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Framework for Virtualized Network Functions (VNFs) in Cloud of Things Based on Network Traffic Services

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Abstract: The cloud of things (CoT), which combines the Internet of Things (IoT) and cloud computing, may offer Virtualized Network Functions (VNFs) for IoT devices on a dynamic basis based on service-specific requirements. Although the provisioning of VNFs in CoT is described as an online decision-making problem, most widely used techniques primarily focus on defining the environment using simple models in order to discover the optimum solution. This leads to inefficient and coarse-grained provisioning since the Quality of Service (QoS) requirements for different types of CoT services are not considered, and important historical experience on how to provide for the best long-term benefits is disregarded. This paper suggests a methodology for providing VNFs intelligently in order to schedule adaptive CoT resources in line with the detection of traffic from diverse network services. The system makes decisions based on Deep Reinforcement Learning (DRL) based models that take into account the complexity of network configurations and traffic changes. To obtain stable performance in this model, a special surrogate objective function and a policy gradient DRL method known as Policy Optimisation using Kronecker-Factored Trust Region (POKTR) are utilised. The assertion that our strategy improves CoT QoS through real-time VNF provisioning is supported by experimental results. The POKTR algorithm-based DRL-based model maximises throughput while minimising network congestion compared to earlier DRL algorithms.

Keywords: Cloud computing, virtual network functions, IoT, cloud of things, reinforcement learning, traffic identification, Kronecker-Factored Trust Region.

I. INTRODUCTION

The capacity of the Internet of Things (IoT) to link the analogue and digital worlds has attracted a lot of interest from the corporate and academic realms. The interplay of intelligent equipment like household appliances, robots, and sensors makes it feasible to provide a variety of clever health care [1], intelligent parking [2], intelligent surveillance [3], and other services. As a result, massive volumes of data are generated and increased dramatically, necessitating flexible networking solutions for a range of IoT applications. Additionally, numerous Quality of Service (QoS) requirements, including high throughput, low latency, low packet loss rate, and more, have been offered by services for various IoT scenarios [4]. The development of a strategy that permits the flexible delivery of network services by both seasoned network devices and freshly emerging IoT devices is crucial. However, these gadgets are constrained by older technology' preset, programmed nature [6].

Fortunately, cloud computing provides workable solutions to a number of underlying IoT-related issues [7]. The combination of cloud computing with IoT has produced the Cloud of Things (CoT), which [9] allows for the complete resolution of certain service requirements [10]. Network Function Virtualization (NFV), a cloud computing approach, distributes hardware resources by employing virtualization technologies to separate network activities from the traditional hardware. Customer Premise Equipment (CPE), Load Balancing, Firewalls, Network Address Translation (NAT), and Deep Packet Inspections (DPI) are among the network services employed in NFV, which are referred to as Virtualized Network services (VNFs). These VNFs may be flexible deployed on IoT physical devices, gateways, access points, or base stations in CoT at a pace that is similar to line speed. The Service Function Chain (SFC), which involves several VNFs, specifies the sequence in which network services are implemented. When a CoT service is used, the data gathered by IoT devices and the command messages are precisely packed as traffic packets that sequentially transit the physical nodes that host the VNFs of a certain SFC. The VNFs can function as the nodes of the corresponding virtual networks in accordance with the requirements of each CoT service. It makes logical that network performance and QoS are significantly impacted by the provisioning of VNFs in CoT.

Since there may be several transmission lines that satisfy the sequence of VNFs according to the SFC, choosing the right way is essential for reducing the overhead of packet transmission in CoT.

Without taking into consideration the various demands of traffic packets in CoT, simple and typical solutions for network scheduling optimisation strive to have all packets reach the destination node as rapidly as possible. For instance, while the online video streaming data for the Virtual Reality (VR) service requires a lower packet loss rate than the recording data for the Intelligent Metering service, it is delay-sensitive. Current traffic scheduling techniques for CoT networks may cause significant resource consumption by traffic packets containing recording data as opposed to video-streaming data, leading to poor service quality for users of VR services.

Better solutions may be created if traffic identification is done from here for fine-grained network resource management in CoT. After determining whose service a packet belongs to, it is feasible to try and schedule network resources to match its requirements for latency or packet loss rate. In our prior study, we delved into further depth about the role that traffic identification plays in network resource management. The precise CoT network resource scheduling requires the efficient online adaptive VNF path selection for each traffic packet. Since a complex real CoT network environment contains a high number of links, a time-varying workload, and a variety of service requirements, it might be challenging to adequately characterise the NFV and its IoT underpinning components. A technique for autonomous decision-making known as reinforcement learning (RL) develops the capacity to deal with problems in a flexible way over time.

Resource management problems have been solved using RL's model-free and long-term optimal outcomes properties in a variety of domains [17]. Some of them, nevertheless, display erratic behaviour or work best in state spaces and action spaces with little dimensions.

The CoT network referenced in this paper is an infrastructure-based network, not an ad hoc network, it should be highlighted. Despite consisting of a specific set of Internet-connected smart devices and sensors, its architecture may be considered to be quite stable. In this study, we develop a VNF provisioning system with intelligent scheduling of CoT network resources. It combines deep reinforcement learning-based VNF path selection with deep learning-based traffic identification for exact resource scheduling. Multi-Layered Gradient Boosting Decision Trees (mGBDT) [22] are used to find various traffic data classifications. Gradient Boosting Decision Trees (GBDTs) for regression are stacked in many layers to create these trees. In order to obtain stable scheduling while utilising the DRL technique, we also improve the state-of-the-art algorithm Actor Critic using Kronecker-Factored Trust Region (ACKTR) [23] by altering its surrogate loss function, namely Policy Optimisation using Kronecker-Factored Trust Region (POKTR). In contrast to traditional modelling methodologies and heuristic algorithms, our DRL algorithm may learn policy of making judgements from significant historical experience for the biggest long-term advantages. It carries over the advantages of ACKTR, which combines scalable trust area natural gradient with actor-critical approach.

The following is a brief summary of our contribution:

We provide a traffic identification- and DRL-based VNF path selection-based architecture for intelligent VNF provisioning in CoT. Traffic identification increases real-time network performance by providing an exact transmission need for fine-grained scheduling of each packet.

The framework chooses a VNF path using a customised DRL-based model. The goal of this model is to reduce the amount of rejected packets and average slowness in CoT. In order to choose transmission routes, it keeps track of the network's bandwidth and computing resource conditions.

To get a steady decision performance we enhance the most recent DRL algorithm, which we name POKTR. It uses a unique surrogate loss function and an appropriate learning step in each episode to reduce the discrepancies between new and old policies.

II. RELATED WORK

Our suggested provisioning structure in CoT is based on traffic identification and offers precise transmission needs

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for various packets. The majority of current attempts in this subject use machine learning methods after getting through the port numbers based and payload data based phases. The categorization of network traffic uses a variety of flow-level or packet-level characteristics as well as certain feature engineering techniques [25]. Numerous innovative flow characteristics that Dong 4C 0; found operate well in detecting various kinds of video traffic.

By extracting innovative characteristics from data from Transport Layer Statistics (TLS) sessions, Anderson 4C 0; intended to get beyond the constraints of detection of malicious network traffic. The Gradient Boosting Machine (GBM) approach was used by the authors in a ground-breaking work to identify big size flow using information gleaned from past traffic matrices. Recent research have begun to use deep learning algorithms to recognise traffic.

These experiments did not significantly outperform earlier ones that used statistical classification methods since they were still restricted to a small number of particular unencrypted applications.

Most cloud computing resource management strategies strive to reduce the quantity of hardware or improve QoS [14]. The Joint Energy Consumption Minimization Problem of Device Activation, Rule Installation, and Data Transmission (JMDRD) was shown in [3] to be NP-complete, and the authors offered the Green Network method as a heuristic solution. In multiprovider NFV systems, Eramo 4C 0; [6] concentrated on cloud resource allocation and offered an algorithm for minimising the expenses associated with cloud infrastructure providers. By concentrating on the processing capabilities of nodes [34] and the bandwidth capabilities of networks [35], some research offered efficient scheduling techniques for common unicast difficulties. There are more and more studies that look at how VNFs affect the scheduling of network resources.

In order to guarantee the order of functions in an SFC, Thi-Minh 4C 0; took into account the use of flow restrictions and provided a model for the problem of large-scale resource scheduling in NFV. Some publications that concentrated on the first dynamic placement of VNFs might be seen as the foundational works for the system we suggested. On the other hand, the writers of [40] sought to reduce the amount of resources needed, whilst the authors of sought to maximise energy consumption. The methodologies of machine learning have been applied to the field of placing VNFs in order to combat the NFV environment's high degree of dynamicity.

Wahab 4C 0 published an enhanced k-medoids clustering approach that intelligently eliminates some cost functions from the optimisation problem by proactive partitioning the substrate network into a number of disjoint on-demand clusters. The authors transformed the Network Utility Maximisation (NUM) problem into a non-convex optimisation problem and shown that it is NP-hard in by accounting for end-to-end delays and other operating costs. Then they proposed a DRL technique, whose model needed to be trained on each node, for the joint optimisation of VNF orchestration and flow scheduling. The author of [4] used deep reinforcement learning and ignored the source and destination nodes for the traffic data when deploying VNFs in a fixed set of network nodes for the first time.

Deep reinforcement learning methods are excellent at making judgements, therefore several research projects have employed DRL algorithms to schedule resources across a variety of industries. Using evolving DRL to handle difficult control and resource allocation concerns, such traffic engineering in communication networks, was initially proposed by Liu 4C 0; in a seminal publication [5]. Chinchali 4C 0; employed the Deep Deterministic Policy Gradient (DDPG) [46] approach to give traffic in mobile networks a range of scheduling priorities and data demands. Zhang created clouds that automatically and successfully negotiate the optimal configuration using a modified DQN technique called SAQNetwork (SAQN). The two attempts produced complex DRL-based models based on neural network layers: LSTM and stacked autoencoder, whereas some other research just used the standard DQN model. This is due to the fact that state space is altered in different settings. DRL algorithms have also been shown to be capable of scheduling a single kind of resource [20] or a variety of resources.

As has already indicated, the majority of earlier techniques for identifying traffic are restricted to a few particular network services or unique contexts. Since more and more communication packets are being encrypted, it has become more challenging to extract several attributes that are utilised for identification. DRL algorithms have been used to manage resources in a variety of industries and have shown good results for online decision-making. However, for their models to function properly, these DRL-based attempts must operate in low-dimension state space and action space.

There is no ongoing development to provide VNFs in CoT that use DRL-based models. Furthermore, the diverse QoS needs of traffic packets were not taken into account in research regarding allocating network resources.

Because of this, they never gave traffic identification technologies a thought when allocating cloud resources and needed to know the transmission priorities of different packets.

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III. ARCHITECTURE OF THE WORK

A network service in CoT is dependent on its unique SFC, which is made up of a series of VNFs. As a result, effectively supplying and deploying VNFs has already emerged as the key to scheduling network resources. We create an intelligent provisioning framework using VNFs to schedule traffic packets more effectively in the current CoT networks. However, a wide array of switches, datacenters, and smart devices in CoT host the VNFs that build various SFCs. As a result, this framework uses a fine-grained mode to manage the challenging real CoT network situations. We integrate the provisioning of VNFs inside the network with the traffic identification at the source node. This framework's architecture is seen in Fig. 1 and detailed below.

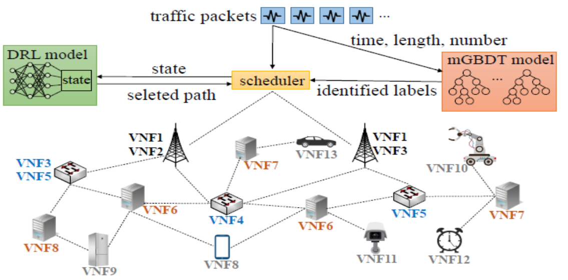

Figure 1. DRL-based VNFs provisioning traffic identification in CoT.

The scheduler for the framework as well as the DRL-based selection model and related traffic identification model are first deployed on the source node. After features from packets arriving at the source node have been retrieved, the framework feeds those characteristics to a trained traffic identification model produced using the mGBDT approach. This technique distinguishes traffic packets based on user behavioural attributes and QoS requirements rather than employing specific complicated and restrictive criteria. As a result, the majority of traffic packets in CoT, rather than only those from a select few applications, are covered by the identification model, which serves as the foundation for resource management.

Second, the framework checks QoS criteria such input packet delay and packet loss rate and adopts suitable transmission strategies for them based on identification findings. Then, without further identification required, we label the succeeding packets of the specified traffic flow and capture the information of that flow.

Our framework scans the network to identify idle resources before new packets enter the system. It then generates status information together with the prior transmission needs of the incoming packets.

The DRL-based model selects a transmission path from the source node to the destination node for each packet in accordance with the state information. In this case, the network is abstracted into a directed acyclic graph, where each node (IoT device or gateway) is represented by a vertex, and each edge represents a transmission link connecting two nodes. Table 1 gathers some of the most important notes made in this article for quick access.

$$T_i = \sum_{e \in E_i} D_e + \sum_{n \in N_i} W_n \tag{1}$$

Packet 8 is given a certain Maximum Transmission Time (MTT) to meet the QoS criteria of the traffic class for which it is classified. During the transmission process, a constraint function restricts the current time C based on the requirements:

$$t \leq s_i + MTT_i \tag{2}$$

where S_i is the transmission process's start time. The packet will be sent to the following node on its path if it complies with the constraint function.

The DRL-based model will eventually be rewarded positively if the packet arrives at the target node within the allotted time, increasing the likelihood that this policy will be followed. Otherwise, the model will make it less likely that the policy will be constantly optimised.

IV. TRAFFIC IDENTIFICATION MODEL

The provisioning framework uses a DRL-based decision model to deliver VNFs for packets sequentially depending on the results of traffic identification. As a result, the precision of traffic detection determines the efficacy of our architecture. We segregated the traffic data in [15] for various QoS requirements of several network services, comprising the majority of traffic packets in actual CoT networks, based on user behaviours. Multi-Grained Cascade Forest (gcForest) [9] is used to classify the traffic data in [15], which used fine-grained scanning and cascade operations to give high performance in a wide range of activities. It is uncertain how to utilise forests to create multi-layered models that explicitly assess their ability to learn representations because gcForest only performs well in supervised learning settings. By stacking several layers of regression GBDTs as its core unit, the most current model for both classification and regression tasks, the mGBDT, is provided to study the ability to learn hierarchical representations. In our experiments, mGBDT showed improved performance for traffic identification compared to older approaches that are used to complete classification tasks.

In the framework, which uses mGBDT to detect traffic data, the key ideas are described below.

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Since deep neural networks excel in so many areas, it is thought that their hierarchical or "deep" architecture hold the secret to extracting useful representations from unstructured data. Due to how successfully it trains differentiable learning systems, back-propagation and stochastic gradient descent are currently used in the majority of deep learning models.

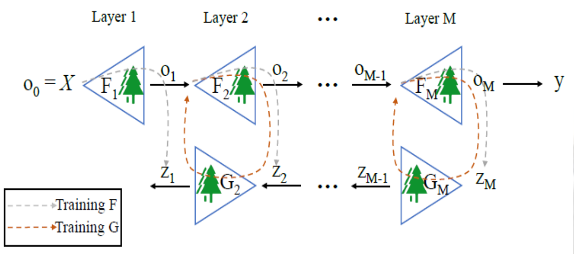

Figure 2. The design of the mGBDT. By stacking many layers of regression GBDTs as its fundamental unit, the model explicitly emphasises studying the capacity to learn hierarchical representations.

However, because of their non-differentiable feature, tree-based ensembles like Random Forest or GBDTs cannot use back-propagation when modelling discrete or tabular data. In order to achieve collaborative training of such multi-layered nondifferentiable models without the use of back-propagation, mGBDT is presented.

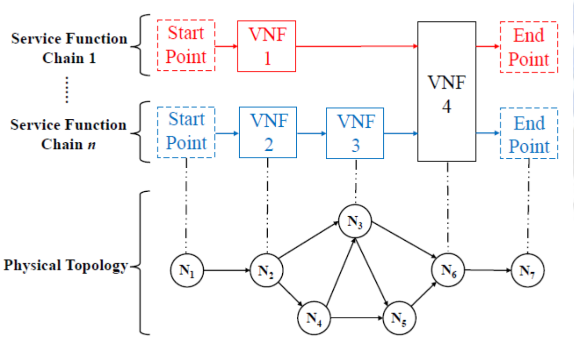

Figure 3. A sample CoT network. Following the SFC sequence from the source node to the destination node, traffic packets move via some nodes.

mGBDT provides both the expressive power of hierarchical distributed representations and the higher performance of tree ensembles as compared to other widely-used approaches. Both supervised and unsupervised settings can be used to train the model. Additionally, the lower layers of the mGBDT may train a linear separable feature re-representation, significantly enhancing the model's performance in classification tasks, by utilising a linear classifier as the forward mapping in the top layer. Therefore, we use mGBDT as the paradigm for traffic identification in the provisioning system.

V. VNF PATH SELECTION

In our approach, we choose the packet transmission channels made up of VNF nodes using a DRL-based model.

Within the Markov Decision Processes (MDP) paradigm, traditional reinforcement learning develops a control strategy based on previous observations of transition data and stochastic uncertainty. RL-based techniques can train behaviour to accomplish their own goals rather than depending on the final environment model or other inputs. Convolutional and fully connected neural network layers are used in the DRL technique to tackle difficult online autonomous decision-making problems with high-dimension state space. The brain serves as the agent in the DRL field, learning to evaluate and enhance its policies as it goes. At each level of interaction with the environment, the agent observes the world and decides what to do from there. In line with the results of rewards or penalties, the policy is improved.

Fig. 3's example CoT network illustrates how our DRL-based decision model functions in relation to various SFCs. Depending on the specific SFC, the network can be divided into the appropriate VNF layers. As observed, one node may host several VNFs, such as #2, and numerous SFCs may share a single VNF, like +#4.

Each SFC also has bandwidth and end-to-end latency specifications based on the specific network service for which it is accountable. The transmission between two devices in a CoT is still impacted by a variety of factors, such as latency, bandwidth, packet loss rate, nodal processing power, separation distance, and power of the network devices, among others. Every decision-making process must take into consideration the existing state of the network and the SFC needs since true CoT network setups are so complex and diverse.

The DRL approach is then used to the provisioning of VNFs since it can draw conclusions from past performance without having to simulate the dynamic network environment using these complex elements. The DRL agent can evaluate the current situation and, using its expertise, forecast potential changes in congestion in the following environment.

Following that, it chooses a path that best satisfies the current state's needs for the particular traffic packet with varying QoS criteria. The entire network's latency and congestion are decreased in this way.

Because SFCs are so crucial to the management of network resources, we refer to the DRL-based scheduling model in our framework as DRL-SFC. The scheduler of the framework first acts as an agent by scanning the network for any paths that successively pass through different VNF layers before starting scheduling operations in DRL-SFC. The scheduler selects a transmission channel at the instant each traffic packet arrives in line with the results of traffic identification while taking into consideration network real-time bandwidth and computer resources. This method is continuous-

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time based and event-driven. We offer a suitable state configuration for applying DRL techniques.

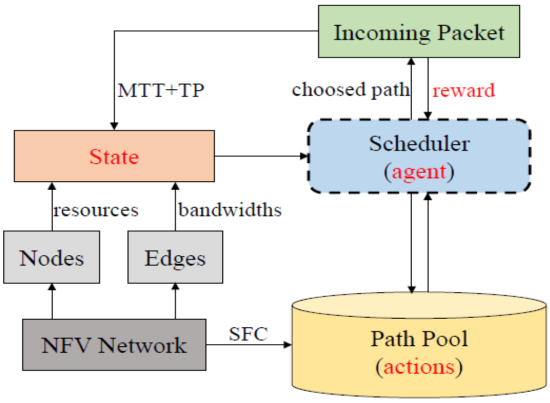

Figure 4. illustrates the mechanism for the DRL-SFC and its space, action space, and reward system.

State Area: The scheduler first calculates a packet's Maximum Transmission Time (MTT) and Transmission Priority (TP) when it arrives at the source node based on the results of traffic identification. The allowable transmission time delay (MTT) based on the QoS criterion. Our framework must consider both the bandwidths of the network's edges and the nodes' processing power, as was described in the section above.

For the agent to develop an appropriate policy for the new environment, it is important to gather sufficient transition samples. The optimal method for re-training the agent while minimising time and expense is a significant research area and is outside the purview of this work; it will be examined in the future.

When a packet enters a VNF layer during the transmission process, it is first examined to see if it fulfils the constraint function described in (2). If not, the packet is immediately rejected; otherwise, it is added to this layer's queue and waits to be sent. The packet with the highest TP value is then forwarded to its subsequent VNF layer once the packets in the queue have been sorted according to the values of their TP. The definition of the layer 8 packet's TP is:

Due to the fact that the values of U and V are affected by network circumstances, the agent can take into account the chance that this packet will successfully reach the destination layer in due time. Up until the packet is deleted or reaches the target layer, sorting and transmission continue.

$$\hat{G}_i^t = arg\ min_{G_i^t} \mathbb{E}_x \left[L^{inverse} \left(o_{i-1}, G_i^t \left(F_i^{t-1} \left(o_{i-1} \right) \right) \right) \right]$$
$$L^{inverse} = \left\| G_i^t \left(F_i \left(o_{i-1} + \varepsilon \right) \right) - \left(o_{i-1} + \varepsilon \right) \right\|,$$
$$\varepsilon \sim N \left(0, diag \left(\sigma^2 \right) \right) \quad \text{------ (2)}$$

In contrast to other widely-used methods, mGBDT combines the higher performance of tree ensembles with the expressive power of hierarchical distributed representations. Both supervised and unsupervised settings can be used to train the model. Additionally, the lower layers of the mGBDT may train a linear separable feature re-representation, significantly enhancing the model's performance in classification tasks, by utilising a linear classifier as the forward mapping in the top layer. Therefore, we use mGBDT as the paradigm for traffic identification in the provisioning system.

Please take note that in [15] we mentioned how our traffic identification algorithm relies on attributes that are flowlevel. However, in actual CoT networks, it is not always viable to have traffic flows wait for being extracted characteristics for a short period of time. To maintain our framework effective, a list was used to record each traffic flow that has already been recognised. This list includes a unique hot update method.

VI. KRONECKER-FACTORED TRUST REGION

The accuracy of traffic identification is a foundational tenet of the VNF provisioning architecture. We have run various tests to show how the new flow characteristics, which are estimated using the time, amount, and length data of packets in [15], lead to increased performance. Using traffic packets from a dataset [56] that contains traffic from 8 classes—browsing, chat, audio- and video-streaming, email, VoIP, P2P, and FTP—we repeat previous findings on traffic identification. This illustrates how the mGBDT may represent hierarchically and widely. The 8.3G total size of the dataset is made up of data from more than 18 sample applications, including Facebook, Skype, Spotify, and others. It is a tagged real-world traffic dataset.

$$z_i^t = \begin{cases} G_i \left(z_{i+1}^t \right), i < M \\ o_M - \alpha \frac{\partial L(o_M, y)}{\partial o_M}, i = M \end{cases}$$

$$R_i^t = -\frac{\partial L \left(F_i^{t-1} \left(o_{i-1} \right), z_i^t \right)}{\partial F_i^{t-1} \left(o_{i-1} \right)} \quad \text{----------(3)}$$

If the flow data dramatically change, such as with the appearance of new network services that are not present in the training dataset, the mGBDT model just has to be updated. The mGBDT model is updated by updating the dataset and retraining the model with the new dataset.

Table 2 examines the effectiveness of various identification techniques using the Precision Rate (PR) and Recall Rate (RC) values for various traffic flow durations. It is clear that the mGBDT significantly improves recognition accuracy and recall rates in comparison to earlier approaches in all situations of flow lengths. This is because of the mGBDT's superior performance of the hierarchical forest structure.

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Traffic Flow Length	mGBDT		gcForest		Random Forest		Decision Tree		KNN		SVM		DNN	
	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC	PR	RC
5s	0.9324	0.9320	0.9179	0.9164	0.9043	0.9083	0.8839	0.8880	0.8906	0.8959	0.7594	0.7186	0.8868	0.8830
10s	0.9347	0.9356	0.9161	0.9134	0.9069	0.9110	0.8870	0.8914	0.8866	0.8901	0.7980	0.7272	0.8872	0.8834
15s	0.9354	0.9352	0.9190	0.9167	0.9072	0.9119	0.8860	0.8896	0.8856	0.8919	0.7938	0.7153	0.8836	0.8822
20s	0.9408	0.9417	0.9213	0.9205	0.9061	0.9097	0.8858	0.8871	0.8889	0.8930	0.7555	0.7171	0.8966	0.8933

Table 2. Results of Experiments Providing for Traffic Flow Length.

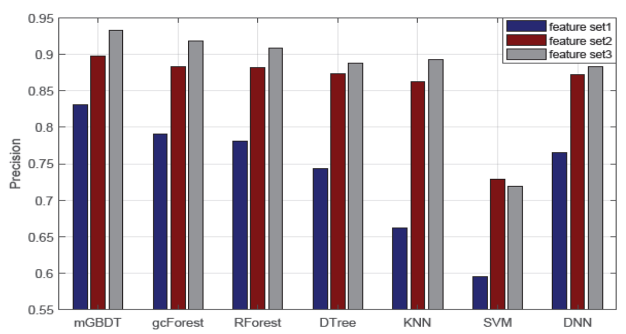
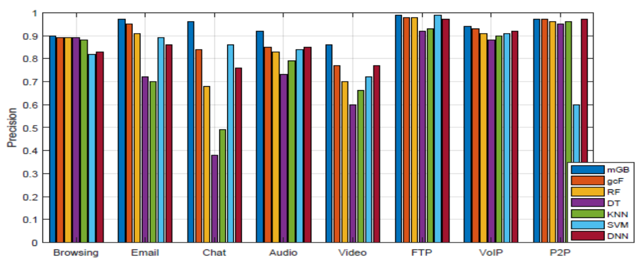


Figure 5. When the same percentage of the labels are randomly selected and flipped, the accuracy of various feature sets is compared between mGBDT and earlier identification techniques.

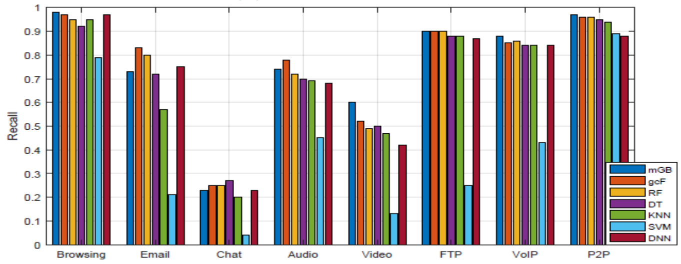
We evaluate the performance of earlier approaches using a variety of attributes that are provided in Table 3 in order to demonstrate the robustness of mGBDT and validity of the traffic features.

When different features are employed, as shown in Fig. 6, the greatest accuracy rates for mGBDT may be reached. The new features from [15] have higher validity than the older time-based features from [56]. Therefore, mGBDT has the highest resilience in this identification job.

The accuracy and recall rates of each traffic category as determined by mGBDT are then contrasted with those determined by prior techniques, as shown in Figs. 7(a) and 7(b). Multi-layered GBDT forests (mGBDT) have the highest accuracy rates across all traffic classes and equivalent closed recall rates to gcForest.



(a) Precision rates



(b) Recall rates

Figure 6. A comparison of the precision and recall of 8 different types of traffic data using mGBDT and earlier identification techniques.

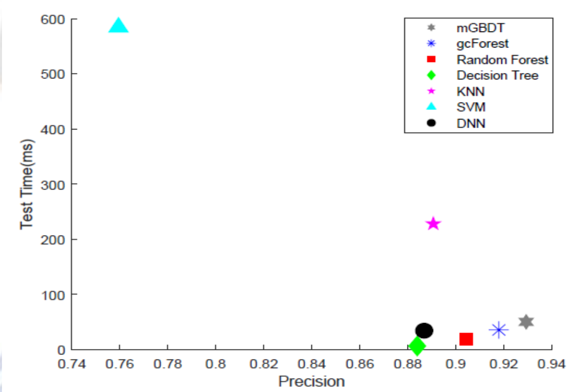


Figure 7. shows a comparison between mGBDT and earlier techniques of identification in terms of the speed and accuracy rates for 1000 flows with a duration of 5 seconds.

Provisioning of VNFs

To show the effectiveness of DRL-SFC, we construct the architecture of the DRL-SFC and its deep neural network using Pytorch, a Python-based framework. All experiments are run on a ThinkCentre machine learning workstation with an Intel core i5 CPU and 8GB of RAM.

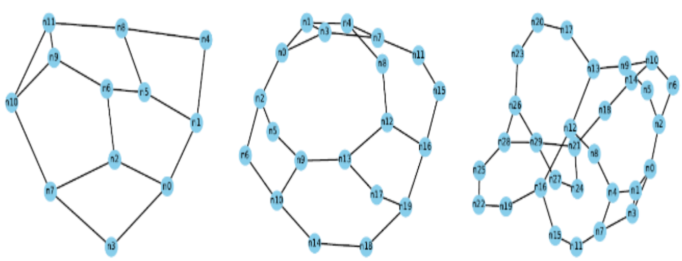


Figure 8. shows three topological networks with 12, 20, and 30 nodes, respectively. The source node in each sub-graph is =0, and the destination node is the one marked with the largest number.

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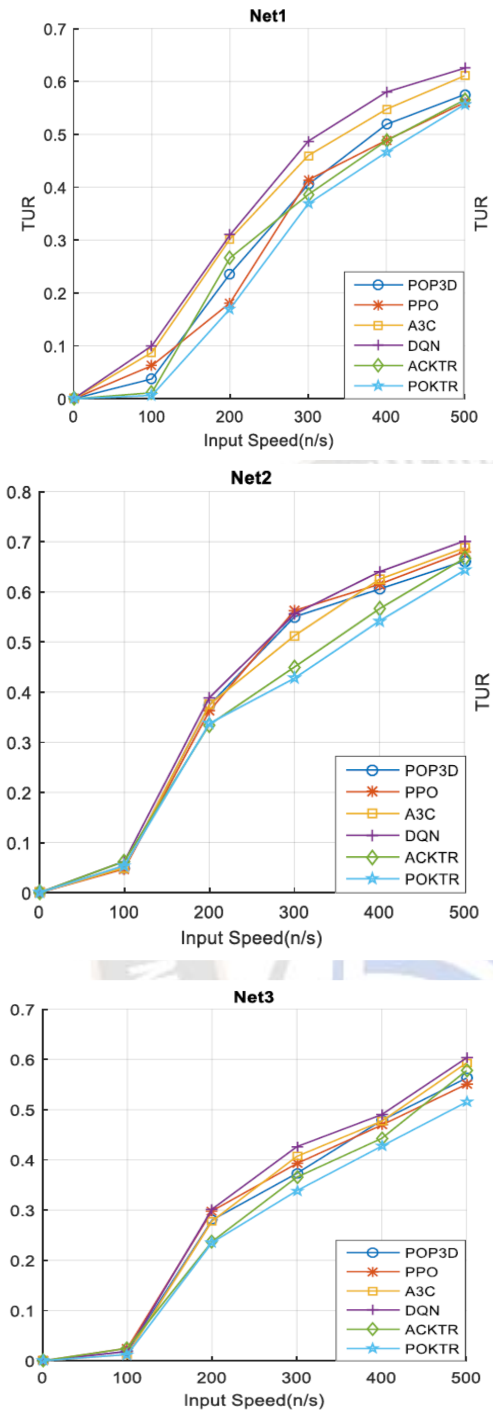


Figure 9. shows the TUR in various NFV networks as calculated using six models at various packet injection rates. The degree of network congestion is depicted on the x-axis, which measures injection speed.

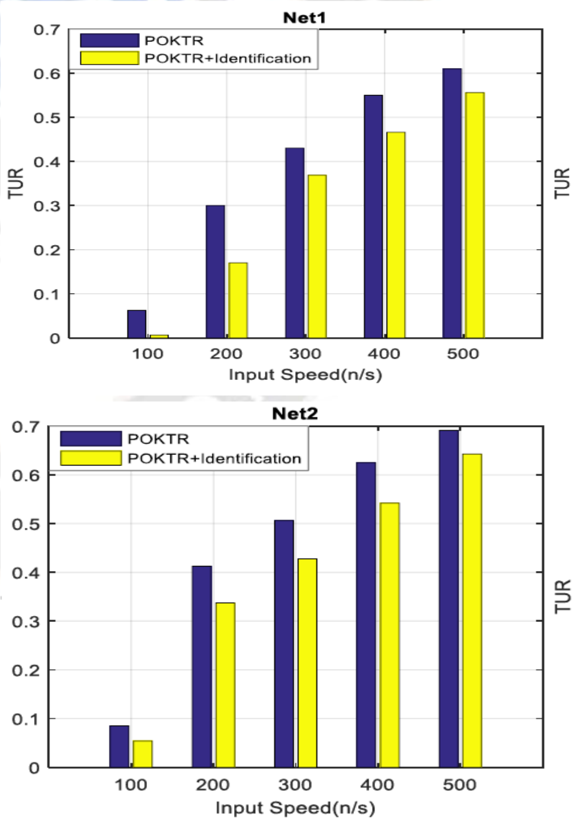
$$TP_i = TP_0 + \alpha(MTT_i - t) - \beta(L - X_l) \qquad \text{-----------(4)}$$

$$\eta(\pi_{new}) = \eta(\pi_{old}) + E_{s_0, a_0, \cdots, \pi_{new}}[\sum_{t=0}^{\infty} \gamma^t A(s_t, a_t))]$$

1, 2, and 3 nets. The network topologies are selected from the Internet Topology Zoo [7], which contains the most well-liked actual network topologies. The networks, which include 12, 20, and 30 nodes respectively, may thus be analogous to actual networks. In these networks, the majority of nodes have deployed at least one VNF, and a network function may have many VNFs on different nodes. With light traffic volumes, numerous SFCs may also share a VNF. Each network's source node is selected at random among those that support the origin network function as specified by the SFC.

Some of these pathways, which have been predetermined to make up the action space of DRL-SFC, meet the order of VNF in SFC. By injecting packets into the source nodes of these networks, we imitate the provisioning of VNFs.

We examine different DRL algorithms based on policy gradient, including A3C, PPO, and POP3D, in order to demonstrate the decision-making performance of the POKTR method on path selection. Additionally, Deep Q-Network (DQN), a different approach that approximates value functions in its decision-making [58, 59], is also contrasted. We conducted tests to see how well these algorithms handled scheduling across the three networks.



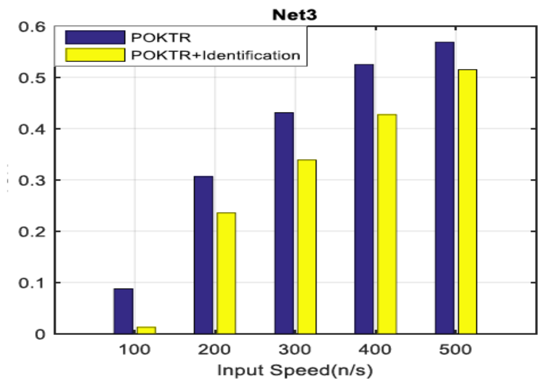


Figure 10. shows the traffic identification process-added TUR in various NFV networks.

To ensure that every packet has a probability of reaching the destination node, we first evaluate the lengths of paths and establish MTTs of the packets in line with their labels. According to their transmission priority, the eight main types of traffic packets—VoIP, Video-streaming, Audio-streaming, Chat, Browsing, Email, P2P, and FTP—are frequently organised in a specified order. According to user QoS requirements, a traffic class's transmission priority is higher and its MTT is shorter. We alter the rate at which we inject packets to produce various degrees of network congestion. The number of packets that successfully arrive at the destination node prior to MTTs is then measured.

For comparison and illustrative reasons, we next select Net3 at random as the experimental environment where packets are injected at a rate of 200 per second. We demonstrate the training of these models using different DRL techniques in Fig. 11. We record the TURs that these models created per 10 episodes for the first 2000 training episodes. The figure shows that all DRL-SFC algorithms perform more consistently throughout training, with the exception of the DRL-SFC using ACKTR. As a result, it becomes clear that the K-FAC method has a big impact on optimising the DRL policy. Additionally, POKTR converges swiftly and achieves the lowest TUR value, suggesting that MAPOKTR has a better possibility of improving its policy and accelerating convergence when the point probability distance is included to the surrogate loss function. Because they were not created for the state space utilised in our investigations, older, commonly used algorithms like DQN and A3C may have underperformed.

Finally, we evaluate whether traffic identification enhances the efficiency of DRLSFC scheduling. In Fig. 10, where each sub-graph represents a topological network, we give the associated simulation results one at a time.

The experimental packets are the same as before, except this time, they are tagged before being injected into the source node. To comparison, these packets have different MTTs while having the same TP as Equation (11).

TRUs grow in the same network at all degrees of congestion when traffic identification is absent. The rationale is that by including traffic identification into our provisioning architecture, the agent is able to deploy scarce network resources more judiciously and effectively to transmit traffic data with a range of QoS requirements. This reduces network congestion and improves overall performance. As a consequence, our architecture improves user QoS even if the identification process takes some time.

VII. CONCLUSION

The challenge of scheduling network resources in CoT is addressed in this research with an intelligent VNFs provisioning framework that can learn from experience rather than a precise and intricate mathematical model. The outcomes of traffic identification form the basis of the DRL-based framework's operation. To enhance the effectiveness of network resource real-time scheduling, the traffic identification approach employs new flow properties. Furthermore, this framework achieves excellent identification precision and continues to function when packets are encrypted since new features are extracted from the external information of traffic packets. The location of VNFs in SFC determines how the network is divided into layers by our framework's DRL-based decision model, DRLSFC. The DRL-SFC agent selects the transmission path for each packet based on a certain state space and incentives. The foundation of DRL-SFC is the proposed DRL algorithm POKTR, which makes use of a unique surrogate objective function to guarantee that the policy is stable and monotonically improved. Our testing demonstrate that DRL-SFC outperforms other DRL algorithms when employing our technique. In networks with different topologies and congestion, including traffic identification with DRL-SFC successfully decreases the TURs. We'll improve the VNF provisioning model in upcoming projects to make it more resemblant of the actual CoT environment, including addressing the problem of re-training the agent when the network environment changes and putting multi-agent DRL algorithms into practise to achieve interchangeable resource management between multiple source and destination nodes in the network.

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