} frame, the queue length of the buffer is expressed as $Q_i(f)$ bits. The data in the queue are transmitted in the form of first-input-first-output. The length of $Q_i(f)$ depends on the queue length in the previous frame $Q_i(f-1)$, the number of bits arriving one frame $\lambda\tau_f$, and the number of bits departing from one frame, $\tau_f R_i^{bf}(f)$. The following equation is used to calculate the queue length in the f^{th} frame for $\forall i \in U$:

$$Q_i(f) = \max\left[Q_i(f-1) + \lambda_i\tau_f - x_i(f)R_i^{bf}(f)\tau_f, 0\right], \quad (2)$$

where $x_i(f)$ is a Boolean variable, and $x_i(f) = 1$ if the frame is assigned to the i^{th} transmitter; otherwise, $x_i(f) = 0$. The buffered data rate $R_i^{bf}(f)$ is defined as the $R_i(f)$ data rate without transmission overhead (T_{oh}):

$$R_i^{bf}(f) = R_i(f) - T_{oh}. \quad (3)$$

In the f^{th} frame, the data in the queue of the i^{th} transmitter, $Q_i(f)$, are transmitted at a maximum rate of $R_i(f)$ bps:

$$R_i(f) \le B\log_2\Big(1 + \gamma_i(f)\Big), \qquad \forall i \in U_o, \quad (4)$$

where B is the total uplink bandwidth offered by the BS, and $\gamma_i(f)$ is the SINR at the intended receiver of the i^{th} transmitter. Note that the intended receiver for the cellular uplink is a BS, whereas that for the D2D link is a D2D user device.

B. D2D LINK AND SINR THRESHOLD

We assumed that there is an N number of candidate D2D pairs that are waiting to be scheduled to share the spectrum with CU. For a D2D receiver, the SINR $\gamma_d(f)$ in Equation 4 is defined as

$$\gamma_d(f) = \frac{p_d(f)h_d(f)}{\sigma^2 + p_c(f)h_c(f) + \sum_{j=1}^{6}(h_{\tilde{c}}p_{\tilde{c}} + h_i p_i)}, \qquad \forall d, c \in U_o, \forall i, \tilde{c} \in U_j \quad (5)$$

where $h_d(f)$ is the channel gain between the d^{th} D2D transmitter and the intended receiver in the f^{th} frame, $p_d(f)$ is the transmission power of the d^{th} D2D transmitter with the bound of P_{max}, $p_c(f)$ is the transmission power of the interfering CU, and $h_c(f)$ is the channel gain between the CU and the intended receiver of the d^{th} D2D pair. For the d^{th} D2D transmitter and receiver pair to be scheduled for transmission, a minimum SINR of Γ_d is required, and it is represented as

$$\gamma_d(f)x_d(f) \ge \Gamma_d, \qquad x_d(f) \in \{0, 1\}. \quad (6)$$

where $x_d(f)$ is the binary variables that indicate whether the D2D transmitter is scheduled (i.e $x_d(f) = 1$ when d^{th} D2D pair is scheduled.)

C. CELLULAR UPLINK

At the BS, the SINR in Equation 4 is defined as

$$\gamma_{bs}(f) = \frac{p_c(f)h_{cb}(f)}{\sigma^2 + \sum_{d=1}^{K} x_d(f)p_d(f)h_d(f) + \sum_{j=1}^{6}(h_{\tilde{c}}p_{\tilde{c}} + h_i p_i)}, \qquad \forall d, c \in U_o, \forall i, \tilde{c} \in U_j, \quad (7)$$

where h_{cb} is the channel gain from a CU to a BS in a frame, h_d represents the channel gain from the scheduled

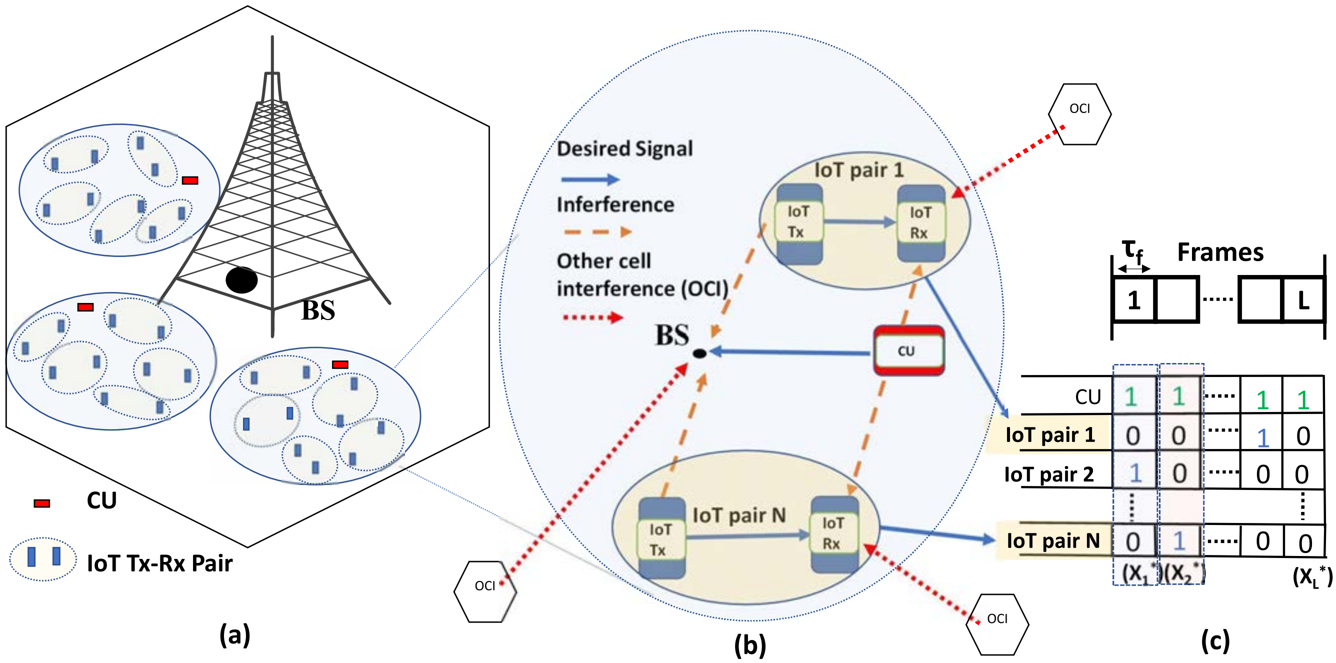

FIGURE 2. System model for NOOA, (a). Clusters of IoT pairs and a CU formed by BS -i.e., a cluster might consist of the sensors that need to communicate with each other in your smart home-, (b). Cross-tier interference on CU's uplink and sum other cell interference (OCI) from six neighbor cells, (c). Scheduling of IoT pairs.

D2D pair, d, (i.e., $x_d(f) = 1$) to BS, and $p_c(f)$ and $p_d(f)$ are the transmission powers of the CU and interfering D2D transmitter, respectively. Same as at the D2D receiver, the SINR at the BS must satisfy the required decoding threshold ($\gamma_{bs}(f) \geq \Gamma_{bs}$) as well.

IV. PROBLEM FORMULATION

First, the opportunistic resource sharing and power control problem is defined by considering the channel conditions, queue lengths, and the minimum rate requirements. Subsequently, the problem is formulated as a MINLP problem. In each frame, only one D2D pair is chosen from a cluster of N D2D pairs waiting for transmission while considering the queue length (delay tolerance) of all user devices. The scheduled D2D pair, i, is determined using the Boolean variable, $x_i(f)$, and its data rate ($R_i(f)$) is added to the data rate of the CU ($R_c(f)$). In each f ($\forall f \in L$) frame, the data rates of the CU and scheduled D2D pair are summed as follows:

$$R^f_{sum}(p^*_c, p^*_d, X^*) = \sum_{i=1}^{N} x_i(f)R_i(f) + R_c(f), \ \forall i \in K_o \quad (8)$$

where p^*_c and p^*_d are the optimum transmission powers for the maximum sum rate, and $X^* = x_1(f), \cdots, x_N(f)$ is the scheduling matrix for the D2D pairs. The goal of the proposed programming is to achieve opportunistic sharing of the uplink resource of a CU with the best D2D pair for the maximum sum rate. The programming maximizes R^f_{sum} by choosing a scheduling matrix, X, for the *D2D* pairs and optimum transmission powers for the CU and scheduled D2D transmitter. The following is the proposed opportunistic resource sharing and power control formulation for a single frame, f:

$$
\begin{aligned}
\max \quad & R^f_{sum}(p^*_c, p^*_d, X^*) && (9)\\
\text{subject to} \quad & x_i(f)R_{min} \leq R_i(f), \\
& \forall i \in U_o, x_i(f) \in \{0, 1\} && (10)\\
& \Gamma_i \leq \gamma_i(f)x_i(f), \quad \forall i \in K_o && (11)\\
& \Gamma_{bs} \leq \gamma_{bs}(f), && (12)\\
& \sum_{i=1}^{N} x_i(f) = 1, \quad \forall i \in K_o && (13)\\
& x_i(f)p_i(f) = p_i(f), \quad \forall i \in K_o && (14)\\
& x_i(f)p_i(f) + p_c(f) \leq p_{max}, \quad \forall i \in K_o && (15)\\
& p_{min} \leq p_i(f) \leq p_{max} \quad \forall i \in U_o. && (16)
\end{aligned}
$$

Constraint (10) defines the lower bound on the required minimum rate (R_{min}) for the user devices. Further, constraints (11) and (12) determine the SINR threshold for successful decoding and opportunistic scheduling of the D2D pairs, and constraint (13) ensures that only one D2D pair can be scheduled to share the resource with the CU in a frame f. Constraint (14) prevents nonscheduled pairs from transmitting. Finally, constraint (15) limits the total transmission power by p_{max}, and constraint (16) determines the minimum and maximum transmission powers for the users. It should be noted that the objective function (9) will be changed to (18) later on to incorporate the delay. (See Section V). Since the problem is nonconvex, a controlled random search algorithm is used to find a solution for the formulated MINLP problem.

A. ALGORITHM FOR THE SOLUTION OF THE MINLP PROBLEM

Algorithm 1 summarizes the overall controlled random search algorithm to solve the optimization problem. At first, the algorithm checks if the frame number is one (Step 1). Then, an M-size random power set, p_s is first created within the minimum and maximum ranges (Step 2). The size of the power set is selected large enough to minimize suboptimality. Thereafter, the elements of the power set are rearranged in ascending order for tractability (Step 3), and every possible power pair is selected while considering the respected decoding thresholds for SINR, (11) and (12), and total power limitation, (15) (Step 4). As a result of this selection, two power subsets are obtained for CU (a p_{cu} subset of size C) and D2D (a p_{d2d} subset of size D), with each corresponding to the transmission powers (Step 4). It is worth noting that the number of possible pairs is calculated as CD and is always less than $M^2/2$ because p_s is sorted in ascending order and the total power limitation (15) is considered. For each possible power pair, the CU rate ($R_c(p_c, p_d)$), D2D rate ($R_k(p_c, p_d)$) and sum rate ($R_{sum_k(p_c,p_d)}$) are calculated for all candidate D2D pairs (Step 9). For the p_s power set, the sum rate matrix, $R^{p_s}_{sum}(i, j)$, is obtained by selecting the maximum sum rate ($(max(R_{sum_1}, .., R_{sum_N}))$) for the power pair, i, j (Step 13). Afterward, the D2D pair with the maximum sum rate is selected, and the corresponding scheduling matrix and related transmission powers (p_c and p_k) are saved. Thus, Algorithm 1 returns the maximum value of $R^{p_s}_{sum}(i, j)$, the corresponding transmission powers, and the scheduling matrix (X^*) for frame f.

The computational complexity of Algorithm 1 is dominated by the D2D cluster size (N), M-size random power set, and the sizes of two controlled random power subsets (C and D), and is indicated with $O(NCD + 2M)$. To obtain the estimated delay of the newly generated data at the user devices, we developed a delay calculation algorithm that solves the MINLP problem by running Algorithm 1 for L successive frames. The details of the algorithm are presented in the next section.

V. DELAY CALCULATION ALGORITHM AND OPPORTUNISTIC SCHEDULING

This section introduces an algorithm for obtaining a delay estimate of the opportunistic scheduling of N D2D pairs to share a CU's uplink resource. To consider the delay, a weighting factor is defined by normalizing a residual queue length, $Q_i(f)$, (2) at each frame with a maximum queue length (Q_{max}) as follows:

$$w^i(f) = \frac{Q_i(f)}{Q_{max}}, \quad \forall i \in K_o. \tag{17}$$

Q_{max} is calculated by multiplying the average data arrival rate with the total number of frames of interest, where $Q_{max} = \lambda_i L$. The solution of the MINLP problem obtained from equations (9)-(16) allows one D2D pair to be scheduled in a single frame. The scheduling matrix and resulting transmission powers are optimal for maximizing the sum throughput.

Algorithm 1 Pseudocode for Controlled Random Search Algorithm

```
Result: p_c^*(f), p_d^*(f) and X^*
1  if f==1 then
2      Create an M size random transmission power set
         (3dBm ≤ p_s ≤ 23dBm) ;
3      Sort p_s in ascending order.;
4      Select every possible power pairs based
         on (11), (12) and (15) and obtain two power
         subsets for CU and D2D with size C and size D,
         respectively;
5  end
6  for i = 1 to C do
7      pc = p_cu(i);
8      for j = 1 to D do
9          pd = p_d2d(j);
10         for k = 1 to N do
11             Calculate R_c(p_c, p_d), R_k(p_c, p_d) by (4),
                 and R_sum_k(p_c, p_d) by (9) ;
12         end
13         Calculate R_sum^{p_s}(i, j) = max(R_sum_1, ..., R_sum_N);
14     end
15 end
16 R_sum^f(p_c^*, p_d^*, X^*) = max(R_sum^{p_s}(i, j));
17 Obtain corresponding optimum transmission powers
     p_c*, p_d* and the scheduling matrix X*;
```

The delay-aware scheduling decision is introduced by integrating the weighting factor (17) into the objective function (9) of the MINLP problem as follows:

$$R^f_{sum}(p^*_c, p^*_d, X) = \sum_{i=1}^{N} x_i(f) R_i(f) w_i(f) + R_c(f). \tag{18}$$

To calculate the delay, the MINLP problem is solved for L successive frames by using the delay-aware objective function defined in (18) with the constraints (10)-(16). After attaining a solution for each frame, the residual queue length and weighting factor are updated accordingly.

The algorithm calculates the residual queue lengths at each L frame for each user device, with a focus on the estimated delay for the newly generated data at the application layer of the user devices. To this end, the average delay in the form of a number of frames can be calculated using Little's Law:

$$D_i = \frac{mean(Q_i(1), Q_i(2), \ldots, Q_i(L))}{\lambda_i \tau_f} \quad \forall i \in U_o, \tag{19}$$

where $Q_i(.)$ is the queue length of the user device, i, after the solution of the problem at the f^{th} frame. At each frame, the scheduling decision is modeled using the Boolean variable, $x_i(f)$, in the queue length equation (2). Successive scheduling of the D2D pair, i, results in smaller $Q_i(f)$ and D_i values unless the arrival rate changes, but no scheduling of the i^th pair for many successive frames results in larger $Q_i(f)$ and D_i values. In the first frame, the problem is solved by employing an empty queue (i.e., to obtain a valid weighting factor, an empty queue is represented as $Q_i(f) = 1$ despite it being zero in (17)). For any successive frame ($f < L$), the residual queue sizes of the user device are considered for the scheduling decision. The queue length of each D2D is considered by the queue weighting factor $w_i(f)$ (17) and it is embedded into the optimization problem by replacing the objective function (8) to (18). Therefore, priority in the scheduling is given to D2D pairs with the highest queue length that maximizes the overall throughput. Implementing the delay consideration through the weighting factor makes it possible to avoid giving priority to a D2D pair with very low channel gain unless its queue length is relatively high. Algorithm 2 outlines this model. The complexity of Algorithm 2 is dominated by that of Algorithm 1 and is indicated with $O(L)O(NCD+2M)$. Figure 3 flowchart depicts the full procedure, including Algorithms 1 and 2.

Algorithm 2 Delay Calculation Algorithm

Result: $R_c(f)$, $R_i(f)$ and D_i ;
Initialize $f = 1$, $Q_i(f) = 1$;
Set $\lambda_i = \lambda$;
while $f \leq L$ **do**
  Obtain $R^f_{sum}(p_c, p_k, X)$, $R_c(f)$ and $R_i(f)$ by performing Algorithm 1 using ((18)) as objective function;
  Obtain the optimum transmission powers p_c*, p_k*;
  Obtain the scheduling matrix $X*$;
  Calculate $Q_i(f)$ using equation (2) ;
  if $Q_i(f) == 0$ **then**
    $Q_i(f) = 1$
  else
    update $Q_i(f)$
  end
  Update $w^i(f)$ with the new $Q_i(f)$;
  f++ ;
end
Calculate D_i from (19).

VI. RESULTS AND DISCUSSIONS

A. SYSTEM PARAMETERS

In this section, we evaluated the performance of the proposed model by performing Monte Carlo simulations. In each hexagon cell with a radius of 200 m, N IoT transmitters (IoTTx) were randomly distributed over, and a single BS was placed at the center of the area, and a CU was located randomly around it. Configuration of D2D links, CU links, and interference in a multicell environment is illustrated in Fig. The IoT receivers (IoTRx) were randomly and independently placed around their associated

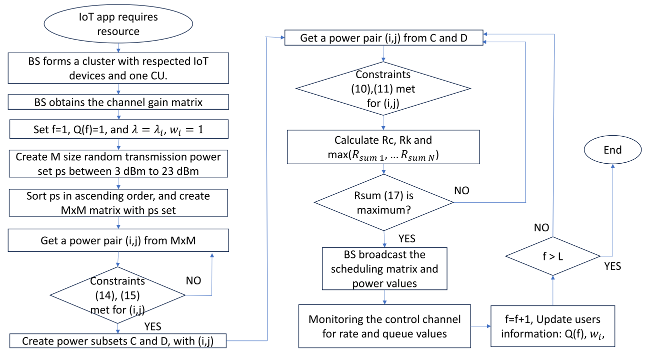

FIGURE 3. Flowchart of proposed NOOA process.

transmitters. The distance between IoTTx-IoTRx and CU-BS was chosen as Gaussian distributed with $N(75, 6)$ (set to obtain $50 - 100$ m) and $N(50, 9)$ (set to obtain $10 - 90$ m), respectively, and the maximum value is set 200 m for both. There is an ongoing uplink communication of CU and an opportunistically chosen D2D pair underlay this uplink resource. In each cell, users are also exposed to other cell interference from the users that are located in six hexagonal neighborhoods.

The minimum SINR threshold was set to $\Gamma_i = -80$ dB. The numerical results are obtained by averaging 1000 randomly generated networks, and the results for each network correspond to an average of $L = 100$ frames of 10 ms each ($\tau_f = 10$ ms). The noise power was set to -174 dBm, and the maximum and minimum transmission powers were set to 23 dBm and 3 dBm, respectively [28]. The total transmission power on the channel was restricted to $p_{total} = p_{min} + p_{max}$. (Note that we used p_{total} rather than the p_{max} in constraint (16) to be able to compare the model to the optimum binary power control strategy.) A common path loss model was used with a path loss exponent of 3.5 for both the CU and D2D links. The fading channel coefficients have a unit mean and follow an exponential distribution. They are constant in a frame and independent from other frames. The CU and D2DTxs were assumed to generate data with Gaussian distribution, $N(3, 0.6)$ (set to obtain $0.5 - 5.5$ $Mbps$). The communication was assumed to be interrupted if the delay exceeded the benchmark values of 300 ms and 500 ms for voice traffic and video streaming, respectively. Therefore, the cluster size parameter is set for a maximum of twenty IoT pairs.

The solution of the formulated MINLP attains adaptive transmission powers under delay consideration, hence we named it NOOA-APC (adaptive power control). We consider two baseline power control strategies for NOOA-enabled cellular uplink as well; i) Binary Power Control (BPC) [16], ii) Channel inversion power control (CIPC) [29], [30]), and named them as NOOA-BPC and NOOA-CIPC accordingly. For a fair comparison, NOOA-BPC and NOOA-CIPC also consider the delay by prioritizing the IoT pairs with higher queue lengths, while NOOA-APC considers delay by queue weighting factor in the objective function of MINLP. In BPC we used two fixed power values as pmax (for poor link)

TABLE 1. Notations and numerical values.

Symbol	Quantity	Definition
Pc_{min}, Pc_{max}	3 dBm, 23 dBm	Minimum and Maximum transmit power of cellular user
Pd_{min}, Pd_{max}	3 dBm, 23 dBm	Minimum and Maximum transmit power of D2D user
σ^2	174 dBm	Noise power
α	3.5	Path loss exponent
Γ_i	-80 dB	Receiver sensitivity for user i

and pmin (for strong link) while for CIPC we utilized the following formulation to determine transmission powers; $P_{transmision} = P_{average} * R^{\alpha\varepsilon}$, where R is the link distance, α is path loss exponent, and ε is a parameter which is selected as $\varepsilon = 0.0414$ based on the maximum allowed distance for minimum SINR threshold and maximum-minimum transmission power limitations. The parameters used in the numerical results is given in the table 1.

B. DESIGN PARAMETERS

In the following, we study the effect of two main design parameters on the performance of proposed NOOA-enabled IoT underlying cellular networks, namely, the cluster size N and the power control strategy. We focus on two main criteria for performance comparison: spectral efficiency and delay.

In Fig. 4 and Fig. 5 we investigate the effect of cluster size on the delay performance of NOOA with different power control strategies for IoT and CU, respectively. The plot gives the probability that the average delay experienced by the user would be at most a bound value of D, i.e., it gives the cumulative distribution function (CDF) of delay, Di (19), i.e P[Di < D]. Note that BS is responsible for forming clusters based on predetermined distances between D2D pairs and itself. Fig. 5 shows that CU's delay value increases slightly for larger cluster sizes in NOOA-BPC and NOOA-CIPC schemes while decreasing slightly in NOOA-APC. This is because IoT pairs are selected for scheduling by prioritizing the ones with longer queue lengths in NOOA-BPC and NOOA-CIPC, therefore they might have been scheduled for communication even though they would create more interference to CU and detriment the individual rates or overall sum rate. Furthermore, IoT pairs in larger clusters suffer from higher queue length due to longer scheduling wait times, but the proposed NOOA-APC achieves optimum transmission power values for maximum sum rate objective, so having more D2D pair options for scheduling results in less delay for larger clusters by increasing the probability of scheduling D2D pairs with high channel gain as well as long queues. In other words, NOOA-APC has more freedom in larger clusters to obtain maximum sum rate and individual rates, but implementing a queue weighting factor for delay awareness rather than prioritizing based on queue lengths caused much more delay compared to others. The plots indicate that cluster size has minimal impact on CU's delay in NOOA-enabled scenarios, whereas the choice of power control strategies significantly influences CU's delay. It is observed that the adaptive power

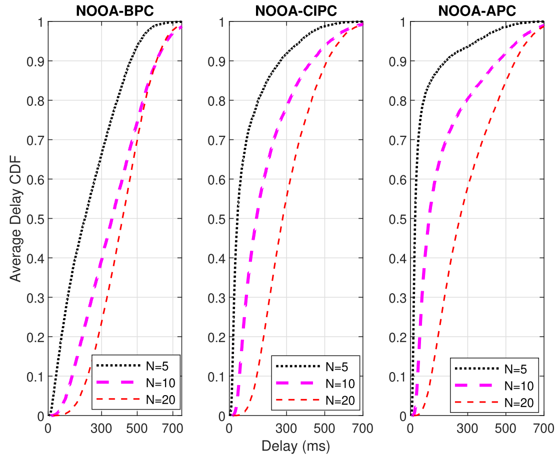

FIGURE 4. IoT delay values vs cluster sizes P[Di < D].

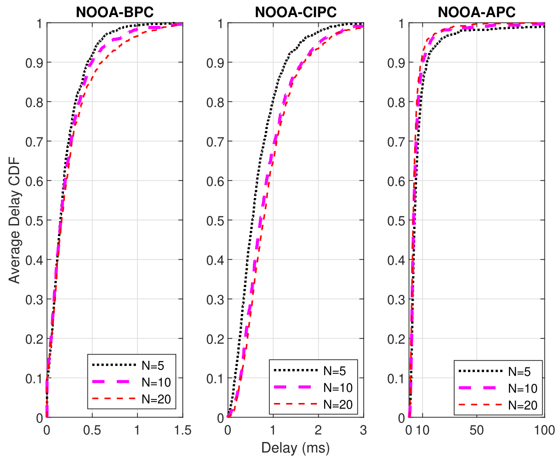

FIGURE 5. CU delay values vs cluster sizes P[Di < D].

control strategy, NOOA-APC, causes the highest delay values for CU, while the binary power control strategy results in the lowest. However, in all power control strategies proposed NOOA-based schemes do not cause a detrimental effect on CU's voice or video traffic based on the defined benchmark values for delay in Section VI.

Fig. 6 and Fig. 7 show how average rates change with cluster size and power strategies for IoT pairs and CU, respectively. The plot gives the probability that a given target rate, R, on the x-axis can be achieved, i.e., it gives the complementary cumulative distribution function (CCDF) of rate, Ri (19), i.e., P[Ri > R]. In the NOOA scheme, there is always one IoT pair that shares the channel with CU, and interference caused by the scheduled IoT pair results in similar rates for CU. Therefore, the curves are almost overlapping for all cluster sizes in Fig. 7. The CU rate only slightly increases as cluster size grows in NOOA-APC. This is due to the fact that larger clusters are more likely to have a D2D pair with high channel gain while the adaptive power setting manages interference. We can conclude that the cluster size parameter is not a very important design parameter for CU's spectral efficiency. However, it has been

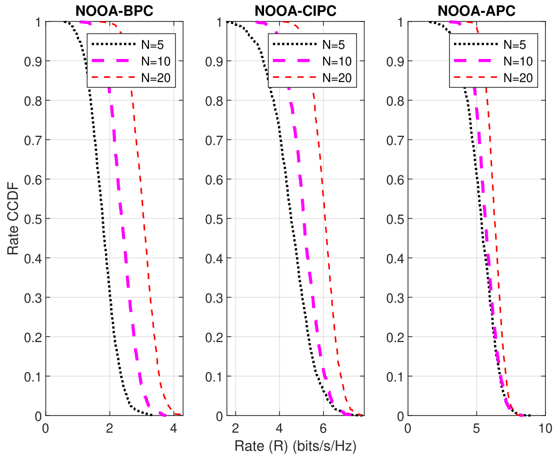

FIGURE 6. IoT rates vs cluster sizes P[Ri > R].

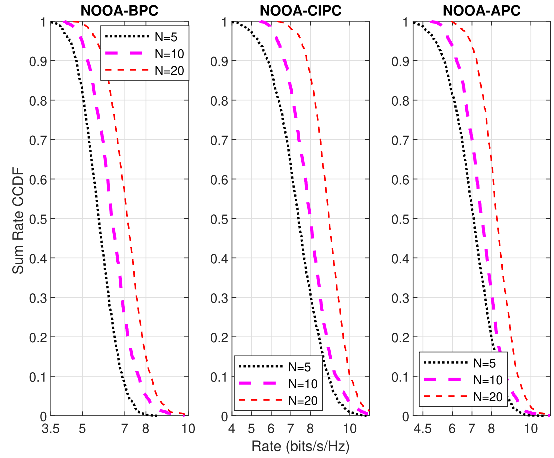

FIGURE 8. Sum rate vs cluster sizes, P[Rsum > R].

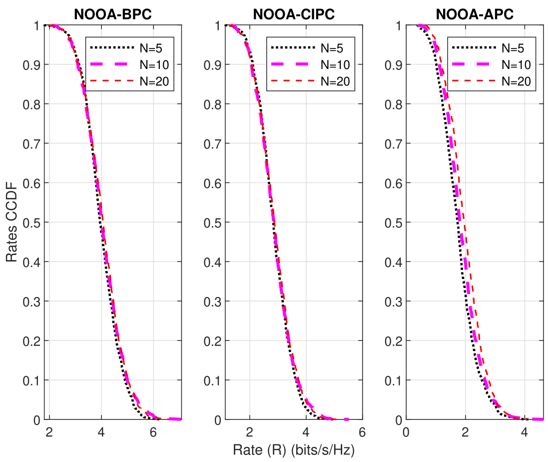

FIGURE 7. CU rates vs cluster sizes P[Ri > R].

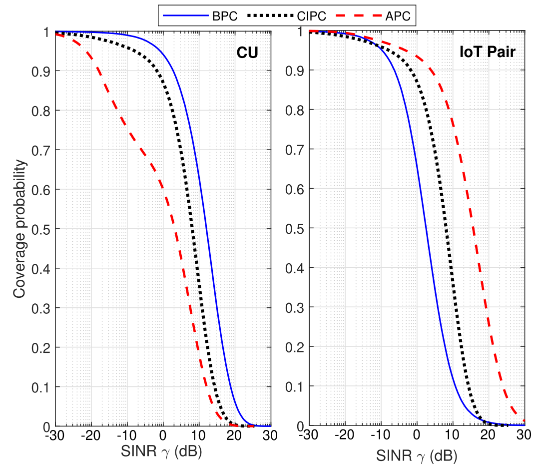

FIGURE 9. Coverage probability, P[$\gamma_i > \gamma$], N = 5.

found that the power control method significantly affects how well the CU performs in terms of spectral efficiency. Fig. 7 demonstrates that NOOA-BPC outperforms the competition while NOOA-APC performs the least well. Assuming a voice call requires a minimum rate of 20 kbps or 100 kbps for VoIP calls, NOOA-APC and NOOA-CIPC clearly do not support these minimum values for even a 20 MHz channel. However, keep in mind that we assume.5 to 5.5 Mbps ($\mathcal{N}(3, 0.6)$ distributed) data output by the application layer of CU and IoT pairs (which is pretty high). This data is queued and subsequently transmitted, therefore rates in the NOOA model are not only interference-limited but also delay-dependent.

According to Fig. 6, the average rate of IoT users is affected by both design parameters, namely cluster size and power control approach. The IoT rate increases with cluster size because the possibility of having IoT pairs with good channels increases, resulting in greater rates in larger clusters. For IoT pairs, NOOA-APC achieves the highest rates, while BIPC achieves the lowest.

Based on the observed data, we infer that cluster size should not exceed twenty because it produces a significant rise in delay values of IoT pairs. This is an unavoidable consequence of scheduling only one pair at a time. These findings show that the proposed NOOA scheme can be utilized to offload extra IoT traffic while having no negative impact on CU's voice or video traffic (based on the expected benchmark values). Therefore, the power control model or cluster size needs to be selected based on IoT application-specific criteria. However, it is observed that because it meets more than 2 bps/Hz data rates for IoT devices, the suggested system would be suitable for many IoT applications such as smart housing, smart parking, or trash management.

Next, Fig. 8 shows the CCDF of the overall sum rate for all power control strategies and how they change with cluster size. The plot illustrates that the probability of the sum rate being greater than the target rate, R, i.e., P[Rsum > R]. Inconsistent with the IoT and CU rate graphs, the plot in Fig. 8 shows that NOOA-APC outperforms thanks to the results obtained by the solution of the MINLP problem. In all power control models the sum rate increases as the cluster size grows because the probability of having an IoT pair with a good channel is higher in larger clusters.

C. COVERAGE COMPARISON

In Fig. 9, Fig 10 and Fig 11, we focus on the coverage probability for CU and IoT pairs. The plot gives the

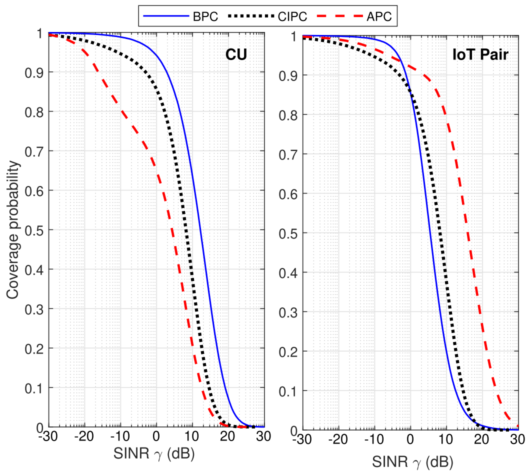

FIGURE 10. Coverage probability, P[$\gamma_i > \gamma$], N = 10.

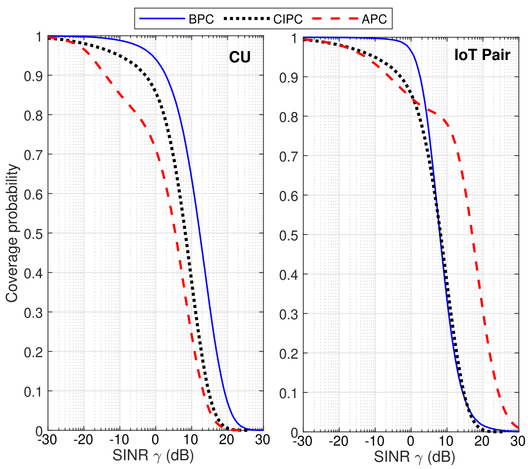

FIGURE 11. Coverage probability, P[$\gamma_i > \gamma$], N = 20.

probability that a given SINR target γ on the x-axis can be achieved, i.e., coverage probability corresponds to the complementary cumulative distribution function (CCDF) of SINR, γ_i i.e., P[$\gamma_i > \gamma$]. A cellular operator must provide at least some coverage to their customer with a very high probability. For example, 0 dB SINR may be a minimum level of quality required to provide a consistent data speed. Fig. 9 and Fig 10 show that the NOOA-APC has a success probability of about 0.6 for N = 5 and N = 10, and about 0.7 for N = 20 in Fig. 11. Obviously, none of these are enough for commercial networks, therefore designers must find the appropriate configuration to maximize coverage probability while fulfilling IoT application requirements. Assuming the NOOA model is interference-limited, utilizing BPC or CIPC methods in bigger clusters might be an effective way to go. However, for IoT pairs, NOOA-APC provides a success chance of roughly 0.9 for all design parameters, which is sufficient for many IoT applications. We can conclude that BS may need to develop adaptive clusters based primarily on CU's performance requirements. It should be emphasized that we assume that both CU and IoT pairs continually use the uplink (their application layer generates data with $N(3, 0.6)$ distribution), however, this is not usual user behavior for uplink. As a result, the proposed NOOA approach would be suitable for uplinks with typical user traffic patterns.

VII. CONCLUSION

In this study, we present a non-orthogonal opportunistic channel access model for IoT devices performing D2D communication, and we analyze whether the suggested model may be used to offload IoT-generated traffic when IoT underlay the cellular uplink. To accomplish this, we explore the quality of service needs for CU and IoT devices. The results in terms of achievable rates and maximum delay show that the proposed NOOA model may be utilized to offload IoT-generated traffic while maintaining minimum rate and delay requirements for CU's voice or video traffic with suitable parameter settings. Specifically, sensors of your smart home can communicate via D2D connections by sharing your mobile's uplink, which would be available most of the time. However, it is needed to mention that, when it comes to using the uplink of your neighbors' mobile there would be many challenges to deal with such as billing, privacy, and authentication. Furthermore, in future studies, a distributed scheduling algorithm should be investigated based on the design parameters (cluster size and power control strategy) and application-specific trade-offs on delay and rate presented in this paper. This is because BS central scheduling would incur additional traffic and, consequently, extra energy costs, which could be problematic for many battery-operated IoT devices.

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