

Deep Learning-Driven Edge Intelligence for Network Optimization of Data Flows in O-RAN

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Abstract—Open Radio Access Network (O-RAN) enables programmable and intelligent radio access control through RAN intelligent controllers, while mobile edge computing (MEC) offers service proximity for time-sensitive resource management. However, dynamic user equipment (UE) traffic creates a persistent mismatch between bandwidth demand and finite resources assigned to O-RAN nodes. This paper presents a conference version of a CNN-based edge intelligence mechanism, named NRA-EI, for dynamic network resource allocation in an integrated MEC and O-RAN environment. NRA-EI formulates the resource-allocation problem by considering dynamic UE traffic demands, O-RAN node associations, bandwidth utilization, QCI requirements, and residual resource availability. The proposed mechanism further incorporates traffic probing, QCI-aware mapping, and compensation-based bandwidth redistribution to improve resource efficiency and fairness across O-RAN nodes. The mechanism transforms recent connection and bandwidth-utilization patterns into lightweight image representations, classifies the resource-demand state by a convolutional neural network (CNN), and adjusts bandwidth allocation among O-RAN nodes and UE data flows. Simulation-oriented analysis indicates that the proposed design improves bandwidth utilization, average bandwidth satisfaction, and Jain's fairness under both uniform and power-law traffic demands.

Index Terms—Network resource allocation, O-RAN, edge intelligence, convolutional neural network, mobile edge computing, QoS.

I. INTRODUCTION

The rapid growth of IoT devices and mobile applications increases both the volume and variability of data traffic in radio access networks. Traditional centralized resource management is often insufficient for simultaneously maintaining throughput, latency, and fairness when a large number of data flows compete for finite bandwidth resources. O-RAN addresses this issue by introducing an open and programmable architecture in which the non-real-time RAN Intelligent Controller (non-RT RIC) and near-real-time RAN Intelligent Controller (near-RT RIC) can support policy control, intelligent optimization, and xApp/rApp-based network management [1], [2].

MEC further supports service provisioning close to UEs by reducing long-distance transmission and enabling localized resource management [3], [4]. Nevertheless, the deployment of edge nodes and O-RAN nodes may not match the instantaneous distribution of UE traffic. Some nodes may be overloaded, whereas others may retain unused bandwidth. This imbalance reduces bandwidth utilization, lowers the satisfaction of QoS demands, and may create unfair resource distribution among UEs.

To address this issue, this paper proposes *Network Resource Allocation with Edge Intelligence* (NRA-EI), a CNN-assisted resource allocation mechanism for data flows in O-RAN. The main idea is to let the RIC observe recent bandwidth-demand patterns, infer the next resource-allocation state, and coordinate bandwidth compensation among O-RAN nodes before severe congestion occurs. Compared with purely reactive allocation, NRA-EI uses historical traffic states proactively and therefore provides the RIC with a lightweight decision aid.

The contributions of this paper are summarized as follows. First, a dynamic bandwidth-allocation framework is formulated for O-RAN environments by jointly considering UE traffic demands, O-RAN node associations, bandwidth utilization, QCI requirements, and residual resource availability. Second, a CNN-based traffic-state representation is developed to convert bandwidth demand and node-connection patterns into compact input images for proactive resource-state classification. Third, a two-level allocation procedure is designed, in which the RIC coordinates resource distribution among O-RAN nodes while each node allocates available bandwidth to its associated UE flows. Finally, a compensation policy is introduced to redistribute residual bandwidth from resource-sufficient nodes to resource-deficient nodes, thereby improving bandwidth utilization, QoS satisfaction, and allocation fairness.

II. SYSTEM MODEL AND PROBLEM STATEMENT

A. O-RAN and MEC System

We consider an integrated MEC and O-RAN environment consisting of a near-RT RIC, an O-CU, multiple O-RAN edge nodes, and a set of UEs generating data flows. The near-RT RIC monitors traffic status reported from O-RAN nodes and executes allocation policies derived from the learning module. Each O-RAN node has finite bandwidth capacity and serves a subset of UEs whose demands change over time.

Following the OJCOMS model, a system contains $N = \{d_1, \dots, d_j, \dots, d_N\}$ devices in K front fields $A = \{A_1, \dots, A_k, \dots, A_K\}$ and $E = \{e_1, \dots, e_i, \dots, e_E\}$ edge nodes in boundary areas that bridge devices and switches in core networks. Given that every edge node e_i serves N_i devices d_j s in a front field A_k , a switch controller s assigns e_i a restricted bandwidth capacity B_i to transmit data flows over a number of $X_{i,j}$ distinct network connections between e_i and d_j s in A_k .

B. Problem Formulation

For each edge node, two network-specific measures are used: network connection aggregation and bandwidth demand aggregation. The value of $X_{i,j,t}$ equals one or zero depending on whether d_j is connected with e_i at time t . Let $U_{i,j,t}$ indicate the amount of bandwidth demand that d_j subscribes to the system and requests from e_i at time t . Thus, $\sum_j X_{i,j,t}$ describes connection aggregation, and $\sum_j X_{i,j,t} U_{i,j,t}$ describes bandwidth demand aggregation.

A system aims to maximize the overall data throughput generated by $|N|$ devices, passed through $|E|$ edge nodes, and flowed into a switch of the core network. Thus, to find an optimal bandwidth allocation is equivalent to minimizing the disparity between bandwidth demands and system capacity, which is formulated as

$$\begin{aligned} \min_{B_{i,t}} \quad & \sum_i \sum_j |X_{i,j,t} \cdot U_{i,j,t} - b_{i,j,t}|, \\ \text{s.t.} \quad & b_{i,j,t} \geq 0, \quad U_{i,j,t} \geq 0, \\ & 0 \leq \sum_{j=1}^{N_i} b_{i,j,t} \leq B_{i,t}, \\ & \sum_i B_{i,t} \leq B. \end{aligned} \quad (1)$$

where $B_{i,t}$ is the available bandwidth capacity to e_i and $b_{i,j,t}$ is the amount of bandwidth allocated to d_j by e_i in A_k at t .

C. Complexity and Solvability

The allocation problem in (1) is dynamic and combinatorial because UE demand, node association, and residual bandwidth vary over time. The problem is computationally challenging because it generalizes a bin-packing process. Given a total bandwidth capacity B , $|E|$ edge nodes, and $|N|$ devices at time t , the system distributes $B_{i,t}$ to each e_i with $\sum_i B_{i,t} \leq B$. Each e_i then allocates $b_{i,j,t}$ to its associated devices. The inner minimization of the demand-allocation disparity with respect to each $B_i = \sum_j b_{i,j,t}$ can be interpreted as a multi-dimensional packing process.

The dynamic bandwidth-allocation problem is solvable in (1) if the minimum of

$$Q = \max_{b_{i,t}} P\left(\sum_i \sum_j X_{i,j,t} \cdot U_{i,j,t} \geq \sum_i B_{i,t}\right) \quad (2)$$

can be found, where $P(X)$ is the probability of any event X . In the case of $X \cdot U < B$, the system can completely satisfy bandwidth demands. In the case of $X \cdot U \geq B$, the system cannot satisfy all demands, and the probability is bounded by

$$\begin{aligned} P(X \cdot U \geq B) &\leq \left(\frac{X \cdot U}{B}\right)^B e^{B-X \cdot U}, \\ P(X \cdot U \geq B) &> \left(\frac{X \cdot U}{B}\right)^B e^{B-X \cdot U - \epsilon}. \end{aligned} \quad (3)$$

Then, an optimal allocation solution $[B_1, B_2, \dots, B_n]$ is obtained if and only if the equality set holds:

$$\left(\frac{X \cdot U}{B_1}\right)^{B_1} \cdot e^{B_1-X \cdot U} = \dots = \left(\frac{X \cdot U}{B_n}\right)^{B_n} \cdot e^{B_n-X \cdot U}. \quad (4)$$

Let $B_i(\cdot) = \left(\frac{X \cdot U}{B_i}\right)^{B_i} \cdot e^{B_i-X \cdot U}$ be an auxiliary function with an error bound ϵ . The Fair Share algorithm can adjust the lower bound $a = 0$, upper bound $b = 1$, $\rho = (a + b)/2$, and $C = \sum_i B_i(\cdot)$ iteratively by

$$\begin{aligned} b &= \rho, \quad \text{if } C < B - \epsilon, \\ a &= \rho, \quad \text{if } C > B. \end{aligned} \quad (5)$$

The iterative process stops when $B - \epsilon \leq C \leq B$. This complexity motivates NRA-EI: instead of solving every combinatorial instance exhaustively, the RIC uses learning-assisted traffic-state classification to guide resource adjustment.

III. NRA-EI MECHANISM DESIGN

A. Overall Architecture

NRA-EI contains two execution threads. The first is an off-line learning thread in which historical connection and bandwidth-utilization data are transformed into image-like samples and used to train the CNN classifier. The second is an on-line allocation thread in which the near-RT RIC probes current traffic, invokes the trained CNN model, and adjusts the resource distribution for the next decision window.

The design is compatible with the O-RAN control hierarchy. The non-RT RIC can support model training, policy generation, and long-term optimization, whereas the near-RT RIC performs inference and near-real-time control. The O-CU coordinates resource assignment across edge nodes, and each edge node allocates the assigned capacity to local UE data flows. This separation avoids repeated online retraining and keeps the time-critical loop lightweight.

B. Traffic Probing and Image Formation

Against dynamic changes of network resource demands, probing data flows in front fields can benefit bandwidth allocation. Edge nodes periodically acquire information of varied network connections and bandwidth utilization. To be compatible with CNN learning and computation, the system expresses network information through two primitive matrix structures.

In reference to the connection indicator $X_{i,j,t}$, each e_i probes the varied number of connections with respect to d_j at time t . This number is equal to the norm-1 $\|\vec{X}_{i,j,T}\|_1$ of the connection vector $\vec{X}_{i,j,T} = \langle X_{i,j,1}, \dots, X_{i,j,t}, \dots, X_{i,j,T} \rangle$ after a period of T time slots. For all N_i devices, e_i obtains a summation of connection patterns X_c in the matrix form below:

$$X_c = [\vec{X}_{i,1,T}, \dots, \vec{X}_{i,j,T}, \dots, \vec{X}_{i,N_i,T}]^T. \quad (6)$$

During each period T , each e_i also probes the bandwidth utilization $b_{i,j,t}$ with respect to d_j at time t , and then forms a vector of bandwidth utilization $\vec{b}_{i,j,T} = \langle b_{i,j,1}, \dots, b_{i,j,t}, \dots, b_{i,j,T} \rangle$. For all N_i devices, e_i obtains all information of bandwidth utilization as

$$U_b = [\vec{b}_{i,1,T}, \dots, \vec{b}_{i,j,T}, \dots, \vec{b}_{i,N_i,T}]^T. \quad (7)$$

The information of different network resource demands in edge domains can now be written in quantitative elements

inside the primitive connection and bandwidth-utilization matrices. Given the primitive data of X_c and U_b , NRA-EI merges X_c and U_b into a new matrix:

$$M = X_c \odot U_b. \quad (8)$$

where the operation $\odot$ generates a matrix with identical dimension by multiplying corresponding elements in X_c and U_b , i.e., $m_{ij} = x_{ij} \times u_{ij}$ for $m_{ij} \in M$, $x_{ij} \in X_c$, and $u_{ij} \in U_b$. The representation of M can be transformed into a square-shaped image structure for CNN input.

C. QCI Mapping and CNN Classification

After probing, the system applies the notion of QoS Class Identifier (QCI) to represent and distinguish the QoS requirement of any data flow with respect to d_j , denoted as $Q_{i,j,t}$. With the aggregate of resource demands served by e_i , denoted as $Q_{i,t}$, the system assigns an image class label to e_i , denoted as L_i . Accordingly, given the computation result by (8), the mapping of image class is specified as follows:

$$I_i : \begin{cases} \mathcal{Q}(m_{i,j,t}) & \rightarrow Q_{i,j,t}, \\ \Delta(Q_{i,j,t}) & = \sum_t |Q_{i,j,t} - Q_{i,j,t-1}|, \\ \Delta(Q_{i,t}) & = \sum_j \Delta(Q_{i,j,t}), \\ \mathcal{Y}(\Delta(Q_{i,t})) & \rightarrow L_i. \end{cases} \quad (9)$$

Here, $\mathcal{Q}(\cdot)$ is a QoS mapping function between $m_{i,j,t}$ and $Q_{i,j,t}$. $\Delta(Q_{i,j,t})$ is the aggregate of QCI difference with respect to d_j during T , and $\Delta(Q_{i,t})$ aggregates all d_j s belonging to e_i . The function $\mathcal{Y}(\cdot)$ decides L_i of image I_i as a result of $\Delta(Q_{i,t})$ over T .

Let the system arrange k distinct QCI indices corresponding to differentiated QoS requirements in ascending order. Given B_i of bandwidth capacity allocated to e_i , $\mathcal{Q}(\cdot)$ performs as a linear function and assigns $Q_{i,j,t}$ to d_j depending on the ratio of its bandwidth utilization $m_{i,j,t}$ to B_i :

$$\mathcal{Q}(m_{i,j,t}) = \lceil \frac{m_{i,j,t}}{\max(B_{i,t})} \cdot k \rceil = Q_{i,j,t}, \quad 1 \leq Q_{i,j,t} \leq k. \quad (10)$$

Let the system arrange n distinct image class labels corresponding to various outputs by the CNN model. With a label collection of L_i s from all edge nodes, the switch adjusts the amount of bandwidth capacity B_i to e_i . Without loss of generality, $\mathcal{Y}(\cdot)$ is expressed as a linear function:

$$\mathcal{Y}(\Delta(Q_{i,t})) = \lceil \frac{\sum_t |\Delta(Q_{i,t})|}{N_i \cdot \delta_q} \cdot n \rceil = L_i, \quad 1 \leq L_i \leq n, \quad (11)$$

where δ_q is a limit of the maximal difference between $Q_{i,j,t}$ and $Q_{i,j,t-1}$, N_i is the number of d_j belonging to e_i , and $N_i \delta_q$ is an upper bound of the variable $Q_{i,t}$.

IV. BANDWIDTH ALLOCATION WITH COMPENSATION

A. Contribution Gain

Considering the use of network resources in practice during T , some edge nodes may have residual or insufficient resources at the end of T . Ideally, the controller reclaims residual resources from sufficient edge nodes to compensate deficient resource allocation to scarce edge nodes. Because

edge nodes still compete for available resources, NRA-EI specifies contribution gain to differentiate allocation priority. The contribution gain with respect to e_i , denoted as G_i , is given as

$$G_i = \hat{G}_i + \frac{B_{i,t} - \sum_j \sum_t m_{i,j,t}}{B}, \quad (12)$$

where $\hat{G}_i$ is the accumulated gain up to the last time period. Thus, G_i is an accumulative contribution gain up to the present decision point. A scarce node with a higher contribution gain is considered earlier for compensation because it has contributed more residual capacity in previous periods.

B. QoS-Driven Allocation

With the computation results of the mapping and CNN classification, the learning model obtains the image class label L_i and the QCI index of e_i . The near-RT RIC allocates bandwidth resources to each edge node according to the ratio between its image class label and the sum of all edge-node labels. Therefore, e_i 's resource capacity is defined as

$$B_{i,t} = \frac{L_{i,t}}{\sum_i L_{i,t}} \cdot B. \quad (13)$$

Then, with the compensation scheme, the controller allocates a sequence of $B_{i,t}$ to e_i at t during T . Given $B_{i,t}$, e_i distributes bandwidth resources to d_j s orderly by referring to their QCI indices. The bandwidth allocated to d_j at t is proportional to the ratio of $Q_{i,j,t}$ to the total of $Q_{i,j,t}$ s from all devices served by e_i in the same front field:

$$b_{i,j,t} = \frac{Q_{i,j,t}}{\sum_j Q_{i,j,t}} \cdot B_{i,t}. \quad (14)$$

Then, e_i updates a sequence of $b_{i,j,t}$ to d_j at t for the next T :

$$\vec{b}_{i,j,T} = \{b_{i,j,1}, \dots, b_{i,j,t}, \dots, b_{i,j,T}\}. \quad (15)$$

Accordingly, the system accommodates bandwidth capacities among all edge nodes by considering three situations of resource demand. The system declares any e_i to be a scarce, even, or sufficient edge node by referring to the following outcome:

$$H_i(\beta) : \begin{cases} B_{i,t} > Q_{i,t}, & \text{sufficient edge node,} \\ B_{i,t} < Q_{i,t}, & \text{scarce edge node,} \\ \text{elsewise,} & \text{even edge node,} \end{cases} \quad (16)$$

where β is a control parameter whose value is set in $[0, 1]$. In the updated form, the controller evaluates whether an edge node has more allocated capacity than its predicted demand, less allocated capacity than its predicted demand, or an even allocation state. The compensation process then transfers unused capacity from sufficient nodes to scarce nodes without exceeding the donor node's own demand requirement.

TABLE I
NRA-EI ONLINE ALLOCATION PROCEDURE

Input: Recent UE demands, O-RAN node associations, and bandwidth capacities.

- 1) Probe traffic features and normalize them into a time-window matrix.
- 2) Transform the matrix into a lightweight image representation.
- 3) Use the trained CNN to classify the resource-demand state.
- 4) Identify resource-sufficient and resource-deficient O-RAN nodes.
- 5) Transfer residual bandwidth from sufficient nodes to deficient nodes.
- 6) Allocate local node bandwidth to UE flows considering QoS and fairness.

Output: Updated bandwidth allocation for the next decision window.

V. PERFORMANCE EVALUATION

A. Evaluation Setup

The proposed mechanism is evaluated by simulation with two traffic-demand distributions. The uniform distribution models a balanced scenario in which UEs have comparable demand probabilities. The power-law distribution models a skewed and more realistic condition in which a small portion of UEs generates high bandwidth demand while many UEs generate relatively low demand. The evaluation focuses on bandwidth utilization, average bandwidth satisfaction, and Jain's fairness index. NRA-EI is compared with Deep Q-learning Task Migration (DQTM) [9], Team Deep Q-learning (TDL) [10], and QoS-aware Task Offloading (QTO) [11]. Fig. 1 reports the O-RU scalability results for the three metrics under uniform traffic and power-law traffic with $\alpha = 1.5$.

B. Discussion of Results

Under uniform traffic, Fig. 1(a)–(c) shows that NRA-EI maintains high bandwidth utilization as the number of O-RUs increases and preserves near-ideal fairness. Since the RIC can infer the next demand state and perform compensation among nodes, idle bandwidth is reduced and overloaded nodes receive additional resources. The same mechanism improves average bandwidth satisfaction because resource-deficient flows are less likely to remain underserved.

Under power-law traffic, Fig. 1(d)–(f) shows that the benefit of NRA-EI remains evident under skewed demand. Methods without inter-node compensation have difficulty redistributing residual resources, whereas NRA-EI uses the RIC to coordinate bandwidth among nodes. When the whole system is already overloaded, all methods naturally become constrained by the lack of available bandwidth; however, NRA-EI still provides a more stable tradeoff among utilization, satisfaction, and fairness.

VI. CONCLUSION

This paper proposed NRA-EI, a CNN-based edge intelligence mechanism for dynamic bandwidth allocation in O-RAN environments. By integrating traffic-state prediction with

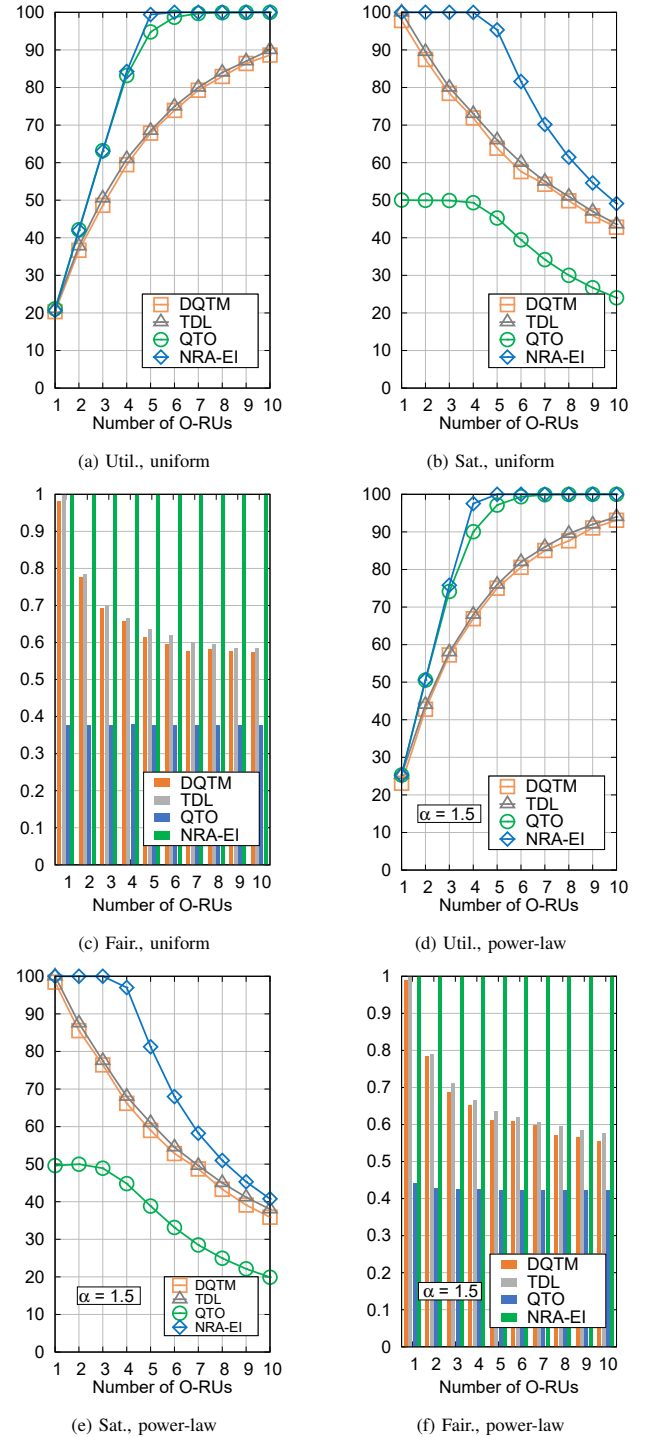


Fig. 1. Simulation results with different numbers of O-RUs.

QoS-aware resource allocation and compensation-based resource redistribution, the proposed mechanism enables the near-RT RIC to proactively adjust bandwidth resources according to variations in network demand. The design incorporates CNN-based learning to capture traffic patterns from connection and bandwidth-utilization information, and then allocates resources among O-RAN nodes and UE data flows based on

the predicted network state.

Simulation results demonstrated that NRA-EI effectively improves bandwidth utilization, average bandwidth satisfaction, and fairness under both uniform and power-law traffic-demand distributions. Compared with existing learning-based and QoS-aware resource allocation approaches, NRA-EI achieves more efficient resource utilization while maintaining a high level of fairness among network entities. The results also indicate that the proposed mechanism remains robust under varying traffic conditions and different numbers of O-RAN nodes.

Future work will focus on implementing the proposed mechanism in practical O-RAN platforms and near-RT RIC environments. In addition, more advanced learning models and large-scale network scenarios will be investigated to further enhance resource-allocation efficiency and adaptability in next-generation wireless networks.

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