A Machine Learning-based xAPP for 5G O-RAN to Mitigate Co-tier Interference and Improve QoE for Various Services in a HetNet Environment

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***Abstract*—Data traffic has skyrocketed as a result of the global proliferation of rich media services. A number of cutting-edge applications are predicted to be supported by 5G networks across the three categories: enhanced mobile broadband, ultra-reliable low latency communications, and enormous machine-type communications. The expectations and goals for the various services in the 5G networks have put a lot of pressure on mobile operators to maintain high Quality of Experience (QoE). The use of 5G Heterogeneous Networks (HetNets), which will provide consumers with the ability to be associated with either Macro Base Stations (MBS) or small cells, is one of the most promising solutions. Among the small cells, femtocells have drawn much attention recently. Yet, the most significant challenge with the deployment of femtocells is the high co-tier interference that can occur between different femtocell users. Artificial Intelligence (AI) and Machine Learning (ML)-based solutions are being incorporated in 5G networks to address this challenge. In this paper, we propose a ML Multi-Classification and Offloading Scheme (MLMCOS) to mitigate co-tier interference in 5G HetNets. MLMCOS classifies users into multiple classes based on their service priority along with their experienced co-tier interference. It then offloads some of them to the nearby Femto Base Stations (FBS) based on the availability of resources to ensure high QoE. ML classification algorithms are evaluated in terms of accuracy, recall, and precision. The performance of MLMCOS is then compared to those of Proportional Fair (PF) scheduling algorithm, Variable Radius and Proportional Fair scheduling (VR+PF) algorithm, and a Cognitive Approach (CA) in terms of Video Multimethod Assessment Fusion (VMAF), R-Factor, and RUM Speed Index (RUMSI).**

I. Introduction

Across the globe, data traffic in cellular networks is now expanding exponentially. According to a study conducted by Ericsson [1], average monthly data usage per user will grow to 40GB by the end of 2027. The anticipated growth in data transmission in the upcoming years creates the foundation for higher-quality services with a variety of requirements, including real-time data processing and low latency. As a result, ensuring excellent QoE for users has become a daunting task that network providers are striving to accomplish given the shortcomings of nowadays networks [2], [3].

One of the promising strategies to confront the rapid expansion of mobile data traffic is to increase the cost-effective density distribution of 5G MBSs and small cells, hence develop 5G HetNets, as illustrated in Fig. 1. This gives flexibility to users to be associated with either MBSs or small cells that provide good communication channel conditions (*i.e.,* high Channel Quality Index (CQI)) [4], [5]. FBSs, also known as femtocells, are one type of small cells that have drawn a lot of attention due to their affordability and ease of deployment [6]. Yet, one of the key problems of femtocells is the inter-cell interference, also known as co-tier interference, which is caused by the dynamic deployment of femtocells. Several approaches [7], [8] and [9] have been proposed in the literature to mitigate this issue. However, none of them was designed for the 5G Open-Radio Access Network (O-RAN) architecture.

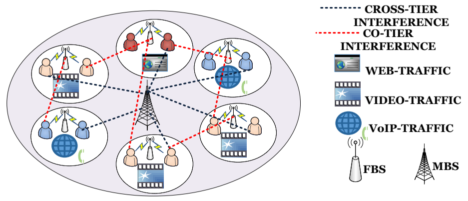

Fig. 1: An example of a heterogeneous network

In this paper, we propose an ML-based Multi-Classification and Offloading Scheme (**MLMCOS**) which enhances users' QoE by first classifying them into multiple classes based on their service priority and experienced co-tier interference. Next, the proposed solution offloads some users to nearby FBSs based on the availability of resources to ensure high QoE. Several ML classification algorithms are evaluated in terms of accuracy, recall, and precision to identify the best classification algorithm to be used for MLMCOS. Its performance is then assessed in terms of VMAF, R-Factor and RUMSI and is compared to those of other existing solutions.

The rest of this paper is organised as follows. Section II surveys some related work. Section III illustrates the system model and describes the system architecture of the proposed MLMCOS algorithm. Performance evaluation including ML model evaluation and QoE assessment, is discussed in Section IV. Finally, section V concludes the paper.

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II. Related Works

The co-tier interference between femtocells is one of the major issues in HetNets. Numerous solutions have been proposed in the literature to address this problem. An interference mitigation technique in a complete HetNet integration system was proposed in [10]. It explores the effects of power adjustment on the Quality of Service (QoS) of video streaming applications after reducing interference. Yet, it only considers the cross-tier interference between FBSs and MBSs. In [11], the authors used Mixed Integer Non-Linear Programming (MINLP) to solve the issue of cross-interference while taking into account QoS measurements and power constraints. They coupled interference mitigation (IM) and resource allocation (RA) in HetNets. However, the proposed scheme has significant processing cost. In [12], authors proposed QEFOS, an efficient scheme for interference mitigation in HetNets. QEFOS categorizes the users into different categories based on the interference levels. However, QEFOS focuses only on the most affected users by high cross-tier interference. The resource allocation scheme put forth by the authors in [13] helps to reduce cross-tier, co-tier and cross-link interferences. Both the uplink and downlink transmission use the Time Division Duplex (TDD) mode. However, employing TDD may result in cross-slot interference. In [14], authors suggested two power control strategies to lessen the impact of interference in a two-tier network using Signal to Interference and Noise Ratio (SINR). The suggested approaches regulate transmission power to lessen the effects of interference. However, QoS and QoE were not taken into account when evaluating the proposed scheme.

Given the shortcomings of the aforementioned schemes, we propose a ML-based solution to classify users into multiple classes depending on their service priority along with the experienced co-tier interference and offload the affected classes to nearby FBSs considering the availability of resources. To the best of our knowledge, this approach is unique as there is no ML-based multi-classification solution in the literature that considers service priority and SINR values to mitigate the co-tier interference.

III. System Model

A. System Architecture

The current RAN technologies supported in the different cellular networks (*i.e.,* 2G/3G/4G) are monolithic units produced by a limited number of vendors and are considered as black boxes by mobile operators. These black boxes have limited RAN reconfigurability as well as limited coordination among the different network nodes, and provide only few options for mobile operators to deploy equipment from multiple vendors [15]. As a result, optimized radio resource management and efficient spectrum utilization in a real-time scenario are extremely challenging for mobile operators [16].

To overcome these shortcomings, O-RAN is considered as the new paradigm for the RAN of the future by 3GPP and O-RAN Alliance [17]. O-RAN is a disaggergated RAN architecture where deployments are based on software-based components which are interoperable across different vendors. This paper considers the O-RAN technology, supported in the 5G network environment. Fig. 2 describes the O-RAN system architecture. It extends the 3GPP NR 7.2 split for base stations [18] and consists of an Open-Distributed Unit (O-DU) and Open-Central Unit for both the Control and User planes (CU-C and CU-U). These components are connected to an intelligence controller known as RAN Intelligence Controller (RIC) that can achieve extreme automation by using various AI/ML models [19]. The O-RAN architectures includes two RICs that perform management and control of the network at near-real-time (10 ms to 1 s) and non-realtime (more than 1 s) time scales [20]. The near-real-time RIC consists of customised logical application known as xApps, defined as microservices that can be used for different use cases as highlighted in Fig. 2 through standardized interfaces and service models. **Our proposed solution is deployed as an xApp in the near real-time RIC.**

B. MLMCOS

As depicted in Fig. 3, MLMCOS includes an Interference System Monitor (ISM) that keeps track of information regarding all types of interference (*i.e.,* cross-tier and co-tier interference) in a 5G HetNets. The proposed scheme focuses only on co-tier interference between femtocells. MLMCOS is made of two main phases: classification and traffic offloading. In the classification phase, users are classified by the ML algorithms based on the priority of their service and their experienced co-tier interference. The co-tier interference is computed based on SINR values. The service priority is decided based on the QoS Class Identifier (QCI) (see Table I). In the offloading phase, users having priority services and experiencing high co-tier interference are offloaded first to nearby FBSs based on the availability of the resources. The Resource Tracker keeps track of resources that are available at each FBS. This information is used by the offloader, which instructs the users in question to perform handover to the selected FBS following the mechanism in [21]. The offloading phase is terminated once all users experiencing co-tier interference are offloaded to nearby FBSs, regardless of their service priority. In this way, MLMCOS reduces the co-tier interference in 5G HetNets while improving users perceived QoE for different services.

To classify users, we used the most commonly deployed ML algorithms, namely, Random Forest (RF), Gradient Boosting (GBT), and Convolution Neural Network (CNN). Using the network simulator NS-3, simulations are carried out for each iteration. After each iteration, the output data is stored in a Comma Separated Value (CSV) file, including SINR, Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), cell ID, packet delay budget and error loss rate. In this paper, SINR and QCI parameters (packet delay budget and error loss rate) are designated as the target attributes for the ML-models whilst the other attributes (RSRP, RSRQ) are non-target attributes. Following that, the dataset is divided into 30% test data and 70% training data, which is the

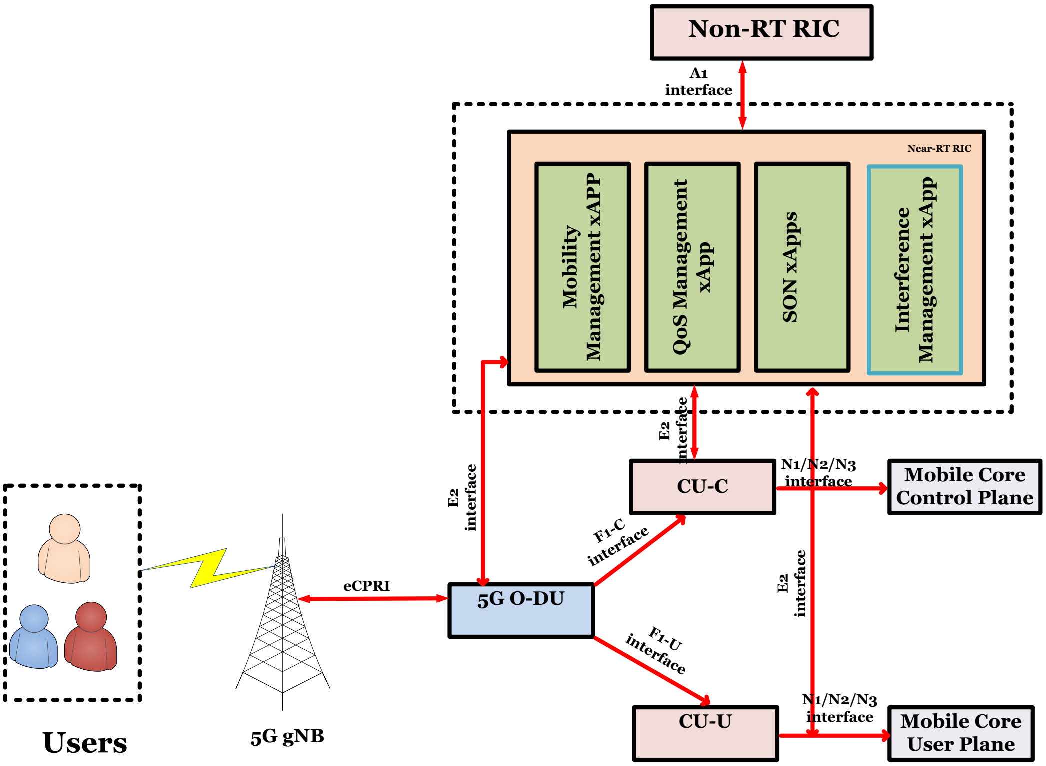


Fig. 2: O-RAN System Architecture

TABLE I: QCI Values [22]

QCI	Priority	Packet Delay Budget	Packet Error Loss Rate	Services
1	2	100 ms	10^{-2}	Voice
2	4	150 ms	10^{-3}	Video (Live Streaming)
3	3	50 ms	10^{-3}	Real Time Gaming
4	5	300 ms	10^{-6}	Buffered Non-Conversational Video
5	1	100 ms	10^{-6}	IMS Signalling
6	6	300 ms	10^{-6}	Buffered Video, TCP-Based Services
7	7	100 ms	10^{-3}	VoIP, Live Video, Interactive Gaming
8	8	300 ms	10^{-6}	Buffered Video, TCP-Based Services
9	9	300 ms	10^{-6}	TCP-Based Services

most typical split for a dataset with several attributes [23]. The Keras library in Python along with GridSearchCV class from the scikit-learn library were used to to put our solution into action. GridSearchCV allows the selection of the best training parameters from a hyper parameter set [24].

IV. Performance Evaluation

We consider the 5G Hetnets scenario for different services illustrated in Fig. 1. For users' requested services, we consider the following distribution: video service (80%), VoIP service (15%), and web browsing (5%). For video transmission, the Gercom's Evalvid Model in NS-3 is employed [25] (See Table II for more details). We use accuracy, precision, and recall to assess the ML classification algorithms. For simulation purposes, we consider only three classes out of the N classes in which the users are classified, and the QoE of each user is evaluated in terms of VMAF for the video service, R-Factor for the VoIP service, and RUMSI for the web browsing service.

A. ML Model Evluation

The three ML models were trained on the dataset collected from simulations in NS-3. Fig. 4a illustrates the accuracy of MLMCOS when employing RF, GBT, and CNN. We observe that out the three ML algorithms, CNN achieves the highest accuracy (97.55%), followed by GBT (95.69%) and RF (90.27%). Fig 4b depicts the precision in terms of percentage

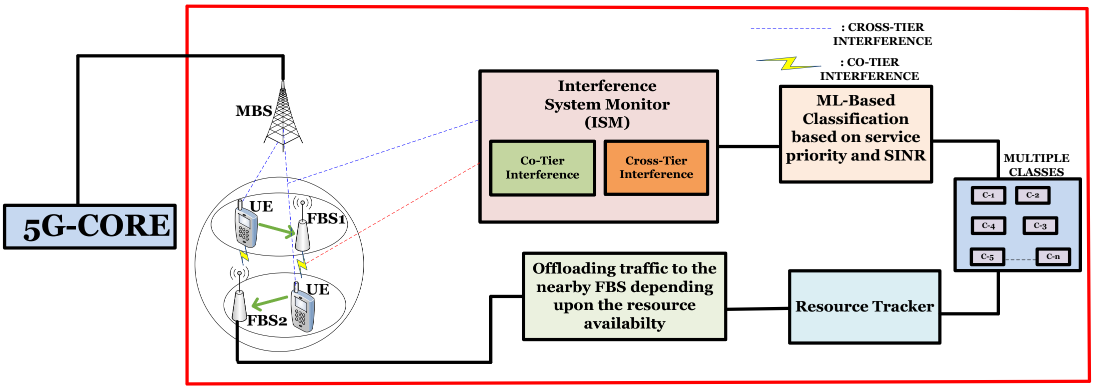


Fig. 3: MLMCOS Architecture

TABLE II: Properties for the Video Used for Transmission

Parameter	Value
Width	1280
Height	720
Data Rate	1209Kbps
Total Bitrate	1209Kbps
Frame Rate	30 fps
Total Duration	10 seconds
Total Frames	300 frames

TABLE III: ACR mapping to VMAF scores

ACR Scale	VMAF Score
1 (Bad)	0-20
2 (Poor)	20-40
3 (Fair)	40-60
4 (Good)	60-80
5 (Excellent)	80-100

TABLE IV: MOS mapping to R-Factor

MOS	R-Factor	Quality
5	90-100	Excellent
4	80-90	Good
3	70-80	Fair
2	50-70	Poor
1	$<$50	Bad

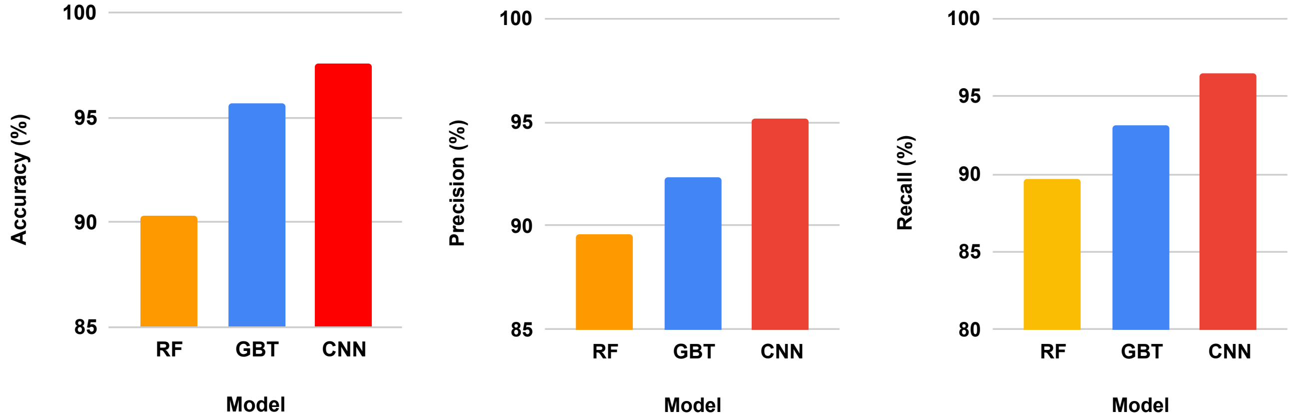
for MLMCOS employing RF, GBT and CNN. We observe that MLMCOS incurs the precision of 95.14%, 92.33% and 89.63% when employing CNN, GBT, and RF, respectively. MLMCOS recall when using RF, GBT, and CNN is shown in Fig. 4c. We observe that recall achieved is 96.49% , 93.15%, and 89.67%, when using CNN, GBT, and RF, respectively. Based on the ML-model evaluation assessment, we select CNN for the testing phase.

B. QoE Analysis

In this paper, we consider three services for simulation purposes. Video services have the highest priority, followed by VoIP, and web browsing. We measure the QoE using different metrics: VMAF for video services, R-factor for VoIP services, and RUMSI for web browsing services. The overall performance of MLMCOS will be compared to other schemes, including PF, VR+PF and CA . VMAF was created by Netflix and provides ratings between 0 and 100, with 0 denoting the lowest quality [26]. Table III shows the mapping of VMAF scores gainst the Absolute Category Rating (ACR). R-factor is a metric which is derived from the QoS parameters (latency, jitter, and packet loss) as per ITU-T Recommendation G.107, with a typical score ranging from 50 (bad) to 90 (excellent). The mapping between R-factor and Mean Opinion Score (MOS) is given in Table IV. RUMSI is an efficient approximation to Speed Index (SI) that captures network dynamics more precisely [27]. SI is a page load performance indicator that gauges how quickly a page's contents are visibly populated.
Fig 5 show the QoE results for the video services in terms of VMAF, respectively. We observe that, compared to other schemes, MLMCOS consistently delivers the greatest VMAF values for the bulk of the frames, indicating that it ensures a higher perceived QoE. Fig 6, illustrates the mean of achieved VMAF under the different schemes. Indeed, MLMCOS incurred a mean VMAF value that is 63.58%, 56.12% and 46.37% higher than those of PF, VR+PF, and CA, respectively. Fig 7, shows the QoE results for the VoIP services in terms of R-Factor, respectively. In this paper, we derive the R-factor in terms of Packet Loss Ratio (PLR) and map it with MOS according to the Table IV. We observe that PF achieves a MOS of 1 (bad), VR+PF achives a MOS of 2.5 (Poor), CA achieves a MOS of 3.5 (Good), and MLMCOS achieves a MOS of 4.5 (excellent). Fig 8 shows the QoE results for a web browsing session in terms of SI, respectively. We observe that packets for a web session are loaded at a faster rate by the MLMCOS scheme as compared to PF, VR+PF and CA schemes respectively.

V. Conclusions

In this paper, we proposed a ML-based algorithm, namely MLMCOS, to mitigate co-tier interference in 5G HetNets. The proposed scheme classifies users into multiple classes based on their service priority along with their experienced co-tier interference. It then offloads users to the nearby FBS based on



(a) Models Accuracy (b) Models Precision (c) Models Recall

Fig. 4: ML Classifier Assessment

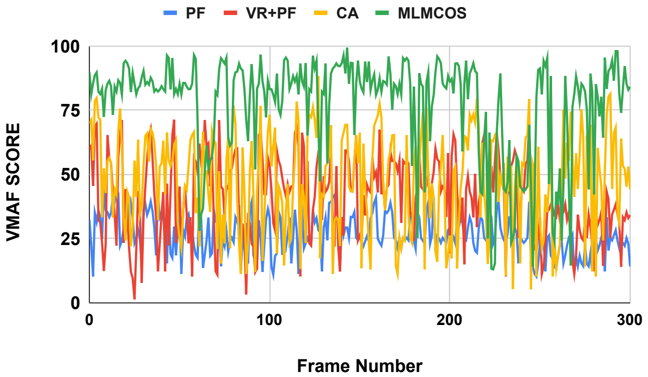


Fig. 5: VMAF Estimation

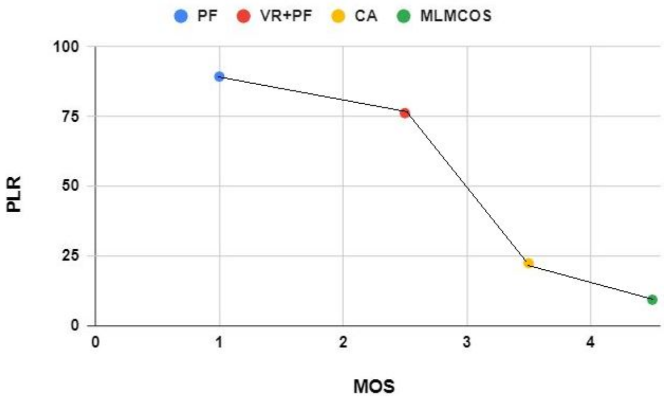


Fig. 7: R-Factor vs MOS

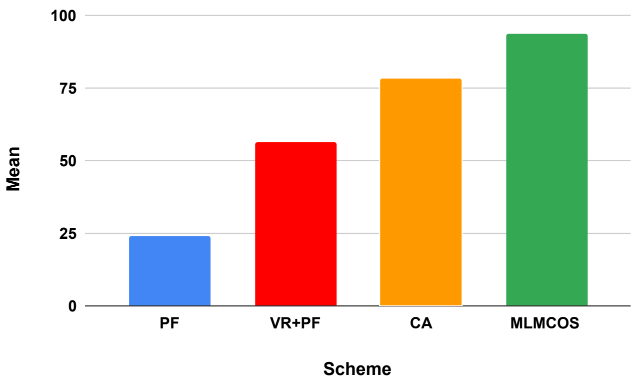


Fig. 6: VMAF Mean Estimation

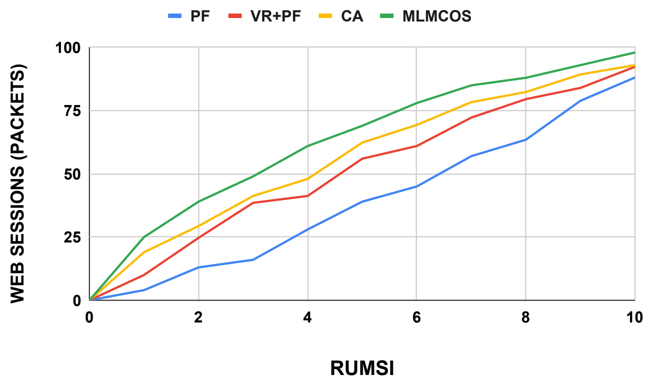


Fig. 8: SI vs Loaded packets for a web session

resource availability. MLMCOS is deployed as a part of the 5G O-RAN architecture in the near real-time RIC as an xApp. Several ML classification algorithms have been assessed in terms of accuracy, precision, and recall. The proposed scheme was compared with existing solutions in terms of VMAF, R-Factor, and RUMSI. Future work will consider extending MLMCOS to mitigate cross-tier and cross-slot interferences.

VI. Acknowledgements

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