The Impact of D2D Connections on Network-Assisted Mobile Data Offloading

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***Abstract*—The exponential increase of mobile data traffic pushes mobile operators to seek more efficient heterogeneous communication techniques. In this study, multi-user extension methods for multiple attribute decision making algorithms for network-assisted data offloading in heterogeneous wireless networks are developed and performance evaluations are performed in the presence of Device-to-Device (D2D) connections. Evaluations are carried out using simulations to point out the metrics and factors influencing data offloading in heterogeneous networks. The simulation results indicate the superiority of incorporating network-based information besides user-based information in offloading decisions. Additionally, up to 67% increase in user satisfaction can be achieved when D2D density is kept 68% under a heavy load scenario. The simulation results also indicate the existence of optimal D2D densities in heterogeneous networks depending on the total number of users and available network capacity.**

***Index Terms*—data offloading, D2D, heterogeneous networks, multiple attribute decision making.**

I. Introduction

The diversity of the wireless networks has increased substantially during the last decade causing connectivity management problems. In addition to the expansion in infrastructure based wireless networks such as Long Term Evolution (LTE) and Wi-Fi, D2D communications are also arising as an alternative or complementary approach for data dissemination opportunities in a cellular network. D2D communications can be considered as a complementary approach to mobile data offloading in parallel with traditional offloading techniques such as Wireless Local Area Networks (WLANs) or small cells (e.g. femtocells, picocells) that are deployed inside cellular networks. In such heterogeneous networks, optimal connectivity management for data dissemination becomes a seriously challenging problem especially in multi-user scenarios. Moreover, the dynamic behaviour of D2D connections further increases the complexity of the problem.

In order to tackle with the optimal connectivity management problem, several Multiple Attribute Decision Making (MADM) algorithms are developed in the literature. Accordingly, in [1] and [2], four major MADM algorithms, namely, Multiplicative Exponent Weighting (MEW), Simple Additive Weighting (SAW), Grey Relational Analysis (GRA), Total Order Preference By Similarity to the Ideal Solution (TOPSIS) are described and compared for utilization in heterogeneous wireless networks. The results have shown that none of the MADM algorithms outperform the others and in general they perform similar to each other.

Incorporating D2D communications concept into cellular networks is a demanding research topic all by itself, irrespective of connectivity management. In this context, D2D communications are currently being studied in conjunction with mobile data offloading techniques in cellular networks in many of the recent works [3], [4], [5], [6], [7], [8]. The authors in [3] consider the problem of cellular data offloading scheme using D2D communications and propose content sharing mechanism among mobile devices. The authors in [4] consider resource allocation problem for D2D communications in cellular networks for selecting the best resource sharing mode depending on the different applications including file-sharing or streaming like applications. In order to cope with data tsunami in cellular networks, the authors in [5] have investigated multiple contents with different popularity offloading via opportunistic D2D communication and derived analytical models for calculating the number of relay users for distributing multiple contents. In [6], the benefits of network assisted D2D connections are presented. Other existing solutions for network assisted mobile data offloading (e.g. Push & Track [7] or EPICS [8]) are working on content dissemination with minimum delay constraints. We refer our readers to [9] and [10] for recent and more comprehensive surveys of mobile data offloading strategies along with D2D based communication opportunities.

Although there exist several studies in the literature on D2D communications and MADM, there exists lack of studies that investigate the impact of D2D connections on MADM algorithms for network-assisted (i.e., operator controlled) data offloading. In fact, in our analysis we did not approach the optimization problem from content dissemination delay minimization point of view but tried to fill out a gap that exists in the literature as well as industry by studying an offloading framework that can accommodate MADM algorithms while exploiting D2D communications. Accordingly in this study, we focus on revealing the performance of MADM algorithms in the presence of D2D connections. First, we propose two multi-user extension methods for MADM algorithms. In the first method, we consider a straightforward application of MADM algorithm, where we optimize individual users performance by sequential handling of the users. In the second method, we take into consideration the network-wide performance by integrating the remaining capacity in WLAN and cellular networks. In order to focus on the performance of extension methods and the impact of D2D connections we use one

MADM algorithm, namely TOPSIS [11], [12] algorithm.

In order to demonstrate the performance of the extension methods and the impact of D2D connections, we take benefit of computer simulations. The primary goal of the simulations is to provide an assessment of the impact of D2D connections to offloading algorithms in terms of user satisfaction metrics. The simulation results reveal the performance comparisons of the two extension methods. Concurrently, the results also reveal how the user satisfaction fluctuates in the presence of D2D connections under different total load levels in the network.

The rest of the paper is organized as follows. In Section II, the generic scenario and the studied use case are described. In Secion III, the two multi-user extensions to MADM algorithms are explained. Then, in Section IV, the simulation results of the MADM algorithm extensions in the presence of D2D connections is presented. Finally, in Section V, we give conclusions and potential future work extensions.

II. Scenario and Use Case

In this study, we consider the case where users may either be served by an operator through a cellular or a WiFi infrastructure, or D2D communications. Based on this, we investigate how to schedule users across these technologies in an optimal manner. A centralized platform calculates the best infrastructure connection (WiFi or eNodeB) for the users, using a MADM algorithm, provided that a certain ratio of the users communicate via D2D. The target heterogeneous network scenario is shown in Figure 1 where access technologies, LTE and Wi-Fi together with D2D nodes are depicted. The black dashed circles demonstrate the assumed range of Wi-Fi Access Points (APs). The eNodeB range is assumed to cover all users, and D2D range is short so that it can only cover neighbouring users. Based on this scenario, users receiving data from the evolved Node-B (eNodeB) (green dashed arrows) or Wi-Fi AP (blue dashed arrows) can disseminate the data to nearby users via D2D connections as depicted with yellow dashed arrows in Figure 1.

The considered scenario is more common in crowded environments, such as stadiums and shopping malls. These type of environments include different types of access networks and technologies together with numerous users. In such heterogeneous environments, data dissemination to users by offloading via Wi-Fi or D2D saves user and network based resources and consequently increases system level efficiency.

III. MADM Algorithm and its Extensions

MADM techniques are extensively used in making automated decisions between several options with several attributes. Applications of MADM techniques extend a wide range from selection of ideal construction location to selection of ideal oil tanker. A MADM technique needs two inputs for decision making; attribute value matrix and weights of each attribute. Attribute matrix is composed of measured values of attributes per each option and the weights can be adjusted based on the needs of decision makers. Mode details on MADM methods are given in [13].

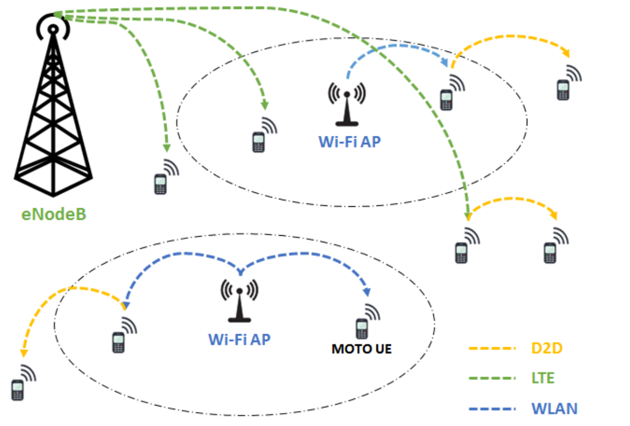

Fig. 1: Heterogeneous Network Scenario with eNodeB, Wi-Fi APs and D2D connections.

MADM techniques can be also used for selecting the ideal network when a mobile user can access a heterogeneous network [2], [14]. The process of selecting the ideal network can be centrally controlled by the cellular operators to maximize system level performance. As presented in the scenario definition provided in Section II, the centralized platform executes a MADM algorithm to perform selection on the best network connection. All MADM algorithms need an attribute matrix $\mathbf{A} = [a_{ij}]_{p \times m}$, where m refers to size of the multiple attribute set S $= \{s_1, s_2, ..., s_m\}$ consisting of elements such as backhaul remaining capcity, quality of radio link, e2e latency, etc., whereas p refers to size of the multiple decision set E $= \{e_1, e_2, ..., e_p\}$ which consists of candidate networks such as LTE, WLAN, or femtocell technologies for a given user. In this paper, for our analysis we transform all the attributes to have positive impact with increasing value.

The aim of a MADM algorithm is to decide on the optimal $e^* \in$ E based on the attribute matrix $\mathbf{A}$ at any given time instant. In the following sections, we define two extensions for MADM algorithms, Standard MADM (S-MADM) and Capacity Aware MADM (CA-MADM), to cover multiple users in a realistic heterogeneous network scenario.

A. S-MADM Method

S-MADM method is a simple extension of MADM. It takes into account the individual channel utilization demands of users in a multi-user environment. The details are as follows:
Method's Input Parameters: The attribute matrix of n-th user $\mathbf{A}^n$, $1 \leq n \leq N$, and the multiple decision set (set of networks) E, where N is total number of users registered to the offloading platform.
Method's Output Parameters: Channel utilization vector for one-user channel $\mathbf{CU}^e = [CU_1^e, ..., CU_N^e]$, $e \in$ E.

1) For $\mathbf{A}^n$ $1 \leq n \leq N$, simultaneously use MADM algorithm for all the users in the network to select the optimal decision points e^*.
2) By summing each users' channel utilization demands over the selected decision point, update the channel utilization vector $\mathbf{CU}^e$.

B. CA-MADM Method

In this method, for all users a new network-based attribute vector $\hat{\mathbf{u}} = [\hat{u}_1, ..., \hat{u}_p]$ is utilized in the attribute matrix $\mathbf{A}$. The decision for each user is handled sequentially by the centralized platform. Therefore, the system level performance can be maximized using this method. The remaining available capacity in the decision point e_i is kept in the network-based attribute $\hat{u}_i$ and can be obtained by

$$\hat{u}_i = CU_{\text{TH}}^{e_i} - \sum_{n=1}^{N} CU_n^{e_i}, \quad 1 \le i \le p \qquad (1)$$

where $CU_{\text{TH}}^{e_i}$ represents the capacity threshold of network option e_i. The algorithm details are as follows:

Method's Input Parameters: n^{th} arriving user's extended attribute matrix $\hat{\mathbf{A}}^n = [\mathbf{A}^n, \hat{\mathbf{u}}^{\text{T}}]$, $1 \le n \le N$ and the multiple decision set (set of networks) E.

Method's Output Parameters: Channel utilization vector $\mathbf{CU}^e = [CU_1^e, ..., CU_N^e]$, $e \in$ E for one-user channel.

1) Set $\mathbf{CU}^e = 0$, $j = 0$ where $j \le N$ is both the number of arrived users and number of iterations
2) Set $j = j + 1$ when a new user accesses the network
3) For $\hat{\mathbf{A}}^j$, use the MADM algorithm where the optimal decision point e^* is selected.
4) Recalculate the channel utilization vector $\mathbf{CU}^e$ using

$$CU_j^{e^*} = \text{channel demand of user } j$$

5) Update the network-based attribute vector $\hat{\mathbf{u}}$ using (1).
6) If $j = N$, **stop**, else goto **Step 2**.

IV. Simulations and Results

A. Simulation Scenario

Opportunistic D2D offloading platforms target dense heterogeneous networks where bandwidth is scarce. In this study, we use a stadium scenario to simulate a dense heterogeneous network. The stadium is assumed to hold 10K audience with several Wi-Fi APs and eNodeBs access nodes. We denote the users that are registered to the opportunistic offloading platform as MOTO[1] users (or terminals). Out of the 10K audience in the stadium 50, 100 or 200 terminals are selected at random to as the MOTO users. A sample user distribution for 100 MOTO users in a 10K capacity stadium is provided in Figure 3 depicting the locations of Wi-Fi APs and eNodeBs access nodes.

It should be noted that our MOTO platform is not providing MOTO service to all users in the stadium but to subset of users that are subscribed to MOTO platform apriori. In real network settings, as shown in Fig. 2 each eNodeB will also have multiple sectors (generally 3 Sectors) and each sector can include different number of carriers (or cells) e.g. in Fig. 2, sector-1 can have 5 cells, sector-2 can have 7 cells and sector-3 can have 5 cells. Hence, multiple cell-IDs with each cell having different frequencies can accommodate multiple users. Considering the fact that each microcell can accommodate up to 256 eNodeB users in real-life scenarios [15], the assumptions on number of MOTO users and their corresponding BSs and APs made in our simulations are realistic. The locations of Wi-Fi APs are chosen heuristically equally spaced in the mid of the rows of the stadium. However, the locations can also be modified based on operator requirements. The reserved bandwidth (capacity) for MOTO users per each eNodeB and Wi-Fi AP are 75 Mbps and 36 Mbps, respectively. The rest of the bandwidth, if any, can be utilized by non-MOTO users.

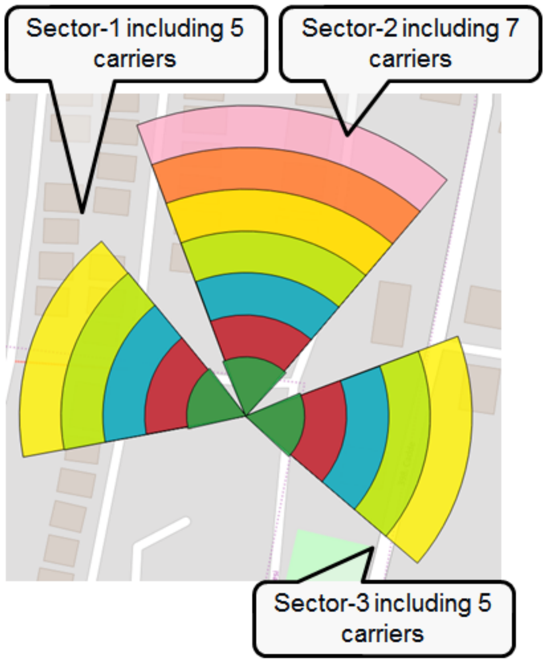

Fig. 2: Sectors in an eNodeB.

In our analysis, we are assuming that MOTO specific APN (Access Point Name) is used inside the core network of the MNO to define the type of service each MOTO user gets. Therefore, MOTO services provided by MOTO platform to MOTO users inside stadium are provided using different and isolated resources, i.e. using the eNodeBs and APs used in the simulations. Therefore, we have used the remaining non-MOTO users in our simulations only for randomization purposes based on location during each Monte-Carlo simulations. We also assume that the number of operators who has agreed with MOTO platform providers is out of scope this paper.

In the scenario, MOTO users request to download streaming video content among the qualities 360p - 1080p similar to YouTube [16]. MOTO users are able to download the content directly from the nearest Wi-Fi AP or eNodeB. The MOTO users that download the content from an infrastructure based access node (Wi-Fi AP or eNodeB) can disseminate the data to nearby users via D2D. The number of MOTO users that will download the content from other MOTO users via D2D is assumed to be fixed for each simulation round. Given the number of such D2D users, the D2D users are selected among the MOTO users that are farther away from the Wi-Fi APs and eNodeBs. If a MOTO user is selected to use D2D, the connection range is assumed to be 10m, similar to that of low-power Bluetooth. D2D users download the content only

[1]MOTO is the acronym for the FP7 project named Mobile Opportunistic Traffic Offloading

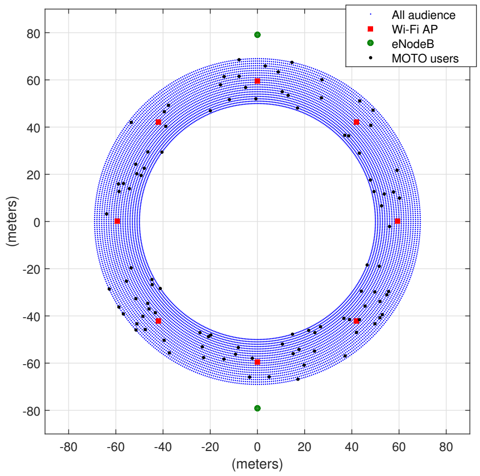

Fig. 3: A sample of MOTO users distribution and locations of Wi-Fi APs and eNodeB

via surrounding MOTO users that are assigned to Wi-Fi APs or eNodeBs.

In the simulations, we use TOPSIS algorithm [11], [12] as the core MADM algorithm and focus on revealing the behaviour of S-MADM and CA-MADM methods in the presence of varying D2D user density. The S-MADM and CA-MADM TOPSIS algorithms are denoted as Standart Multi-User TOPSIS (ST) and Capacity-Aware Multi-User TOPSIS (CAT). The attributes that are mostly related to video transmission are chosen for our MADM algorithms for the simulations. First attribute is the received signal strength calculated by free space propagation principles (i.e., line-of-sight channel) based on the distance between the access node (Wi-Fi or eNodeB) and the MOTO terminal. The second attribute is the requested throughput (i.e., video bitrate) calculated using a received signal strength - bitrate mapping table. Third attribute is the latency which is fixed for a given type of access node. The final attribute is the remaining reserved bandwidth in the access node. Note that, final attribute is only used for the CAT algorithm.

In order to achieve a well-balanced offloading outcome following attributes and weights are used. Received Signal Strength, Throughput, Latency, Remaining Capacity: [0.3, 0.3, 0.3, 0.1]. The latency attribute has lowest weight since our scenario is less sensitive to latency compared to other attributes. The simulation results demonstrate the average of 500 simulations for varying D2D density percentage defined as

$$\sigma = \frac{\text{number of D2D users}}{\text{number of MOTO users}}. \tag{2}$$

All simulation tools, models and results are implemented and generated on MATLAB programming environment.

B. Performance Metrics

We present the simulation results using two performance metrics. First metric is MOTO users' cumulative bandwidth demand from the access nodes. Total bandwidth demand results that are above 100% show that the the network load is above the reserved bandwidth and access nodes can not serve all MOTO users properly. Second metric is user satisfaction ratio. Users connected to Wi-Fi/eNodeB that can successfully download the content are recorded as satisfied. Other users assigned to download the content from nearby seed MOTO users are satisfied if the seed MOTO user is satisfied.

C. Results

Simulations are performed and presented under three different categories. First category of results, given in Table I, show the MOTO users's distribution among Wi-Fi and eNodeB access nodes when the number of D2D users is zero. The results also show the resulting total bandwidth demands. The results in Table I present the offloading distribution between 3GPP and WLAN networks for CAT and ST algorithms for 50, 100 and 200 MOTO users. As the number of MOTO users increases, the network (with the available capacity stated above) becomes more congested and user satisfaction degrades as expected. We define a metric for capacity per user ratio as

$$\rho = \frac{\text{available capacity}}{\text{number of MOTO users}} (Mbps). \tag{3}$$

In the first category of results, $\rho = 8.76, 4.38, 2.19$ for 50, 100 and 200 MOTO users respectively. For all three different capacity per user ratios, the CAT method yields improved balance between user distributions and bandwidth demand, as well as better user satisfactions. The results show that CAT algorithm performs significantly better by using the information on remaining available bandwidth.

The next two categories of simulation results that includes the effect of D2D users are presented in Figure 4 and Figure 5. In these results, the number of D2D users increases from zero to number of MOTO users to present the impact of D2D users density on the user satisfaction metric. In Figure 4, for each simulation result corresponding to different number of MOTO users, a capacity of 75 Mbps per eNodeB and 36 Mbps per Wi-Fi AP are available for MOTO users which corresponds to $\rho = 8.76, 4.38, 2.19$ for 50, 100 and 200 MOTO users respectively. As the number of users increases, the network becomes more congested. When the number of MOTO users is 50, the total demand is lower than the available capacity. Thus, it is possible to satisfy all users if users are properly assigned (offloaded) to the access networks. The demand/capacity ratios of eNodeBs and WLAN APs on the optimal σ points (i.e., the peak points in Figure 4) are provided in Table II. This table depicts the best load-balance points with maximum user satisfaction. In addition to the demand/capacity ratio in percentages, the results in Table II further provide average offloaded traffic on the the optimal σ points for the users that access to content via 3GPP, WLAN and D2D.

As observed from Table II and Figure 4, when the total number of MOTO users is 50, CAT algorithm satisfies nearly all users (99.8%) without the need to utilize D2D. On the other hand, ST algorithm is unsuccessful at satisfying all users (74.26%) despite the available capacity. However, as the number of MOTO users increases, the demand of users

TABLE I: User distribution, bandwidth demands and user satisfaction for CAT and ST at zero σ for increasing ρ

# of Users	Type of MADM	Users' Distribution (avg.%)		Total Bandwidth Demand (Mbps – demand/capacity %)		User Sat. (%)
		3GPP	WLAN	3GPP	WLAN	
50	CAT	37.34%	62.66%	114.2 Mbps – 76.13%	153.3 Mbps – 53.25%	99.80%
	ST	80.82%	19.18%	237.6 Mbps – 158.40%	60.5 Mbps – 21.01%	67.50%
100	CAT	36.87%	63.13%	227.2 Mbps – 151.50%	310.4 Mbps – 107.80%	73.31%
	ST	80.33%	19.67%	474.9 Mbps – 316.90%	120.7 Mbps – 41.92%	40.47%
200	CAT	36.52%	63.48%	454.65 Mbps – 303.10%	624.96 Mbps – 217.10%	34.29%
	ST	80.69%	19.40%	947.70 Mbps – 631.80%	243.67 Mbps – 84.61%	23.08%

TABLE II: User distribution, bandwidth demands and user satisfaction for CAT and ST at optimal σ for increasing ρ

# of Users	Type of MADM	Optimal σ (% of users – Mbps)	Users' Distribution (avg.%)		Total Bandwidth Demand (Mbps offloaded – demand/capacity %)		User Sat. (%)
			3GPP	WLAN	3GPP	WLAN	
50	CAT	0% – 0 Mbps	37.34%	62.66%	114.20 Mbps – 76.13%	153.30 Mbps – 53.25%	99.80%
	ST	28% – 84.89 Mbps	52.82%	19.18%	156.52 Mbps – 104.35%	61.77 Mbps – 21.45%	74.26%
100	CAT	24% – 135.00 Mbps	23.62%	52.38%	146.19 Mbps – 97.46%	281.32 Mbps – 97.68%	82.67%
	ST	58% – 365.89 Mbps	23.73%	18.27%	148.90 Mbps – 99.27%	116.06 Mbps – 40.30%	57.62%
200	CAT	68% – 828.21 Mbps	8.73%	23.27%	110.74 Mbps – 73.83%	279.01 Mbps – 96.88%	57.56%
	ST	74% – 986.05 Mbps	11.43%	14.57%	153.15 Mbps – 102.10%	193.30 Mbps – 67.12%	50.49%

TABLE III: User distribution, bandwidth demands and user satisfaction for CAT and ST at optimal σ for fixed $\rho = 4.38$

# of Users	Type of MADM	Optimal σ (% of users – Mbps)	Users' Distribution (avg.%)		Total Bandwidth Demand (Mbps offloaded – demand/capacity %)		User Sat. (%)
			3GPP	WLAN	3GPP	WLAN	
50	CAT	14% – 38.60 Mbps	30.62%	55.38%	92.70 Mbps – 123.60%	144.43 Mbps – 100.30%	73.03%
	ST	56% – 175.89 Mbps	25.54%	18.46%	80.02 Mbps – 106.70%	58.17 Mbps – 40.40%	46.30%
100	CAT	24% – 135.00 Mbps	23.62%	52.38%	146.19 Mbps – 97.46%	281.31 Mbps – 97.68%	82.67%
	ST	58% – 365.89 Mbps	23.73%	18.27%	145.90 Mbps – 99.27%	116.06 Mbps – 40.30%	57.62%
200	CAT	24% – 271.58 Mbps	23.11%	52.89%	287.60 Mbps – 95.87%	572.42 Mbps – 99.38%	89.27%
	ST	58% – 732.34 Mbps	23.68%	18.32%	296.36 Mbps – 98.79%	233.96 Mbps – 40.62%	67.96%

exceeds available capacity leading to high congestion where 100% user satisfaction via Wi-Fi APs and eNodeBs is impossible. Comparing CAT with ST, it is clear from results that CAT algorithm clearly outperforms ST in distributing and balancing the MOTO users' demand on Wi-Fi APs and eNodeB. Moreover, D2D offloading shows positive impact on the user satisfaction. For example, comparing the results in Table I and Table II for 200 MOTO users (a heavy load scenario with $\rho = 2.19$), it is observed that user satisfaction increases from 34.29% ($\sigma = 0\%$) to 57.56% ($\sigma = 68\%$) corresponding to an increase of 67% using the CAT algorithm.

In Figure 5, simulation results for fixed capacity per user ratio is presented, i.e. $\rho = 4.38$. The rationale behind this simulation is to demonstrate the benefit of D2D offloading as the number of MOTO users increases in a heterogeneous network. The results demonstrate that for same ρ, the user satisfaction increases with increasing number of MOTO users. This is mainly caused by the increase in the probability of the existence of 3GPP/WLAN users in the range of D2D users.

The utilization rate of APs on the optimal σ points are provided in Table III which depicts the best load-balance points with maximum user satisfaction for fixed ρ. As the number of MOTO users increases from 50 to 200, the user satisfaction percentage increases from 73.03% to 89.27% for CAT algorithm. Additionally, comparing the results in Table I and Table III for 100 MOTO users for CAT algorithm, it is observed that user satisfaction increases from 73.31% ($\sigma = 0\%$) to 82.67% ($\sigma = 24\%$) corresponding to an increase around 20%. Similar to the increasing ρ case, the results in Table III provide average offloaded traffic for all types of connections. The results indicate that for CAT algorithm, as number of users increases from 50 to 200, the total bandwidth demand on eNodeB increases from 92.70 Mbps to 287.60 Mbps. At the same time, the demand per capacity ratio decreases from 123.60% to 95.87% which increases the user satisfaction owing to more efficient D2D offloading. Similar to previous results, CAT performs significantly better than ST in all scenarios.

V. Conclusions and Future Work

In this study, we analyzed the performance of two proposed MADM extension algorithms in the presence of D2D connections based on user satisfaction metric. The capacity-aware algorithm that takes into account the network-based attribute of remaining capacity in network nodes besides user-based attributes yielded better performance in terms of the two metrics. The impact of D2D communications on the MADM algorithms are presented and the existence of optimal user satisfaction rate per the density of D2D users is depicted via simulation results. As a future work, an integrated algorithm that can adaptively and automatically decide on the optimal D2D density based on the underlying MADM algorithm and user parameters can be developed. Moreover, content dissem-

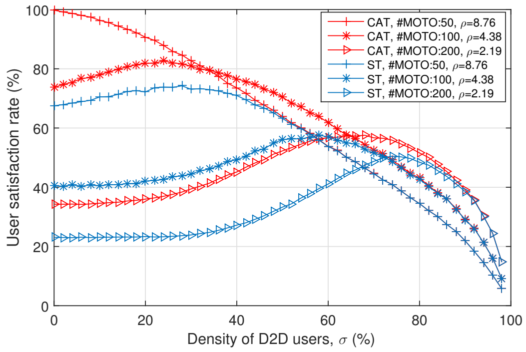

Fig. 4: User satisfaction curves for increasing ρ in CAT and ST algorithms

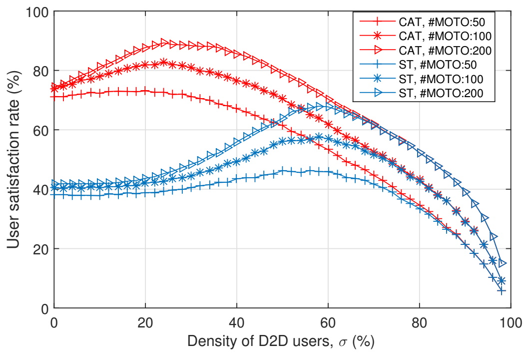

Fig. 5: User satisfaction curves for $\rho = 4.38$ in CAT and ST algorithms

ination delay considerations can also be considered to be an additional metric into the MADM algorithms.

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