

A Novel Transformer Reinforcement Learning-based NFV Service Placement in MEC Networks

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Abstract—The advent of 5G networks has facilitated various Industry 4.0 applications requiring stringent Quality-of-Service (QoS) demands, notably Ultra-Reliable Low-Latency Communication (URLLC). Multi-Access Edge Computing (MEC) has emerged as a key technology to support these URLLC applications by bringing computational resources closer to the user, thus reducing latency. Meanwhile, Network Function Virtualization (NFV) plays a broader role in supporting 5G networks by offering flexibility and scalability in service provisioning across a range of applications. Despite their benefits, MEC networks must adapt to dynamically fluctuating user demands and varying workloads, which can create challenges in maintaining QoS. This paper addresses the Virtual Network Function (VNF) placement problem in MEC networks, focusing on minimizing costs while ensuring QoS through VNF reuse. We propose a novel solution based on the Deep Transformer Q-network (DTQN) algorithm, leveraging reinforcement learning to optimize VNF placement and redeployment. Extensive simulations demonstrate that our DTQN algorithm outperforms baseline approaches, achieving up to a 9% improvement over the D3T-based method and up to 56% over the DQN-based method in terms of average rewards under certain scenarios. This leads to significant enhancements in cost efficiency, resource utilization, and QoS maintenance.

Index Terms—Network function placement, network function chaining, deep Transformer Q-network (DTQN), reinforcement learning, edge computing, service migration.

I. INTRODUCTION

The advent of 5th generation (5G) networks has facilitated various Industry 4.0 applications, including connected and autonomous vehicles, remote surgery, industrial automation, and mission-critical Internet-of-Things (IoT) services. These applications, classified as Ultra-Reliable Low-Latency Communication (URLLC) in 5G, demand stringent Quality-of-Service (QoS) requirements, notably low latency, and high reliability [1].

Two key technologies have emerged to support the flexible and cost-effective provisioning of applications while ensuring QoS requirements, namely Network Function Virtualization (NFV) and Multi-Access Edge Computing (MEC). On the one hand, NFV has become fundamental for service provisioning, enabling software-defined virtual networks to offer flexibility and scalability. Delivering a specific service requires composing and mapping an ordered chain of Virtual Network Functions (VNFs) to the underlying network infrastructure [2]. On the other hand, MEC alleviates resource demands and reduces user-perceived latency by extending cloud computing

capabilities and IT services to the edge of the network [3]. Despite their advantages, MEC nodes possess comparatively limited storage and computational resources compared to the cloud.

In this context, a significant challenge in deploying VNFs for URLLC applications in MEC networks arises from the dynamic nature of user demands, application requirements, and traffic conditions, which may lead to several violations of QoS requirements. Furthermore, the typically ephemeral nature of VNFs means that deployed instances become inactive or must be deactivated once the related service is completed, thereby incurring additional costs or leading to inefficient resource usage [4].

In the literature, typical solutions for NFV deployment in MEC networks involve modifying the deployed VNFs through various redeployment schemes, including VNF migration, VNF sharing, and scaling [5]–[10]. VNF migration is frequently used to achieve load balancing in congested networks, conserve energy in underutilized segments, ensure reliability during physical node failures, and minimize costs. However, VNF migration has to guarantee stringent latency requirements between VNFs within a VNF chain. Traditional migration strategies typically move a single VNF at a time, which incurs significant transmission costs and introduces potential service disruptions due to the resource overhead required for migration, such as processing power and bandwidth to transfer VNF states. These inefficiencies can degrade user experience, strain network resources, and potentially lead to service-level agreement (SLA) violations [11]. To mitigate these drawbacks, recent research by Afrasiabi *et al.* [12] has proposed cluster migration, where groups of coupled VNFs are migrated together either within a single physical node or across multiple nodes. This approach addresses some of the inefficiencies associated with single-VNF migrations, yet the challenge of maintaining reliable service delivery remains a significant concern. Additionally, frequent migrations, whether of single VNFs or clusters, can lead to resource fragmentation, further reducing overall network efficiency and complicating resource management.

In contrast, VNF reuse ensures consistency in service delivery and minimizes the risk of service interruptions, thus reducing downtime and eliminating the need for migrating VNF states and data across nodes. It leverages tested and stable configurations to enhance the reliability and reduce the

complexity of fault management. VNF reuse is cost-efficient as it avoids transmissions and operational costs of migration, maintains low latency levels (by keeping VNFs in their optimal locations), and ensures better resource utilization. However, only a few studies explored reuse schemes [4], [13], [14], and they generally overlooked the impact of traffic redirection on the operation and reliability of Service Function Chains (SFCs). Moreover, most existing works proposed heuristic algorithms that may require long execution times, yielding only suboptimal solutions and facing exponential computational complexity with network scaling.

Consequently, we focus in this paper on solving the problem of SFC/VNF placement in MEC networks for mission-critical applications, aiming to guarantee QoS requirements through VNF redeployment and reuse schemes. Given that the SFC/VNF placement problem is NP-hard [15], [16], [17], the complexity of our problem, encompassing SFC/VNF placement, recomposition, and redeployment, is also NP-hard. To address it, we formulate the problem as a Markov Decision Process (MDP) and solve it using a novel reinforcement learning (RL)-based framework. Specifically, we propose a novel and intelligent VNF/SFC placement strategy based on the deep Transformer Q-network (DTQN) algorithm. This approach is designed to learn complex data representations, thus enabling accurate and efficient decision-making. Particularly, our goal is to minimize the costs associated with VNF placement/redeployment (e.g., migration, removal), while favoring VNF reuse to reduce service disruptions and satisfy QoS requirements.

Our contributions can be summarized as follows:

- 1) We formulate, through Mixed-Integer Non-Linear Programming (MINLP), the problem of VNF/SFC placement in MEC networks for mission-critical applications.
- 2) Given the NP-hardness of the formulated problem, we propose a novel DTQN-based approach to solve it.
- 3) We conduct extensive simulations that demonstrate the efficiency of our solution in terms of cost, VNF placement, reuse, and migration, compared to baseline approaches.

The remainder of the paper is organized as follows: Section II discusses the related works. In Section III, we present the system model, while Section IV formulates the VNF placement problem. Section V details our proposed solution and Section VI provides the simulation results. Finally, Section VII concludes the paper.

II. RELATED WORK

To address the critical challenges of URLLC application provisioning in MEC networks, several key requirements must be met, including minimizing latency to satisfy stringent QoS demands, reducing operational costs to ensure scalability, and maintaining the reliability of services through effective VNF reuse and minimal service disruptions. Comprehensive overviews of NFV placement strategies within MEC networks have been provided in surveys [18], [19], [20], [21].

In the context of latency minimization and cost efficiency, the advent of NFV and MEC as fundamental technologies for agile network service deployment in 5G has led to extensive research. Early studies primarily employed heuristic and

optimization-based approaches to address these challenges. For example, Yala *et al.* [22] used a genetic algorithm to balance the conflicting objectives of minimizing latency and maximizing availability in NFV-MEC networks. Kiran *et al.* [14] focused on reducing placement and resource costs through coordinated VNF placement, demonstrating its effectiveness in lowering overall costs. Jin *et al.* [23] addressed VNF chain deployment in MEC environments by formulating the problem as a Mixed Integer Linear Programming (MILP) model to optimize resource consumption. They proposed a two-phase deployment scheme: a constrained depth-first search algorithm to identify feasible paths and a path-based greedy algorithm to maximize resource reuse while minimizing new allocations. Simulations revealed that this method achieved near-optimal performance, reducing resource consumption by up to 25.6% compared to heuristic baselines, while meeting latency constraints. Similarly, Afrasiabi *et al.* [12] proposed clustering coupled VNFs and migrating them within or across physical nodes using two look-ahead heuristics to reduce embedding costs and avoid local optima. Despite their merits, these approaches do not address reliability issues comprehensively.

The increasing dynamism of network environments necessitates scalable and adaptive solutions. Reconfiguration-based strategies, such as VNF migration, have been widely studied to sustain service performance. Li *et al.* [11] introduced a delay-aware migration strategy to reduce end-to-end latency in SFC deployments, while Cho *et al.* [24] investigated optimization techniques for VNF migration in dynamic cloud environments. Kuo *et al.* [25] proposed a joint VNF placement and path selection approach to maximize served traffic demands, using a stress-testing-inspired algorithm to adapt resource allocation dynamically. This method demonstrated superior performance in terms of link and Virtual Machine (VM) resource utilization, outperforming traditional heuristics. However, scalability remains a challenge, as many of these solutions struggle to maintain optimal performance in highly dynamic conditions.

Zhu *et al.* [26] similarly noted that while these strategies can be effective, they often fall short in environments requiring rapid adaptation to changing conditions.

An alternative strategy to enhance reliability and reduce frequent redeployments or migrations involves reusing VNFs. Addressing this gap, Doan *et al.* [27] proposed the Subchain-Aware NFV Service Placement (SAP) model, which optimizes network function reuse in MEC environments. By focusing on subchain reuse, SAP reduces configuration and deployment costs while enhancing reliability. The authors developed Tabu-SAP, a Tabu search-based solution, and implemented the Automated Provisioning framework for MEC (APMEC) on OpenStack. Tabu-SAP demonstrated scalability and supported eight times more SFC requests, achieving over a 50 percent cost reduction compared to state-of-the-art methods.

To overcome the limitations of traditional approaches, recent studies have adopted machine learning (ML) and RL methods, which offer improved adaptability and scalability. For instance, Abouaomar *et al.* [28] applied deep reinforcement learning to optimize service migration in MEC vehicular environments, minimizing latency and service disruptions. Similarly, Subramanya *et al.* [29] utilized neural networks to enable auto-

scaling of VNFs based on traffic demand and latency requirements. While these approaches show promise, traditional ML methods often face challenges in stability, scalability, and efficiently capturing long-term dependencies in dynamic settings.

Transformer-based techniques have emerged as a promising solution to address these challenges. Wu *et al.* [30] introduced the Double Deep Q-Network Decision Transformer (D3T), which combines a Decision Transformer (DT) with a Double Deep Q-Network (DDQN). The DDQN generates trajectory data for offline training, while the DT models sequences to optimize placement decisions, effectively handling high-dimensional state-action distributions and mitigating issues such as error propagation and value overestimation. D3T achieved a 25% reduction in rejection ratio and a 7% reduction in delay compared to previous methods. However, it does not fully address reliability or redeployment strategies to ensure continuous service delivery.

In summary, the existing body of research on NFV and MEC highlights substantial progress in optimizing service deployment for 5G applications, particularly in latency-sensitive and cost-efficient scenarios. Early heuristic and optimization-based approaches provided foundational insights but faced challenges in scalability and dynamic adaptability. More recent reinforcement learning methods have improved decision-making in such dynamic environments, yet often fail to fully address temporal dependencies and the complexity of large-scale, mission-critical applications. Transformer-based models have shown promise in overcoming these limitations, offering superior capabilities for handling high-dimensional and temporally dependent data. In this context, our work advances the state of the art by introducing a novel DTQN-based framework that leverages the strengths of transformers and reinforcement learning. This approach uniquely focuses on optimizing VNF placement through reuse and intelligent redeployment, addressing critical gaps in scalability, cost efficiency, reliability and QoS adherence.

III. SYSTEM MODEL

We consider a two-tier hierarchical MEC network model. The lowest tier consists of user devices such as sensors, smart gadgets, and cameras that generate and transmit real-time data. This data is forwarded to edge nodes in the above MEC layer for processing. Indeed, the MEC nodes can compute tasks, store data, and network with other nodes.

We assume that time is discretized into periods $T = \{1, 2, \dots, T\}$ with each period denoted by $t \in T$. At the start of each period, placement decisions are made to ensure the provision of NFV-based services within predefined QoS requirements. The system must decide, for each computing request, whether to utilize existing VNF instances or create new ones at time t . Reusing instances incur a reuse cost, which is generally lower than the instantiation cost of a new VNF instance. The length of each time period strikes a balance between the system's responsiveness to dynamic changes in user demands and network conditions and the computational overhead incurred.

The physical network is modeled as a directed graph $G = (N, L)$, where N represents the physical MEC nodes and L represents the physical links. Each node $n \in N$ is characterized by the tuple $\{c_n, C_n, \alpha_n\}$ where c_n represents the maximum computing resource capacity, C_n the unit resource cost, and α_n its reliability. Each link $l \in L$ is characterized by the tuple $\{b_l, d_l, C_l, \alpha_l\}$ where b_l denotes the available bandwidth capacity, d_l indicates the link delay, C_l represents the unit bandwidth cost, and α_l represents the reliability of the link l .

Let K be the set of available VNF types. Assume a licensing model where a maximum number I^k of VNF instances can be instantiated across the network for VNF k , with $i \in \{1, 2, \dots, I^k\}$. Each VNF type $k \in K$ is characterized by the tuple $\{q^k, u^k, c^k, C_n^k, C_n^{i,k}, \alpha^k\}$ where q^k represents the processing demand, u^k and c^k represent the resource and processing capacities, C_n^k is the instantiation cost for creating a new instance on node n , $C_n^{i,k}$ is the cost of reusing instance i on node n , and α^k represents the reliability of VNF k .

Define the binary matrix $\mathbf{X}(t) \in \{0, 1\}^{|N| \times |K| \times I^k}$ to indicate whether a new instance i of VNF k is deployed on node n at time t . Let the binary matrix $\mathbf{M}(t) \in \{0, 1\}^{|N| \times |K| \times I^k}$ indicate whether instance i of VNF k is reused on node n at time t or not, and $\mathbf{\Gamma} \in \mathbb{R}^{|N| \times |K| \times I^k}$ denotes the processing load already assigned to instance i of VNF k on node n .

Moreover, let R be the set of requests. A request $r \in R$ is modeled as a directed graph $G_r = (K_r, L_r)$, where K_r is the set of VNFs to be installed on MEC nodes and L_r is the set of virtual edges. A request r is characterized by its delay threshold d_r and its reliability requirement α_r . Each virtual edge $l_r \in L_r$ is characterized by a tuple $\{d_{l_r}, b_{l_r}\}$, where d_{l_r} and b_{l_r} represent the delay and bandwidth requirement, respectively. Finally, the binary matrix $\mathbf{Y}(t) \in \{0, 1\}^{|L_r| \times |L|}$ indicates whether a virtual link l_r is mapped to a physical link l at time t or not.

IV. PROBLEM FORMULATION

In this section, we first outline the constraints necessary for our problem formulation, then provide detailed formulations of the associated costs, and finally formulate the objective function.

A. Constraints

Each instance i of VNF k cannot be deployed more than once in the network. Furthermore, the number of deployed instances for a given VNF k cannot exceed its maximum number of allowed instances I^k . Hence,

$$\sum_{n \in N} \mathbf{X}_{n,k,i}(t) \leq 1, \quad \forall k \in K, i \in I^k, t \in T \quad (1)$$

$$\text{and } \sum_{n \in N} \sum_{t \in T} (\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \leq I^k, \quad (2)$$

$$\forall k \in K, i \in \{1, 2, \dots, I^k\}.$$

At any given time t and for a specific instance i of VNF k on node n , either a new instantiation or reuse should be chosen,

but not both simultaneously. In addition, reuse is only possible if the instance has already been created, i.e.,

$$\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t) \leq 1, \quad \forall k \in K, i \in I_k, n \in N, t \in T, \quad (3)$$

and

$$\mathbf{M}_{n,k,i}(t) \leq \sum_{t' < t} \mathbf{X}_{n,k,i}(t'), \quad \forall k \in K, i \in I_k, n \in N, t, t' \in T, \quad (4)$$

where t' represents a previous time period. Constraint (4) can be linearized by introducing an auxiliary binary variable $\mathbf{Z}_{n,k,i}(t) = 1$ when a VNF k 's instance i was instantiated at node n at $t' < t$ such that

$$\mathbf{Z}_{n,k,i}(t) \geq \mathbf{X}_{n,k,i}(t') \quad \forall t' < t, \forall n \in N, \forall k \in K, \forall i \in I_k, \quad (5)$$

and

$$\mathbf{M}_{n,k,i}(t) \leq \mathbf{Z}_{n,k,i}(t) \quad \forall n \in N, \forall k \in K, \forall i \in I^k, \forall t \in T. \quad (6)$$

The processing load assigned to instance i of VNF k cannot exceed its available processing capacity, i.e.,

$$\sum_{n \in N} q^k(\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \leq c^k - \Gamma_{n,k,i}, \quad \forall k \in K, i \in I_k, t \in T. \quad (7)$$

Given the limited computing resources at node n , we must ensure that its total resource usage is not exceeded at any time as follows:

$$\sum_{k \in K} \sum_{i=1}^{I_k} (\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \cdot u^k \leq c_n \quad \forall n \in N, \forall t \in T. \quad (8)$$

Also, the total bandwidth usage on physical link l should not exceed b_l at any time t , i.e.,

$$\sum_{r \in R} \sum_{l_r \in L_r} \mathbf{Y}_{l,l_r}(t) \cdot b_{l,r} \leq b_l \quad \forall l \in L, \forall t \in T, \quad (9)$$

while the delay requirement of each virtual link must be met,

$$\sum_{l \in L} \mathbf{Y}_{l,l_r}(t) \cdot d_l \leq d_{l_r} \quad \forall l_r \in L_r. \quad (10)$$

Similarly, the delay requirement d_r for each request r should be met. In other words, the total delay of the path assigned to request r should not exceed d_r , as follows:

$$\sum_{l \in L} \sum_{l_r \in L_r} \mathbf{Y}_{l,l_r}(t) \cdot d_l \leq d_r \quad \forall r \in R, \forall t \in T. \quad (11)$$

Since VNFs can be virtually linked together to form a VNF chain or an SFC, the latter should have at least a physical link assigned between them, i.e.,

$$\mathbf{X}_{n,k,i}(t) \cdot \mathbf{X}_{n',k+1,j}(t) \leq \sum_{l \in L} \mathbf{Y}_{l,l_r}(t), \quad \forall n, n' \in N, k \in K, l_r \in L_r, n \neq n'. \quad (12)$$

Constraint (12) can be linearized by introducing an auxiliary binary variable $\mathbf{W}_{n,n',k,j,l_r}(t) \in \{0, 1\}$ such that

$$\mathbf{W}_{n,n',k,j,l_r}(t) \leq \mathbf{X}_{n,k,i}(t) \quad \forall n, n' \in N, \forall k \in K, \forall l_r \in L_r, \forall t \in T, \quad (13)$$

$$\mathbf{W}_{n,n',k,j,l_r}(t) \leq \mathbf{X}_{n',k+1,j}(t) \quad \forall n, n' \in N, \forall k \in K, \forall l_r \in L_r, \forall t \in T, \quad (14)$$

$$\mathbf{W}_{n,n',k,j,l_r}(t) \geq \mathbf{X}_{n,k,i}(t) + \mathbf{X}_{n',k+1,j}(t) - 1 \quad \forall n, n' \in N, \forall k \in K, \forall l_r \in L_r, \forall t \in T, \quad (15)$$

and

$$\mathbf{W}_{n,n',k,j,l_r}(t) \leq \sum_{l \in L} \mathbf{Y}_{l,l_r}(t) \quad \forall n, n' \in N, \forall k \in K, \forall l_r \in L_r, \forall t \in T. \quad (16)$$

Moreover, the reliability requirement α_r for each request $r \in R$ should be met as follows:

$$\prod_{k \in K_r} \prod_{i=1}^{I_k} (\mathbf{X}_{n,k,i}(t) \cdot \alpha^k + \mathbf{M}_{n,k,i}(t) \cdot \alpha^k) \cdot \prod_{l \in L_r} \prod_{l_r \in L_r} (\mathbf{Y}_{l,l_r}(t) \cdot \alpha_l) \geq \alpha_r, \quad \forall r \in R, \forall t \in T. \quad (17)$$

For the sake of simplicity, we transform Constraint (17) into a logarithmic form, thus allowing its support by MINLP solvers. Specifically, we define the auxiliary matrix $\theta(t) \in \mathbb{R}^{|\mathcal{N}| \times |\mathcal{K}| \times |\mathcal{I}|}$ where $\theta_{n,k,i}(t)$ takes the value $\log(\alpha^k)$ if either $\mathbf{X}_{n,k,i}(t)$ or $\mathbf{M}_{n,k,i}(t)$ is equal to 1. We similarly define the auxiliary matrix $\phi(t) = [\phi_{l,l_r}] \in \mathbb{R}^{|\mathcal{L}| \times |\mathcal{L}_r|}$ for the link mappings. Consequently, we obtain the following:

$$\theta_{n,k,i}(t) \geq (\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \cdot \log(\alpha^k), \quad \forall n \in N, \forall k \in K, \forall i \in I^k, \forall t \in T, \quad (18)$$

$$\phi_{l,l_r}(t) \geq \mathbf{Y}_{l,l_r}(t) \cdot \log(\alpha_l), \quad \forall l \in L, \forall l_r \in L_r, \forall t \in T, \quad (19)$$

and

$$\sum_{k \in K_r} \sum_{i=1}^{I_k} \theta_{n,k,i}(t) + \sum_{l \in L_r} \sum_{l_r \in L_r} \phi_{l,l_r}(t) \geq \log(\alpha_r), \quad \forall r \in R, \forall t \in T. \quad (20)$$

B. Costs and Objective Function

The cost associated with the resource usage of MEC nodes is given by

$$C_{res}(t) = \sum_{n \in N} \sum_{k \in K} \sum_{i=1}^{I_k} (\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \cdot u^k \cdot C_n. \quad (21)$$

Also, we derive the costs related to instantiation and reuse of VNF instances as follows:

$$C_{pla}(t) = \sum_{k \in K} \sum_{i=1}^{I_k} \sum_{n \in N} \mathbf{X}_{n,k,i}(t) \cdot C^k + \mathbf{M}_{n,k,i}(t) \cdot C^{l,k}. \quad (22)$$

Moreover, we deduce the costs associated with the bandwidth usage of physical links by

$$C_{bw}(t) = \sum_{l \in L} \sum_{r \in R} \sum_{l_r \in L_r} \mathbf{Y}_{l,l_r}(t) \cdot b_{l,r} \cdot C_l. \quad (23)$$

Hence, the total cost is defined by

$$C_{tot}(t) = C_{res}(t) + C_{pla}(t) + C_{bw}(t). \quad (24)$$

Finally, the objective of our optimization problem is formulated as

$$\min_{\substack{\mathbf{X}(t), \mathbf{M}(t), \mathbf{Y}(t), \\ \mathbf{Z}(t), \mathbf{W}(t), \theta(t), \phi(t)}} \sum_{t \in T} C_{tot}(t), \quad (25)$$

where the objective function aims to reduce the total cost of VNF deployment over the observation time T . The resulting problem (P1), formed by equations (1)–(3), (5)–(11), (13)–(16), (18)–(20) and (25) is NP-hard. To prove this, we leverage the NP-hardness reduction approach by considering a simplified single-time slot problem where VNFs are placed in nodes to minimize costs while guaranteeing end-user QoS requirements. We further focus on the particular case of homogeneous nodes (same capacity), while VNFs may have different resource requirements. This particular problem can be easily understood as the well-known Generalized Assignment Problem (GAP) [31]. In GAP, the objective is to obtain a maximum overall profit assignment of tasks with different amounts of resources to agents, such that each task is assigned to precisely one agent, subject to the agents' capacity. Also, each task has a different profit, depending on the assigned agent. The defined problem can be seen as a GAP where the agents are assimilated to nodes, VNFs to tasks, and task profit as cost savings. Since GAP is known to be NP-hard [31], then, by restriction, our simplified version of the problem is also NP-hard.

V. PROPOSED SOLUTION

In this section, we propose a solution to the problem (P1), which addresses the total cost of SFC placement in MEC networks with redeployment schemes. We propose a DTQN-based approach that learns a policy for placing and routing network functions to ensure QoS requirements, and taking into account real-time network conditions and operational objectives.

A. Background

Deep neural networks, particularly DQN, form the computational backbone of RL-based approaches, enabling robust performance across various domains [32]. Within the context of NFV, DQN significantly enhances the decision-making process for optimal placement strategies. It provides adaptive learning capabilities that effectively manage dynamic network environments and the complex and high-dimensional state space that encompasses parameters like network topology, resource availability, and traffic demands.

Several advancements have refined the performance of DQNs. For instance, Double DQN [33] addressed the over-estimation bias of Q-values inherent in standard DQN by decoupling action selection from Q-value evaluation, resulting in more stable and accurate learning. Similarly, Dueling DQN [34] separated the representation of the state value function and the advantage function, allowing the network to estimate better the value of specific actions in given states. However, a

key challenge for most deep RL approaches is the assumption of a fully observable environment, which is often not applicable in practice. In many areas, including VNF placement, the environment is partially observable, meaning the agent lacks complete state information at each time step. Also, temporal dependencies significantly influence network state and resource demands, leading to suboptimal decisions if not properly addressed.

To mitigate this issue, architectural or training support is essential [35], [36], [37], [32]. Recent approaches incorporated Recurrent Neural Networks (RNNs) into the DQN framework to maintain a memory of past observations and actions, thus capturing critical temporal dependencies for effective VNF placement. However, RNNs can be fragile and difficult to train, often necessitating complex “warm-up” strategies to initialize hidden states at the start of each training batch [32], [38].

In contrast, the Transformer model has demonstrated superior handling of temporal dependencies compared to RNNs and is increasingly prevalent [39]. Transformers are designed to handle sequential data by processing entire sequences at once rather than iteratively, as in traditional RNNs. This allows transformers to capture complex state representations and address partially observable domains. The key innovation in transformers is the self-attention mechanism, which allows the model to weigh the importance of different parts of the input sequence dynamically, enabling the model to focus on the most important parts [40]. Each element in the input sequence is transformed into three vectors: Query (Q), Key (K), and Value (V). These vectors are learned representations to compute attention scores. The attention score for a pair of elements is calculated as follows:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{\delta_k}} \mathbf{V}, \quad (26)$$

where $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ are the query, key, and value matrices, respectively, δ_k is the dimension of the keys, and $()^T$ is the matrix transpose operator. The value vectors in matrix $\mathbf{V}$ are weighted using the weights resulting from the softmax operation. The softmax function ensures that the attention scores are normalized to sum up to one. The attention scores are then used to compute a weighted sum of the value vectors, representing the attention output and emphasizing the most relevant parts of the input sequence.

In DTQNs, the transformer network processes sequences of past states and actions to produce a rich representation of the current state. This state representation is used to approximate the Q-value function $Q(s, a; \theta)$, where θ denotes the network parameters. The Q-value function $Q(s, a)$ represents the expected cumulative reward for taking action a in state s and is updated iteratively using the Bellman equation as

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha (r_t + \gamma \max_{a \in A} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)), \quad (27)$$

where α is the learning rate, r_t is the reward received at time t , γ is the discount factor, s_{t+1} is the subsequent state, and $\max_{a \in A} Q(s_t, a_t)$ is the maximum Q-value for the next state over all possible actions. The network parameters are

optimized by minimizing a loss function that measures the difference between predicted Q-values and target Q-values, written as

$$L(\theta) = E_{(s_t, a_t, r_t, s_{t+1}) \sim D} \left[r_t + \gamma \max_{a \in A} Q(s_{t+1}, a; \theta) - Q(s_t, a_t; \theta) \right]^2, \quad (28)$$

where E is the expectation operator, the experience replay buffer D stores past experiences (s_t, a_t, r_t, s_{t+1}) , and the target network parameters θ^- are periodically updated to stabilize training.

B. Proposed DTQN-based VNF placement solution

This subsection presents the proposed DTQN-based VNF placement solution for incoming requests. To this end, we reformulate problem (P1) as an MDP. Specifically, we define the states, actions, and rewards as follows:

State: A state s_t must represent the current configuration of the network, encompassing aspects such as node capacities, resource availability, and the deployment of VNF instances. Consequently, we include the node states such as the available computing resources:

$$c_n^{\text{avail}}(t) = c_n - \sum_{k \in K} \sum_{i=1}^k (\mathbf{X}_{n,k,i}(t) + \mathbf{M}_{n,k,i}(t)) \cdot u^k. \quad (29)$$

We also consider the link states, such as the available bandwidth on each link

$$b_l^{\text{avail}}(t) = b_l - \sum_{r \in R} \sum_{l_r \in L_r} \mathbf{Y}_{l,l_r}(t) \cdot b_{l,r}. \quad (30)$$

Moreover, we consider the node resource costs C_n , the node reliability α_n , the link delay d_l , the bandwidth cost C_l , and the link reliability α_l . Furthermore, we take into account the request states, such as the delay threshold d_r and reliability requirement α_r , and the virtual-to-physical mapping $\mathbf{Y}_{l,l_r}(t)$. Finally, we include the VNF reliability parameter α^k , the instantiation and reuse costs C_n^k and $C_n^{i,k}$, the instantiation and reuse status matrices $\mathbf{X}_{n,k,i}(t)$ and $\mathbf{M}_{n,k,i}(t)$, and the current processing load assigned to each VNF instance on each MEC node $\Gamma_{n,k,i}(t)$. Hence, the state s_t can be defined by

$$s_t = (c_n^{\text{avail}}(t), C_n, \alpha_n, b_l^{\text{avail}}(t), d_l, C_l, \alpha_l, \mathbf{X}_{n,k,i}(t), \mathbf{M}_{n,k,i}(t), \Gamma_{n,k,i}(t), C_n^k, C_n^{i,k}, \alpha^k, d_r, \alpha_r, \mathbf{Y}_{l,l_r}(t)). \quad (31)$$

Actions: We define an action a_t through the following quadruple:

$$a_t = (\mathbf{X}_{n,k,i}(t), \mathbf{M}_{n,k,i}(t), \Gamma_{n,k,i}(t), \mathbf{Y}_{l,l_r}(t)). \quad (32)$$

Specifically, the DTQN agent must decide whether to instantiate a new VNF instance or reuse an existing instance, how many resources to allocate and the virtual-to-physical link mapping.

Algorithm 1 Proposed DTQN-based solution

Require: Initial state s_0 , learning rate α , discount factor γ

Ensure: Optimized Q-function

```

1: Initialize Q-function with random weights
2: for  $t = 1$  to  $T$  do
3:    $s'_t = \text{TransformerStateProcessing}(s_t)$  (Algo. 2)
4:   Choose action  $a_t$  using  $\epsilon$ -greedy strategy
5:   Execute  $a_t$  and observe reward  $r_t$  and new state  $s_{t+1}$ 
6:    $s'_{t+1} = \text{TransformerStateProcessing}(s_{t+1})$  (Algo. 2)
7:   Compute target  $y_t = r_t + \gamma \max_{a \in A} Q(s'_{t+1}, a)$ 
8:   Update Q-function:
9:      $Q(s'_t, a_t) \leftarrow Q(s'_t, a_t) + \alpha(y_t - Q(s'_t, a_t))$ 
10:     $s_t \leftarrow s_{t+1}$ 
11: end for

```

Algorithm 2 State processing with Transformer

Require: State s_t

Ensure: Compressed representation s'_t

```

1: function TRANSFORMERSTATEPROCESSING(s)
2:    $e = \text{EmbeddingLayer}(s)$ 
3:    $a = \text{MultiHeadAttention}(e)$ 
4:    $s'_t = \text{FeedForward}(a)$ 
5:   return  $s'_t$ 
6: end function

```

Reward: We leverage a reward mechanism that positively rewards the agent if costs are reduced compared to the previous time slot. Hence, we define this reward as

$$R_{\text{dec}} = \max(C_{\text{tot}}(t-1) - C_{\text{tot}}(t), 0). \quad (33)$$

Also, we penalize the agent if there are QoS violations, i.e., we define a delay violation penalty such that

$$P_{\text{delay}}(t) = \sum_{r \in R} \max(0, \sum_{l \in L} \sum_{l_r \in L_r} \mathbf{Y}_{l,l_r}(t) \cdot d_l - d_r). \quad (34)$$

A reliability penalty is also defined as follows:

$$P_{\text{rel}}(t) = \sum_{r \in R} \max(0, \alpha_r - \sum_{k \in K} \sum_{i=1}^k (\mathbf{X}_{n,k,i}(t) \cdot \alpha^k + \mathbf{M}_{n,k,i}(t) \cdot \alpha^k) \cdot \sum_{l \in L} \sum_{l_r \in L_r} (\mathbf{Y}_{l,l_r}(t) \cdot \alpha_l)). \quad (35)$$

Finally, the reward function $r(t)$ can now be defined as

$$r(t) = R_{\text{dec}}(t) - (C_{\text{tot}}(t) + P_{\text{delay}}(t) + P_{\text{rel}}(t)). \quad (36)$$

Based on the above, we develop our DTQN-based VNF placement solution as summarized in Algo. 1. Specifically, in Algo. 1, we start by initializing the Q-function with random weights. At each step, the current network state is transformed into a compressed representation through the *TransformerStateProcessing* function (Lines 3 and 6 in Algo. 1), as detailed in Algo. 2. This function extracts relevant features to facilitate policy learning. It begins by processing the network

state s_t through the embedding layer of the Transformer, converting s_t into a dense representation. The multi-head attention mechanism of the Transformer then captures complex relationships among different network entities, considering both spatial and temporal interactions. This representation is subsequently passed through the feed-forward neural network of the Transformer resulting in the final condensed representation s'_t .

After executing the *TransformerStateProcessing* function, the remaining DTQN execution is similar to that of DQN, where the RL agent learns the Q-values by minimizing the loss function based on the Bellman equation. An action is selected based on the exploration strategy, such as the ϵ -greedy method (Line 4 in Algo. 1). The RL agent then observes the received reward and the new state, which is also transformed into a compressed representation (Lines 5-6 in Algo. 1). A target is calculated, comprising the observed reward and the estimated best future action, discounted by the factor γ (Line 7 in Algo. 1). The Q-function is updated based on this target using a learning rate α (Lines 8-9 in Algo. 1). This procedure is repeated over a specified number of steps to optimize the Q-function for accurate estimation of expected future rewards.

C. Complexity Analysis

The time complexity of the proposed DTQN algorithm arises from both the RL training loop and the Transformer-based neural network component used for Q-value approximation. In DTQN, the Transformer encoder, which processes state representations, determines the per-step computational complexity. Specifically, the self-attention mechanism within the Transformer dominates the complexity due to pairwise comparisons among input sequence elements, resulting in a quadratic dependency on the sequence length H . Combined with the embedding dimension v , the per-step complexity of the forward pass through the Transformer encoder is $O(H^2 \cdot v)$ [41]. Additional operations, such as feed-forward layers and normalization, contribute linearly or quasi-linearly to this complexity.

For the overall RL training loop, each step involves sampling a mini-batch of size G from the replay buffer, executing forward passes through the Transformer-based model for both the current and next states, and performing a backward pass to update the network parameters. The forward and backward passes share a similar computational cost, making the per-step training complexity approximately $O(G \cdot H^2 \cdot v)$. Over T_{train} total training steps, the overall complexity is $O(T_{train} \cdot G \cdot H^2 \cdot v)$.

Hence, the computational intensity of the DTQN arises primarily from the sequence modeling capabilities of the Transformer encoder. While this architecture entails higher computational costs than traditional methods, its ability to effectively capture complex temporal and spatial dependencies greatly enhances the accuracy and efficiency of decision-making in VNF placement and redeployment.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the simulations conducted to evaluate the performance of our proposed solution against existing

baselines. We begin by describing the simulation environment, followed by a presentation of the obtained results.

A. Simulation Setup

We conduct our simulations on Google Colab using the Tesla T4 GPU, which features a Turing architecture with 2,560 CUDA cores and 320 Tensor cores. This GPU provides up to 8.1 Floating Point Operations Per Second (TFLOPS) of single precision floating point performance, combined with 16 GB of GDDR6 memory and a bandwidth of up to 320 GB/s.

The simulation parameters, including network configurations, request characteristics, and hyperparameter values, were selected based on representative benchmarks and practices in MEC and NFV research, as well as reinforcement learning standards, such as [42], [43], [44], to ensure realistic and challenging test conditions.

Our substrate network comprises users uniformly distributed across the network, and [5-10] MEC nodes, with each MEC server featuring one to five outgoing links, randomly assigned to other MEC nodes to reflect network topology variability and dynamism. Each MEC node is configured as a multi-core system with a maximum computing resource capacity ranging from 5 to 10 GHz across all cores, a unit resource cost of 10, and a reliability parameter ranging from 99.9% to 99.999%. Note that in our simulations, we intentionally limit the number of MECs and deliberately set the resource capacity of nodes to provoke migration scenarios.

Each physical communication link is assigned a bandwidth capacity ranging from 100 to 200 Mbps, with a bandwidth cost of 0.05 per Mb and reliability within the range of 95% to 99.9%. The required processing capacity for the VNFs ranges from 1 to 4 GHz, and the resource storage capacity for each VNF ranges from 50 to 200 MB. The VNF reliability requirement is set between 99.9% and 99.999%, reflecting the stringent requirements of URLLC applications. The instantiation cost for a VNF is fixed at 10, and the reuse cost is set to 5.

In our experiments, we consider incoming service requests initiated by end-users that require a VNF-based SFC to be deployed in the MEC network. These service requests are categorized into four types, depending on the number of VNFs within the service chain, ranging from 1 to 4 VNFs. Service requests are generated following a Poisson distribution with an arrival rate parameter δ that varies within the set {30, 50, 80, 100}. Each request has a delay threshold between 1 and 10 milliseconds (ms), and the reliability requirement is randomly selected from the range [99%, 99.9%].

The proposed solution, referred to as DTQN, is evaluated against three baseline algorithms: a DQN-based method (DQN), a heuristic approach relying on random placement (Heuristic), and a D3T-based method [30], which has been modified to incorporate redeployment strategies to ensure fairness. The DTQN architecture has an input layer sized to the state vector and an embedding layer with a size of 128. It is followed by a transformer encoder layer, comprising a multi-head attention mechanism with two heads where each head has a size of 64. The feed-forward network within each

TABLE I
SELECTED HYPERPARAMETERS FOR LEARNING-BASED METHODS

Hyperparameter	Value
Replay memory size	20000
Discount factor	0.99
Exploration rate	1.0, decaying to 0.01
Exploration rate decay	0.995
Learning rate	0.0005
Batch size	256
Number of episodes	1000
Frequency of target update	500

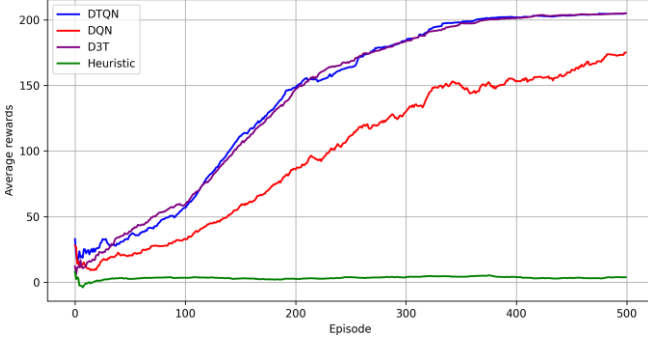


Fig. 1. Average rewards per episodes ($N = 5$).

transformer encoder layer consists of two fully connected layers with 128 ReLU neurons each. Layer normalization and dropout (with a rate of 0.1) are applied after each sub-layer in the transformer encoder. The final output layer is a fully connected layer that produces Q-values, sized to the number of potential actions. The D3T architecture builds on the transformer-based approach, similar to DTQN, but differs in its decision-making process. It includes a single transformer encoder layer with two multi-head attention heads and a feed-forward network of 128 neurons per layer, ultimately outputting Q-values for action selection. The DQN architecture is configured with an input layer sized to the state vector and includes three fully connected layers, each with 128 ReLU neurons. The final output layer is a fully connected layer that produces Q-values, sized to the number of actions. The used hyperparameters for the DTQN, D3T and DQN are summarized in Table I. To incentivize reuse over migration, we assign a reward factor of 7 for reuse and 4 for migration. Conversely, failure to fulfill a request due to a violation of QoS requirements is penalized with a reward factor of -5.

B. Simulation Results and Discussion

We begin by examining the impact of increasing the number of nodes and the arrival rates δ for each algorithm. The average rewards per episode for each algorithm are presented in Fig. 1, which considers 5 nodes with $\delta = 30$, while in Fig. 2, we consider 10 nodes with $\delta = 100$. It is important to note that, in each episode, network link mappings among nodes vary to capture the variability and dynamism of the network topology. Furthermore, strict adherence to QoS requirements is enforced for all requests, with partial satisfaction being rejected. Consequently, only fully accepted requests are included in the results

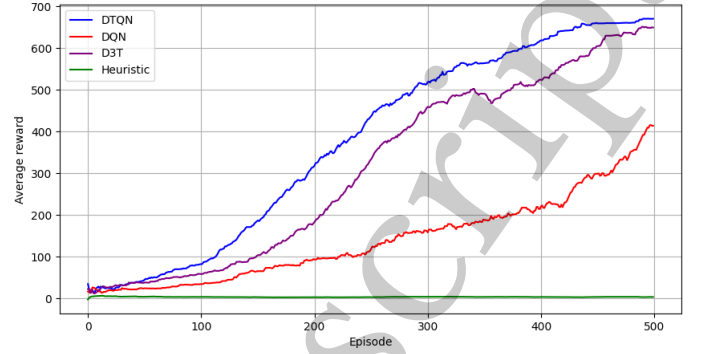


Fig. 2. Average rewards per episodes ($N = 10$).

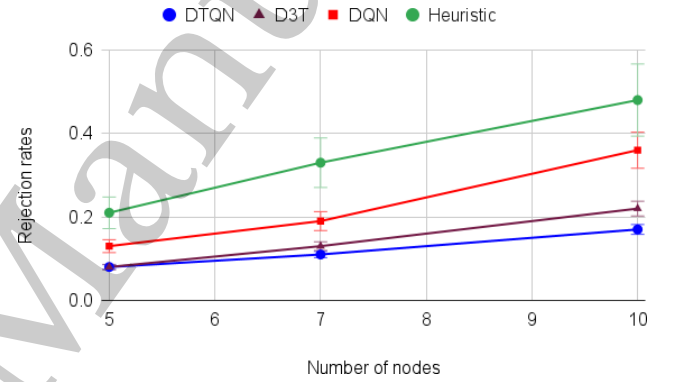


Fig. 3. Rejection rates vs number of nodes ($\delta = 50$).

presented in Figs. 1 and 2.

For any δ (Figs. 1 and 2), the proposed DTQN solution consistently achieves the highest rewards, despite its greater computational demands and longer training times compared to baseline algorithms such as DQN and Heuristic. While DTQN and D3T exhibit similar reward performance at a smaller scale, DTQN surpasses D3T as the number of users increases. In contrast, the Heuristic approach consistently yields the lowest rewards. This trend is further supported by Fig. 3, which presents the average rejection rates over five simulation runs with $\delta = 50$. The results indicate that DTQN achieves the lowest rejection rate, followed respectively by D3T and DQN, with the Heuristic approach exhibiting the highest rejection rate.

Notably, the performance gap between DTQN, D3T and DQN in Figs. 1 and 2 widens as the number of nodes in the topology and δ increase. This is likely due to the enhanced ability of DTQN to capture temporal dependencies, leading to more accurate SFC placement decisions that prioritize reuse over migration. As the request arrival rate δ increases and network resources become saturated, optimizing VNF placement and reuse decisions becomes crucial to avoid network overloading.

This observation is further validated by Fig. 4 ($N = 10$, $\delta = 30$) and Fig. 5 ($N = 10$, $\delta = 100$), which illustrate the SFC embedding strategies adopted by each evaluated approach. The Heuristic method, which achieves the lowest average

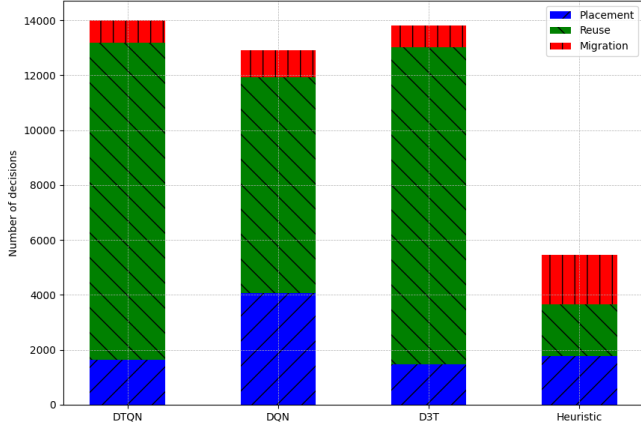


Fig. 4. Distribution of SFC embedding decisions ($N = 10$ and $\delta = 30$).

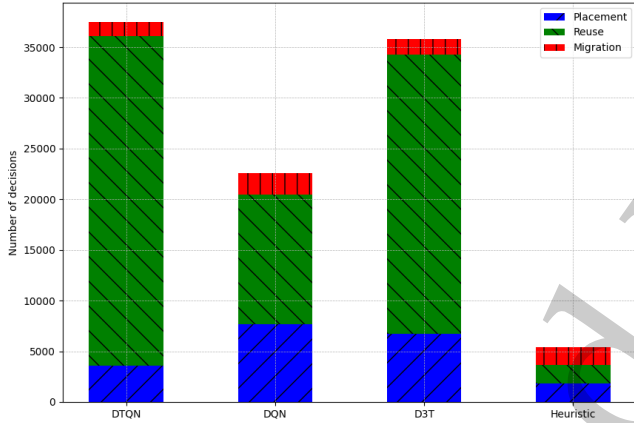


Fig. 5. Distribution of SFC embedding decisions ($N = 10$ and $\delta = 100$).

rewards, exhibits a relatively uniform distribution across new VNF instantiation, migration, and reuse placement decisions, regardless of the arrival rate δ . In contrast, the DQN baseline demonstrates a more adaptive strategy, adjusting the balance between VNF placement and reuse based on the value of δ . Meanwhile, both DTQN and D3T-based solutions consistently prioritize VNF instance reuse across all values of δ . As the number of users increases, DTQN further differentiates itself from D3T by placing even greater emphasis on VNF instance reuse.

This preference can be attributed to several factors. First, the simulation parameters set the reuse cost lower than the migration cost, making VNF reuse more cost-effective than instantiating new VNFs. Moreover, migration induces extra bandwidth consumption, potentially jeopardizing QoS requirements and incurring penalties, particularly at high δ . By prioritizing VNF reuse, the DTQN-based solution minimizes unnecessary resource allocations and bandwidth usage, thereby maintaining a more stable and efficient MEC network. Furthermore, the enhanced ability of our solution to capture temporal dependencies enables more informed placement decisions, striking a strategic balance between immediate resource utilization and

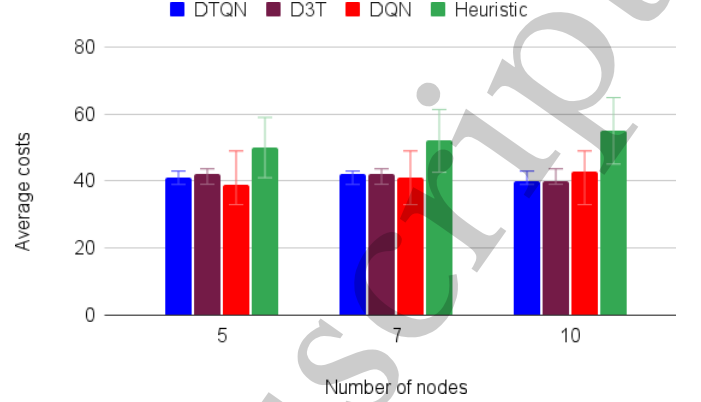


Fig. 6. Average costs vs number of nodes ($\delta = 50$).

long-term network performance.

Fig. 6, which illustrates the average costs of each algorithm as a function of the number of nodes over five simulation runs, supports the previous statement ($\delta = 50$). Despite having the highest rejection rate compared to DTQN, D3T and DQN, the Heuristic approach incurs the highest costs due to its inadequate placement strategy and excessive bandwidth consumption. At smaller scales, DQN incurs slightly lower costs than DTQN. However, it is important to note that DQN has a higher rejection rate, resulting in fewer satisfied requests. Moreover, as the number of nodes increases, the costs for DTQN decrease relative to those for DQN, as DQN's less optimal decisions become more impactful than the difference in the number of requests served.

These findings suggest that transformer-based RL models, such as DTQN and D3T, hold significant promise for complex decision-making tasks in dynamic networks, particularly in optimizing VNF placement strategies. By prioritizing VNF reuse over new instantiation and migration, DTQN achieves superior performance, cost efficiency, and resource optimization, especially under varying network demands.

VII. CONCLUSION

This paper presents a comprehensive solution for the placement and use of VNFs in MEC networks, specifically tailored for mission-critical applications with stringent QoS requirements. Our DTQN-based approach effectively addressed the dynamic nature of MEC environments by leveraging advanced RL techniques to optimize VNF placement strategies. Simulation results demonstrated the superiority of the proposed method in achieving cost efficiency, minimizing service disruptions, and ensuring better resource utilization compared to baseline approaches. The emphasis on reusing VNFs rather than creating new instances or migrating VNFs highlights the crucial role of smart resource management in supporting dynamic networks and minimizing operational expenses. These findings suggest that Transformer-based RL models are promising for solving complex decision-making tasks in dynamic and resource-constrained network environments. In future work, we will investigate the scalability challenge of the proposed DTQN-based solution in large network settings.

LIST OF ABBREVIATIONS

5G	5th generation
APMEC	Automated Provisioning framework for MEC
DT	Decision Transformer
DDQN	Double Deep Q-Network
DQN	Deep Q-Network
GAP	Generalized Assignment Problem
IoT	Internet-of-Things
IT	Information Technology
MDP	Markov Decision Process
MEC	Multi-Access Edge Computing
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
ML	Machine Learning
NFV	Network Function Virtualization
QoS	Quality-of-Service
RNN	Recurrent Neural Network
RL	Reinforcement Learning
SAP	Subchain-Aware NFV service Placement
SFC	Service Function Chain
SLA	Service-Level Agreement
TFLOPS	Floating Point Operations Per Second
URLLC	Ultra-Reliable Low-Latency Communication
VM	Virtual Machine
VNF	Virtual Network Function

AUTHORS' CONTRIBUTIONS

Conceptualization and supervision, W.J. and F.B.; methodology, A.N. and M.D.; validation, R.G. and F.B.; formal analysis and investigation, A.N. and M.D.; resources, W.J.; writing—original draft preparation, A.N. and M.D.; writing—review and editing, W.J.; F.B. and R.G.; project administration, W.J. and F.B.; funding acquisition, W.J. and F.B. All authors have read and agreed to the published version of the manuscript.

AVAILABILITY OF DATA AND MATERIALS

Data and materials supporting the results of this study are available upon request from the corresponding author.

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding this manuscript.

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