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SECURE SLICING AND ALLOCATION OF RESOURCES OF 5G NETWORKS IN SOFTWARE-DEFINED NETWORKING / NETWORK FUNCTIONS VIRTUALIZATION

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ABSTRACT: In 5G communications, higher data rates and lower latency are needed due to the high traffic rate. Though resource wastage is avoided by secure slicing, sliced networks are exploited by DDoS attackers. Thus, in the present paper, traffic-aware setting up is PRESENTED for resource allocation and secure slicing over the virtualization of 5G networks enabled by software-defined network/network functions. In the proposed method (called T-S^3RA), to authenticate user devices, Boolean logic is used with key derivation based on passwords. Moreover, the traffic arrangement is based on the 5G access points. To implement secure resource allocation and network slicing, deep learning models are used. Renyi entropy computation is employed to predict the DDoS attackers. Through the experimental results, the effectiveness of the presented approach is proved.

ABSTRAK: Melalui komunikasi 5G, kadar data yang tinggi dan latensi yang rendah amat diperlukan kerana kadar trafik yang tinggi. Walaupun pembaziran sumber dapat dielakkan melalui pemotongan selamat, rangkaian yang dipotong sering dieksploitasi oleh penyerang DDoS. Oleh itu, kajian ini menyediakan persekitaran sedar-trafik bagi peruntukan sumber dan pemotongan selamat ke atas rangkaian 5G secara maya melalui fungsi rangkaian takrif-perisian. Melaui pendekatan yang dicadangkan (iaitu T-S3RA), peranti pengguna disahkan terlebih dahulu menggunakan logik Boolean dengan perolehan kunci berdasarkan kata laluan. Di samping itu, susunan trafik adalah berdasarkan titik akses 5G. Bagi melaksanakan peruntukan sumber yang selamat dan pemotongan rangkaian, model pembelajaran mendalam telah digunakan. Pengiraan Entropi Renyi dibuat bagi meramal penyerang DDoS. Dapatan eksperimen mengesahkan keberkesanan pendekatan yang dicadangkan.

KEYWORDS: *dynamic offloading; deep learning; resource allocation; network slicing; traffic scheduling*

1. INTRODUCTION

Network slicing is a critical issue for 5G networks beneath a single physical infrastructure. Generally, network slicing is defined as selection of slices and appropriate allocation of resources for each user [1-4]. Presently, higher service-satisfaction rates are required by network equipment. For instance, for a 4K ultra HD video streaming application, it is essential to meet more stringent service requirements like high throughput, high reliability, low latency, and higher storage space. Larger throughput and limited delay are required by this application, thus needing the implementation of resource allocation and network slicing.

Resource allocation and joint network slicing were presented as the main solution for meeting the requirements of users' quality of service (QoS). Using the service type is among the greatest methods to create a slice. Data traffic includes the type of service used for configuring the network slicing. Moreover, a quick and dynamic response should be offered to satisfy the constraints of service level agreement (SLA). Mainly, the present solutions for resource allocation and network slicing are expensive computationally while not supporting the mixed slice requests [5,6].

Appropriate support is provided by a software-defined network (SDN) for resource allocation and network slicing since it includes the functionality of processing the slice requests and performing data traffic arrangement [7]. SDNs have various benefits based on network slicing. Moreover, they currently are extensively researched for numerous applications. These advantages include reliable communication, long-distance, urgent solutions, and communication for optimizing problems [8-10]. For similar cases, a heuristic algorithm is utilized. Computations require a huge deal of time in these algorithms, due to their complexity.

Poor results are obtained by the present resource-allocation and network-slicing methods owing to the massive arrival rate of resource requests, numerous network slice requests, and high data traffic within a network slice [11]. Moreover, concentrated SDN controllers are also influenced since they behave as a single-point failure, unable to control most urgent service requests (ultralow latency). Through a multi-controller SDN environment, these issues are solved. The final decision is made by the controller in the SDN/network function virtualization (NFV)-based slicing to appropriately direct the slices [12-15].

The present study aims to handle the massive heterogeneous services from diverse tools with 5G networks connections [16-22]. Currently, three key services are evolved in 5G namely, ultra-reliable low-latency communication (URLLC), massive machine-type communication (mMTC), and enhanced mobile broadband (eMBB) (Table I).

The QoS and security requirements of networks were increased by integrating SDN/NFV and 5G. Resource allocation and network slicing in a 5G network enabled by SDN/NFV are challenging since the optimum set of resources and proper slice must be defined. Resource allocation and network slicing are implemented in most studies for a few heterogeneous services while considering very restricted metrics. Furthermore, fast resource allocation and network slicing are required owing to various throughputs, mobilities, data rates, and delays in different services. The QoS can be improved by a universal system.

For proper resource allocation and slice selection, a concentrated SDN controller is not practicable since slice privacy and security are not considered and there is higher participation of DDoS attackers. Thus, massive quantities of traffic are sent to a particular slice by these attackers. Nevertheless, the QoS requirement for UE cannot be satisfied by the secure network slicing alone since it is essential to serve the high-priority traffic first, in terms of the type of service.

The slice network is performed by the global controller while allocating optimal resources to achieve diverse service needs from users. The present study mainly includes the following points.

The 5G AP audits each authority in a VAP to insert, eliminate, and adjust the operations. Using a password-based key derivation function 2 (PBKDF2) in terms of Boolean logic is considered along with three input parameters including a physically unclonable function (PUF), secret key, and timestamp. An asymmetric queue model was used to perform traffic scheduling oriented by Bernoulli's theorem. Packet delay, data rate, and packet length were used to schedule the traffic flow. Two high- and low-priority queues were fixed within the 5G AP. Each queue includes asymmetric service rates based on the arrival rate. The international mobile subscriber identity, traffic type, fair SLA, device mobility, and slice capacity are considered in network slicing.

The present work primarily focused on SLA constraints between the service provider and user leading to the fair SLA while slicing the network. First, it tried to calculate the service availability ratio (SAR), throughput ratio (TR), response time ratio (RTR), and service reliability ratio (SRR) accompanied by the fairness or weight for each service. To perform resource allocation, HopFieldNet is used as a quick neural network to find resources for each slice. Through the proposed dynamic-flow offloading outline at the local control plane, overloading at network slices is handled. Using a fast-weighted bipartite graph ($F\omega BG$) was considered in terms of transmission rate, switch service capacity, and loss rate to map multiple flows to the optimal switches enhancing the network reputation. Packet classification through Renyi entropy was run along with the device authentication. The bandwidth usage is estimated here, for the switches. Ultimately, the NS3.26 simulator was used for the experiments to assess the proposed scheme exhibiting highly satisfactory performance compared to the formerly presented schemes based on several metrics like throughput, response time, latency, packet loss ratio, packet transmission ratio, bandwidth consumption, slice acceptance ratio, and slice capacity.

The rest of this paper is organized as follows. Earlier studies on resource allocation and network slicing are provided in Section 2 to recognize the research gap. The main problems explored from the present studies are highlighted in Section 3. The presented traffic-aware scheduling is detailed in Section 4 for resource allocation and secure slicing (T-S^{3}RA) architecture along with its essential algorithms. The proposed architecture is compared in Section 5 with former methods in terms of the experimental results. Finally, our contributions are summarized in Section 6 while outlining future improvements.

2. RELATED WORK

2.1 Secure Network Slicing

Multiple users are allowed to reach a single network followed by authentication through secure slicing. Moreover, users' performances on the slice are assessed by verification of attributes like the strength of passwords and the existence of malware [23]. In the study of Wang et al. [24], mitigation of DoS attacks in an SDN was focused on through switch bandwidth congestion prediction. Specifically, a complete judgment score was determined for each switch representing attack severity. Through trust values, multiple buffer queues the priority can be managed by the manager considering various users' priorities. A weighted round-robin algorithm was used to schedule flow requests from users. The compromises by DoS attackers are estimated. Through authentication of the users, attack prevention is achieved. Thus, attackers are easily eliminated before overloading the controller.

The VIKOR multicriteria decision-making approach was proposed by Porambage et al. [25] for network slicing within a 5G environment to find node significance (topology and resource attributes) and thus rank the nodes. A candidate physical path is defined among the slice nodes, for maximizing the slice acceptance ratio. However, there is a major drawback in VIKOR namely, the marginal slice acceptance ratio, which should be higher for the high-priority traffic.

Accessing the slice by third-party application services, secure keying is made [26], which ensures consent from the monitored devices as well as security features for the keying outline. Hence, the security feature is demonstrated by establishing 5G services. The key distribution server initially creates the cryptographic keys. The ELGamal Cryptosystem was proposed for a key generation where two sets of keys are generated including private and public keys. The resources are made here for key generation.

2.2 Resource Allocation and Network Slicing

The optimal workload allocation was proposed by Ma et al. [27] for distributed 5G-based SDN/NFV networks. An end-to-end network slicing architecture was designed in this method for supporting several services like URLLC and eMBB. Moreover, through slicing the requests from clients in the integrated environment (edge computing, NFV, and SDN), the network operating cost is decreased. Network slicing was performed by Dawaliby et al. [28] in a large-scale Internet of Things (IoT) environment (long-range extensive area network). In this work, three slices of the network were segregated including the reliability and urgency-aware slice, best-effort slice, and reliability-aware slice. First, one-to-many matching (defined by the number of IoT devices allocated to the virtual slices) was used to implement cooperative slicing. Then, a one-to-one matching game was used to allocate the resources for each slice (inter-slice resource allocation). The higher processing time is used by the coalitional multigame theory resulting in higher computational complexity.

Packet-based data traffic scheduling was suggested to enhance resource assignment and sharing in 5G slice networks [29]. Two operations modes are utilized including dynamic sharing resource (DSR) and static sharing resource (SSR). The allocated capacity weight is determined to assign the resource for each slice and thus the allocated one. The fairness for resource distribution per slice is calculated in the final analysis. A global network controller is needed for operating massive types of slices like popular, sensitive, and heavy slices. The radio resource management (RRM) was investigated by Koutlia et al. [30] for multiple slice management. Using the RRM function here, the radio resources are divided and allocated. Slicing and allocation provisioning were proved by an interaction between the SD-RAN and eNB controller. The QoS requirements for real-time traffic are not met by a single controller while not suiting the complex application setups (Drone Control and AR/VR).

A slice management scheme was proposed by An et al. [31] to assign resources in terms of priority. In this scheme, forwarding high-priority slice requests is performed while transmitting the lower-priority slices and shortest paths to other paths. They used 200 nodes to perform the experiments. Through a grid network topology, the nodes were deployed. The average throughput for slices was more than 6%, 13%, and 7% in the final analysis while minimizing the delays of the slices by 11%–14%. The shortest path is used by the flow (high-priority) forwarding within the data plane although it is not available for all cases. Thus, it is essential to install the corresponding flow in the controller when there is no consistency between flow and a flow table. Hence, a bandwidth scarcity problem is a resultant for users under static resource assignment.

A network slice embedding model was presented by Tang et al. [7] in terms of reliability. The number of slice requests is increased by the model while reducing the failure rate of the network slices simultaneously. A Lyapunov optimization model was used in this model to allocate resources and ensure queue stability. The network stability and reliability were guaranteed while effectively improving the network throughput. However, obtaining an abundance of network slices is difficult with lower interoperability between the SDN/NFV and 5G network.

Service function chaining is utilized for network slicing [32], in which a set of service function chains is included in each slice to deal with any traffic per slice. Then, the trade-offs between slicing and execution runtime are examined by designing a greedy-based heuristic algorithm. Ultimately, the required bandwidth and delay are obtained through an optimization model. The mobility of network slices is not taken into account, which reduces the QoS and QoE.

A scheme was developed by Alfoudi et al. for network slicing resource management (NSRM) [33] for the allocation of resources for each slice within a network. An LTE network was considered in this work for various slice allocations and fair distribution of bandwidth among slices. Deploying the controller, all the slices are handled by the LTE slice controller for each slice. The radio network resources are assigned through the LTE slice controller by a virtual eNodeB. It is very difficult to dynamically provision the slice requests. For instance, large slice request handling is required by the Industry 4.0 application.

Narmanlioglu et al. conducted service-aware multi-resource allocation for cellular networks defined by software [34]. In this work, joint network allocation was demonstrated along with scheduling the available network resources for determining the network slices. Based on the SLA priorities and constraints, network resources are specifically provided. For each priority, the analytic hierarchy process (AHP) is utilized to calculate the resources (latency, throughput, reliability, and storage). Through experiments, they evaluated the method for vertical subscribers and industries cost-efficiently. The network slice capacity is the main factor to determine the needed resources. Though, AHP is not able to concurrently support multiple traffic flow resource allocation.

The vehicular ad hoc network environment was examined by a dynamic end-to-end slicing method supporting 5G communications [35]. Two kinds of slice services were examined including Video and Web. Resources were assigned for network slices in a single physical network infrastructure. In both the control and data planes, the handling of different services from numerous users is supported through virtualized network functionality customization. However, high throughput is not provided by this end-to-end method for limited latency service types.

Two eMBB and V2X services were examined by Albonda and Pérez-Romero [36]. They used two approaches of heuristic algorithm and reinforcement learning for resource allocation and network slicing for various slices. According to the simulation results, the latency is reduced by 0.18 s (by 0.26 s for a fixed slicing ratio). However, multiple traffic classes are not supported by this approach in each slice. Furthermore, latency can be further reduced by a global controller for each service type.

An optimal and quick response method is presented for resource slicing within heterogeneous cellular networks [37]. The real-time advent of slice requests is captured first by this technique through a semi-Markov decision procedure (deep double dueling) to predict the service resources and time. Through several experiments, the performance of the presented deep dueling method was demonstrated for resource slicing. Several challenges are caused by large and dynamic network slices in the control and data plane. Such challenges are addressed by presenting load balancing amongst multiple network service

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chains. Hence, a novel concept was used (point of existence) to solve the scalability problem while accepting only limited slice users [38-40].

3. PROBLEM DEFINITION

Resource allocation and network slicing are run in SDN/NFV-based 5G networks based on the service requests of user devices [41-43]. Massive service requests from the user can be handled through a multiclass queuing and traffic analysis model. Low-complexity traffic predictors are employed utilizing a soft gated recurrent unit (GRU) to allocate the resources through deep neural networks (DNNs). Moreover, a multistage analysis is conducted for three various slices (URLLC, mMTC, and eMBB) to carry out M/M/n/K-based queuing.

These studies have the following limitations: first, they are oriented by the load, thus, non-real-time traffic for scheduling before real-time traffic is caused by the high response time for processing high-priority class packets. Second, based on a first-come-first-serve (FCFS) protocol, particular slices are scheduled thus further increasing the response time leading to poor QoS for received requests. Third, a single point of failure occurs in an SDN, when it is not possible to handle the requests from various users through a single controller. Fourth, the response time is incremented by running both DNN and GRU for more realistic and QoS-constrained traffic. Furthermore, a huge deal of energy and time is used by the DNN. Fifth, a random seek pattern is run by the FCFS since requests are not reordered by the slice for minimizing service delay. Besides, fair level SLA constraints are not used by the queuing theory. Since the service must be provided with an availability of 99.99%, ensuring service timeouts of less than 0.01% and completing the 99.99% of the services are essential within the resources. Additionally, resources are not distributed properly when utilizing FCFS for scheduling.

For embedded services, a dynamic flow migration was proposed under SDN/NFV-aided 5G networks to decrease the dynamic traffic load per slice [44]. To address this issue, a heuristic algorithm was used. This approach has the following drawbacks: (1) Adaptive flow migration is needed owing to the limited performance of the Poisson traffic model. (2) An optimal solution was required by the routing path for flow migration and in former approaches, delay-sensitive traffic cannot be run. (3) The heuristic algorithm is not able to present an optimal solution when arriving at an unexpected flow at the controller. In the present work, the above-mentioned problems are resolved through network slicing, dynamic offloading, resource allocation, security, as well as packet classification.

4. SYSTEM MODEL

To design the presented T-S^{3}RA within an SDN/NFV-permitted 5G network, the mobile device authentication processing abilities were used along with network slicing, traffic scheduling, as well as dynamic offloading, and resource allocation.

4.1 Network Overview

Designing the T-S^{3}RA model for resource allocation and secure network slicing included a global control plane, local control plane, user plane, and data plane. Some entities are contained in the suggested T-S^{3}RA model such as tools (d_1 ... d_n), VAP (VA_1 ... VA_n), 5G APs (AP_1 ... AP_n), controllers (GC), switches (PS_1 ... PS_n and VS_1 ... VS_n) and some LCs (LC_1 ... LC_n). The secure credentials are submitted in the devices to the 5G AP. Generally, there are limited components at the data and control planes based on the resources. Moreover, it is essential to use these resources for sending and receiving responses from users as well as for action processing. The VA is removed when not needed. Hence, using the multi controllers resolves the single-controller-failure problem as a result of using both virtual and physical switches. Hence, the overload problem is solved.

In network slicing, more packet losses and delays are induced by massive traffic. Thus, slicing is performed while scheduling the traffic and allocating the resources through deep learning methods. Through dynamic offloading actions, imbalance issues are avoided. Via various credentials, these actions are kept in the data plane while considering the resource wastage problem. Hence, through entropy calculations, DDoS attackers are detected arriving at the switches.

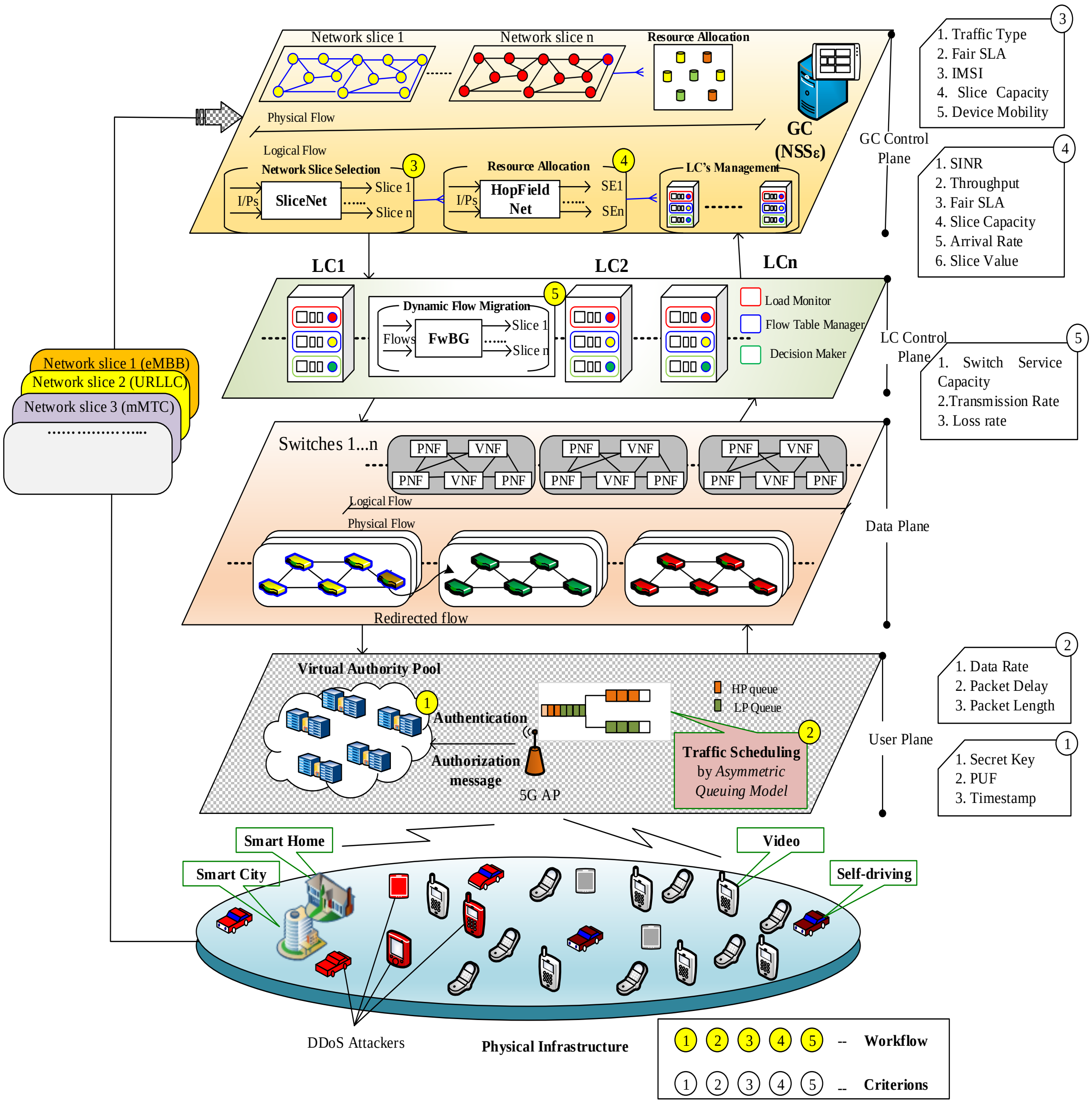

Fig. 1: The system architecture [1].

Figure 1 shows the proposed T-S^{3}RA architecture. The main network entities include: (1) All IoT tools with access to the network through the 5G communications network are known as the tools. Such devices are dynamic in movement and heterogeneous in nature. Higher coverage is required to connect them to the 5G AP. All tools are not approved, and unauthorized user participation is also possible. (2) 5G AP armed with higher communication coverage with a higher data rate, lower latency, and higher throughput. (3)

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VAP is a pool comprising some virtual authorities but not a single entity. It is often denoted as a specific entity balancing the authentication process. The 5G AP handles the VA creation and deletion process. (4) Switches that are commonly used in the data plane and function by matching the incoming flow with the flow table thus performing the actions. (5) Controllers that are distributed and deployed within the control plane for resource allocation and network slicing. Multiple controllers are utilized in this work to prevent the problem of a single point of failure.

4.2 Device Authentication

The 5G AP audits each authority with a charge for inserting, deleting, and modifying the operations, in the VAP. The PBKDF2 is utilized for authentication using three input parameters including PUF $I?uf$, secret key ς_r, and Timestamp $\dagger$—. The request is accepted for the three valid parameters if not, it is not recognized and ended. The operations are conducted in the Boolean logic function.

PBKDF2 is a function based on the key made by RSA Labs overwhelming the brute force attacks resultant from weak user passwords. The following parameters are used to derive a PBKDF2: an iteration count, i_ς; a pseudorandom function, PRF; a password, pw_d; a salt, $\mathfrak{z}$; an output-derived secret key, ς_r, and a selected output key length, OK_l.

A ς_r of arbitrary length is driven by PBKDF2. In particular, by the PBKDF2, several possible blocks t_i are generated, required for covering the output secret key length. For PRF iteration, each block, t_i is calculated through the count, i_ς. Any number of iterations can be added for a large secret key length. The inputs are the user password in PBKDF2, pw_d l salt values, $\mathfrak{z}$; iteration count, i_ς; ρuf; timestamp, $\dagger$, and selected output key length, OK_l. A secret key, ς_r yields the output.

$$\varsigma_r = PBKDF2\ (pw_d, OK_l, \mathfrak{z}, i_\varsigma) \tag{1}$$

where ς_r denotes all security credentials' concatenation. Here, two processes of enrollment and verification handle the PUF-based authentication. In the enrollment, all response and challenge pairs of the device are stored by the VA, which is verified when entering a device into the network. The device ID is received by the verifier to determine the random $Challenges\ Response\ Pair$. The equivalent response is calculated for the issued challenge. The verifier examines the validity of the response in the database and the made response, ς_r is made for the valid cases.

Here, the Boolean logic operator is represented as o and stated as

$$o\ = \overline{(\dagger.\rho uf)}.\overline{(\dagger + \rho uf)}.\varsigma_r \tag{2}$$

4.3 Traffic Scheduling

Through traffic scheduling in the 5G AP, congestion was avoided at the SDN controller. Here, the devices' traffic flows are categorized and arranged through an asymmetric queue model operating in terms of Bernoulli's theorem [45,46]. Using three parameters, traffic flow was scheduled including packet delay $I?_d$, data rate τ_γ, and packet length ρ_l. Thus, the total queuing service rate is:

$$I_{-1} + I_{-2} = 1 \tag{3}$$

A zero-packet loss rate is obtained by focusing on the adaptive queue within the two queues. Therefore, HP's service rate of δ= 0.75 was reached and exceeded, while the queue was still in process.

A discrete-time system was considered in this study to schedule services dynamically arriving for slicing requests. Regarding the type of slots and service, all arriving requests were diverse. A random variable ɣ(T) was defined to represent the queue current state as:

$$\text{ɣ}(T)= \begin{cases} 0 & \textit{Queue is idle} \\ i & \textit{Queue is busy with n services} \\ l+1 & \textit{Queue is vacant} \end{cases} \tag{4}$$

4.4 Resource Allocation and Network Slicing

The Network slice selection entities (NSS$^{\mathfrak{E}}$s) were fed in the GC to slice the network via SliceNet, which is a light and faster CNN outperforming WaveNet, traditional CNNs, and ByteNet.

Service Type $\mathfrak{s}_t$, Fair SLA $\mathfrak{f}_{SLA}$, Slice Capacity $\mathbb{S}_c$ $IMSI$, and Device mobility $d_{\mathfrak{M}}$ were all taken into account for slicing the network. This work primarily focused on SLA constraints between the service provider and user leading to $\mathfrak{f}_{SLA}$ while slicing the network. Followed by the fairness (weight) for each service, RTR, SAR, TR, and SRR were calculated.

Forwarding a service request to the controller is performed through the 5G AP over network slicing for a tool. The presented SliceNet is sated as a mapping from the input layer to the output layer as:

$$y = f(\mathfrak{s}_t, \mathfrak{f}_{SLA}, IMSI, \mathbb{S}_c, d_{\mathfrak{M}}\ \forall(d_i)), \tag{5}$$

In which d_i represents the tool i. The aforementioned parameters are inserted as inputs into the presented SliceNet where the input encoder, decoder, and I/O mixer, are the key components.

The input is obtained from the devices by a convolutional module in three stages of separable conv, ReLU activation, and the layer normalization. The hidden units are normalized and calculated layer-wise in the normalization. Generally, the conv_module is written as:

$$ConvStep\ (w, x) = LN(SepConv, (w, ReLU(X)), \tag{6}$$

Thus, the conv_module is achieved by stacking 4 convolutional phases:

$$h1(X) = Conv\_Step\ (w_{h1}^{3\times1}, X), \tag{7}$$

$$h2(X) = X + Conv\_Step\ (w_{h2}^{3\times1}, h1(X)), \tag{8}$$

$$h3(X) = Conv\_Step\ _{1,1}(w_{h2}^{15\times1}, h2(X)), \tag{9}$$

$$h4(X) = X + Conv\_Step\ _{1,1}(w_{h2}^{15\times1}, h3(X)), \tag{10}$$

$$Conv_{Module}(X) = \begin{cases} Dropout\ (h4(X), 0.5) & Training \\ h4(X) & Otherwise \end{cases} \tag{11}$$

where h (1…n) (X) represents the number of hidden units, and 0.5 is the learning rate.

The service requirements and input feature vector similarities are calculated based on the service type. Two convolution steps are conducted by the $Softmax$ function in this module:

$$attention\ 1(X) = ConvStep_{1,1}(w_{a1}^{5\times1}X + Time), \tag{12}$$

$$attention\ (Sr, Ta) = Attend\ (Sr, Ta, Convstep_{4,1}\left(w_{a1}^{5\times1}, attention\ 1(Ta)\right) \tag{13}$$

Ultimately, the three components' structure was detailed including I/O mixer, input encoder, and decoder. The concatenation of all the aforementioned components makes the output embedding as:

$$Mix_i = I/O\ (m)[I_e\ (i), O_e(o)], \tag{14}$$

$$Outputs = Decoder\ (mix) \tag{15}$$

Ultimately, $y = (y(1), y(2), \ldots, y(n))$ is obtained in the output layer, which $y(i) = 0{,}1$ is determined as the slice selection indicator. Thus, y denotes three kinds of services including eMBB, mMTC, and URLLC with different resource configurations. Hence, each service type is represented $\mathbb{S}_j = 1 \ldots n$ accompanied by the specified network slice. To run resource allocation, HopFieldNet is used as a quick neural network to find the resource for each slice. Considering $SINR$, $Throughput$, $\mathfrak{f}_{SLA}$, $\mathbb{S}_c$, arrival rate A_r, and slice value s_v, the resources were determined for each slice request. Here, the resources are assigned for three various processes including computation, communication, and caching as c_j, c_i and c_k respectively.

HopFieldNet is an artificial neural network (ANN) comprising nodes on a single layer. The input nodes in HopFieldNet are synchronously updated in terms of clock time variations. Here, there are the contributing nodes with the connectivity in terms of the defined weight values. The outcomes from network slices are used by HopFieldNet as input to compute the resources for the three groups of slices as URLLC, mMTC, and eMBB. The performance of input loops intended in this network is based on the capability of enriching knowledge, which is operative to resolve complicated computational problems. Designing HopFieldNet with a single layer of input nodes linked to other nodes as feedback connections, redirection of the output to the input is assisted. Here, there is an equal number of inputs, nodes, and outputs, in this T-S^{3}RA system, and totally R_1, R_2, R_3……,R_N nodes are made by resources.

The received input weight value is strong-minded from the separate slice service necessities stated in terms of the weight values in the connection as well as the node's state. The weighted summation of the nodes U is:

$$U_i = \sum_{j=1}^{N} we_{ij} st_j, \tag{16}$$

where we_{ij} denotes the connectivity weight between i and j, and st_j 10ft he state 10ft he node j. To control the training in HopFieldNet, the Storkey learning rule is used for minimizing the errors well. The Storkey learning rule is mathematically formulated as:

$$we_{ij}^{0} = 0 \quad \forall\, i, j, \tag{17}$$

$$we_{ij}^{k} = we_{ij}^{k-1} + \frac{1}{N} I_{-i}^{\ k} I_{-j}^{\ k} - \frac{1}{N} I_{-i}^{\ k} h_{ji}^{k} - \frac{1}{N} h_{ij}^{k} I_{-j}^{\ k} \tag{18}$$

The weight estimated between i and j is represented by w_{ij}^{ek} in (17) and (18) only after learning the k^{th} pattern, while ξ^k represents the new knowledge pattern. The local field H_{ij}^k is:

$$H_{ij}^k = \sum_{n=1,n\neq i,j}^{N} we_{in}^{k-1} I_{-n}^{k}, \tag{19}$$

Premeditating the HopFieldNet, the resources are categorized in terms of the slice service requirements.

As seen in Fig. 5, for categorizing the available resource blocks from the slices, the HopFieldNet with a single layer is $\{x_1, x_2, \ldots x_i \ldots x_N\}$ and the equivalent outputs are $\{Y_1, Y_2, Y_3, \ldots Y_i \ldots Y_N\}$. The inputs are received from all NS defined as $\{R_1, R_2, R_3 \ldots \ldots, R_N\}$. For each separate NS, the output in HopFieldNet is attained.

The advantage of HopFieldNet is its process for associative memory to store part of the information and allocate the rest of the pattern. Recalling the former patterns, using prior information of the resource amount is enabled for each NS. The resource is classified into 3 states. In the suggested T-S^{3}RA, the states of the nodes are estimated as:

$$St = \begin{pmatrix} s_{t1} & s_{t2} & \cdots & s_{ti} & \cdots & s_{tN} \end{pmatrix} \tag{20}$$

For each node, the states *st* are formulated in a trained matrix, where the three groups, c_i, c_j and c_k are the possible states for the resource. The node st_i state is defined as:

$$st_i = sign(U_i - THRES_N), \tag{21}$$

in which $THRES_N$ represents the threshold, $sign(x) = 1 \forall X \geq 0$, and $sign(x) = -1 \forall X < 0$. No node is related to itself as in this network and all nodes need to follow $w(e) = w(e)$. Thus, the node connectivity weights are stated as:

$$WE = \begin{pmatrix} 0 & w(e)_{12} & \cdots & w(e)_{1i} & \cdots & w(e)_{1N} \\ w(e)_{21} & 0 & ,\cdots & w(e)_{2i} & \cdots & w(e)_{2N} \\ \vdots & \vdots & & \ddots\ \vdots & \cdots & \vdots \\ w(e)_{i1} & w(e)_{i2} & \cdots & 0 & \cdots & w(e)_{iN} \\ \vdots & \vdots & & \cdots\ \vdots & \ddots & \vdots \\ w(e)_{N1} & w(e)_{N2} & \cdots & w(e)_{Ni} & \cdots & 0 \end{pmatrix} \tag{22}$$

For each node, the threshold $THRES_i$ is presented based on its service requirements. The threshold for the nodes is presented in matrix format as:

$$THRES_N = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_i \\ \vdots \\ \theta_N \end{pmatrix} \tag{23}$$

where $\{\theta_1, \theta_2, \ldots \ldots \theta_N\}$ represent the separate threshold values for each node. The threshold can be varied considering the existence of the slice requests in each NS. The threshold is updated when a new slice request is included in the device or user. Using the class of the resources at the NS is recognized followed by finding the resources for the NS. Then, the individual NS payment status is confirmed to exactly predict the use of the load by the NS.

4.5 Dynamic Flow Offloading

A higher traffic volume of slices is resultant from an inadequate bandwidth for switches. Comprised $F\omega BG$ is used in terms of the transmission rate, switch service capacity, and loss rate. By $F\omega BG$, multiple flows are mapped to the optimal switches increasing the network reputation. Furthermore, $F\omega BG$ helps to prevent slice capacity problems.

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5. RESULTS AND DISCUSSION

5.1 Simulation Setup

To evaluate the proposed T-S^{3}RA model, the network simulator tool V.NS3.26 was used, which can incorporate the technologies and network modules needed to simulate a network properly. The network simulator was mounted on a system with a 32-bit dual-core processor, the Ubuntu 14.04 LTS OS, and 2 GB of RAM. Table 1 presents the simulation parameters for designing the testbed.

Figure 2 represents the suggested T-S^{3}RA architecture model simulation results. The proposed system with various planes is explained based on the simulation steps, as shown above.

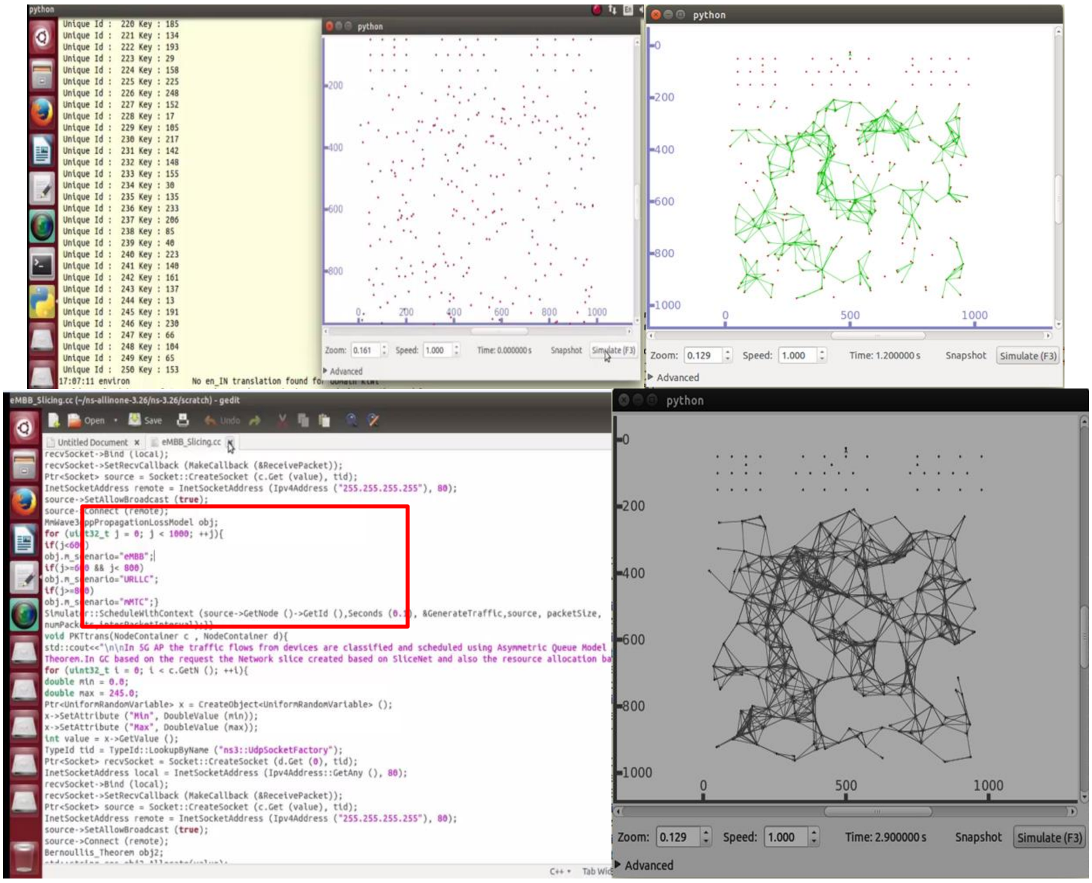

Fig. 2: The Simulation results for key generation, network slicing, and node deployment.

5.2 Comparative Analysis

In this comparative analysis section, the efficiencies of the proposed T-S^{3}RA *are* evaluated based on the methods assessed previously. To compare with the proposed system, some significant metrics are taken into account. To illustrate the performance of former resource allocation and network slicing schemes, the present approaches concentrate on dynamic flow migration (load balancing), resource allocation, or network slicing during network slicing. Thus, the present work focusing on all three procedures accompanied by security helps to avoid resource wastage in the control planes and data. A comparison was made on the performances of T-S^{3}RA for three slices, URLLC, mMTC, and eMBB represented as S1, S2, and S3 respectively.

5.2.1 Effect on Throughput

The throughput performance is demonstrated in Fig. 3 based on the number of slice requests. As seen, the network's throughput possesses greater values in the presented T-S^{3}RA than the GRU-DNN [42].

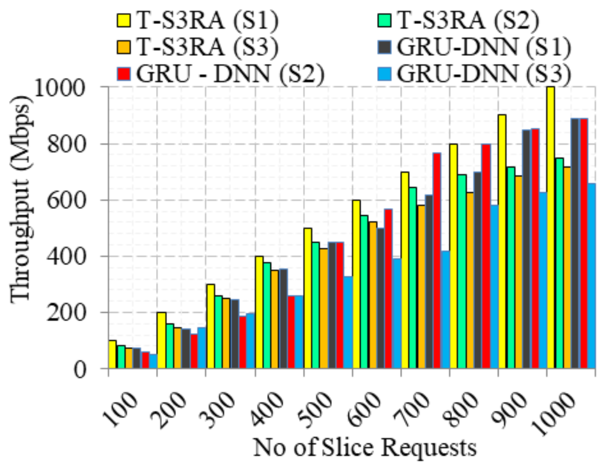

Fig. 3: The throughput against the number of slice requests.

5.2.2 Effect on Latency

Figure 4 shows the comparison of latency performance. A lower latency was obtained by the presented T-S^{3}RA since it utilizes fast algorithms as well as effective resource allocation and network slicing. More time is required to calculate the hyperparameters and tuning required for the DNN.

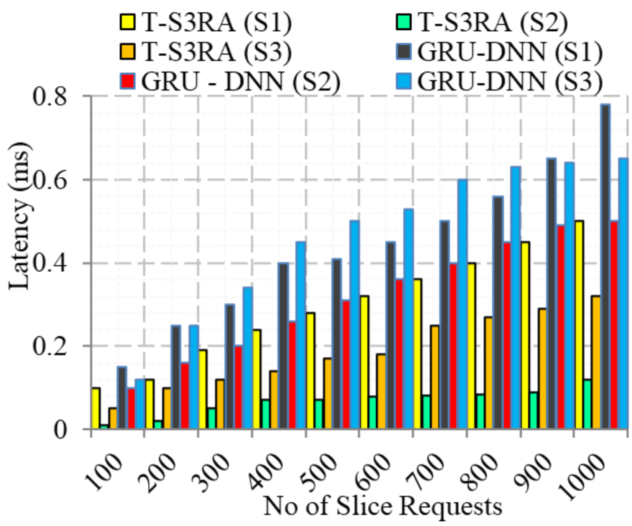

Fig. 4: The latency against the number of slice requests.

5.2.3 Effects on Response Time

According to Fig. 5, the response time performance is improved, by minimizing the latency. The results of the response time comparison are presented in Fig. 5. A considerably small response time was obtained since T-S^{3}RA is effective and end-to-end secure. An effective algorithm was not used in the present work.

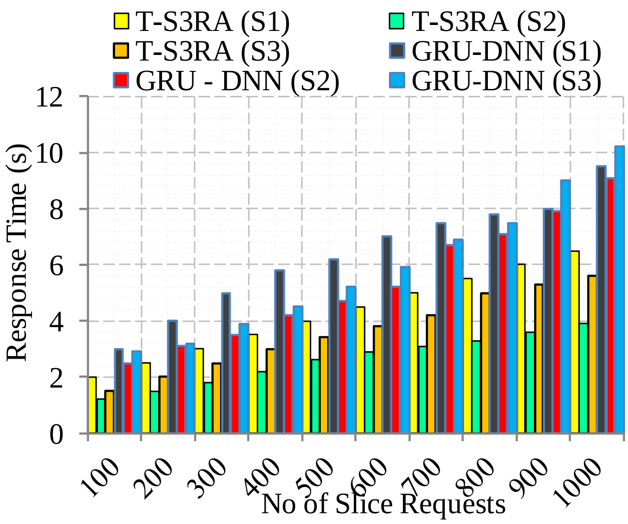

Fig. 5: The response time and the number of slice requests.

5.2.4 Effects on Transmission Ratio

Utilizing the asymmetric queue model, the traffic is arranged at the 5G AP increasing the packet transmission ratio. Moreover, for all slice requests, resources are optimally allocated resulting in a higher packet transmission ratio. The highest packet transmission ratio was obtained for S2 since highly reliable responses are required by these services.

5.2.5 Effects on Packet Loss Ratio

To assess the packet loss performance, the number of devices is considered. According to Fig.11, the packet loss is lower in the considered T-S^{3}RA than in the GRU-DNN.

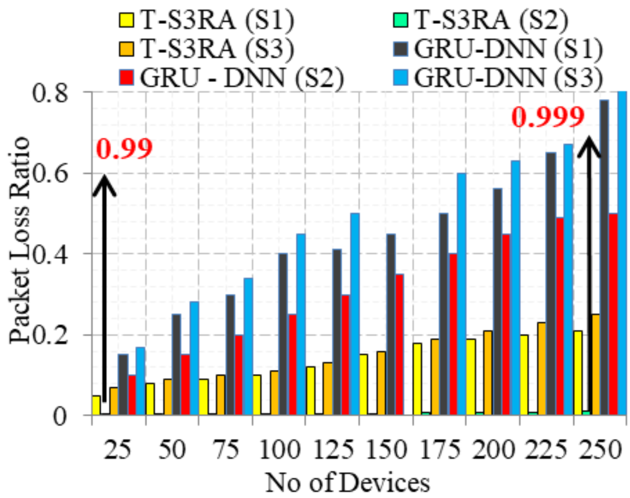

Fig. 6: The packet loss ratio versus the number of devices.

5.2.6 Effects on Slice Capacity

The comparison of the slice capacity vs. the number of devices is presented in Fig. 7. Based on the analysis of slice capacity, high performance is obtained by the proposed T-S^{3}RA.

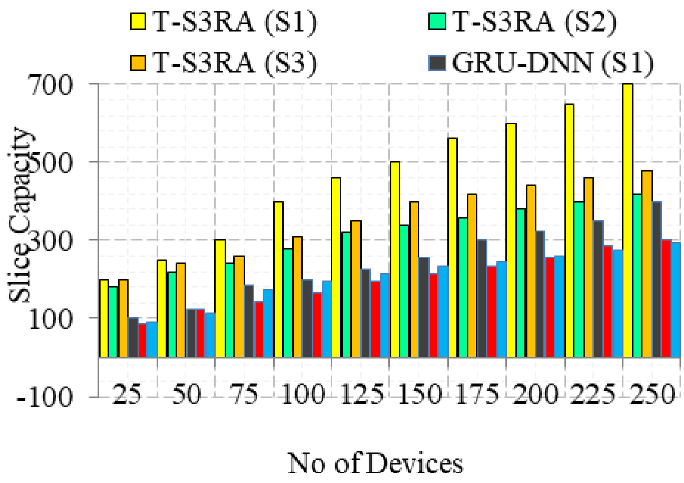

Fig. 7: The slice capacity against the number of devices.

5.2.7 Effects on Bandwidth Consumption

The bandwidth consumptions of the estimated and present outlines are presented in Fig. 8. Traffic offloading along with a multi-controller environment is used by the presented scheme, hence, the lower bandwidth is consumed. However, the higher bandwidth is used for GRU-DNN since there are no single controller problems and massive traffic handling.

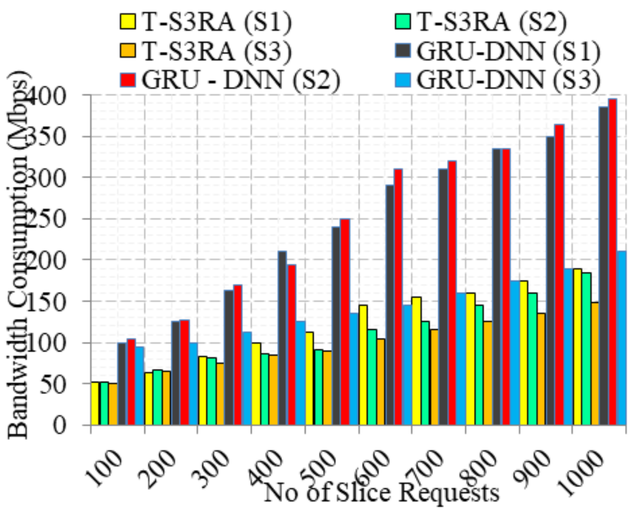

Fig. 8: The bandwidth consumption versus the number of slices.

5.2.8 Effect on Slice Acceptance Ratio

The acceptance ratios of the slice of T-S^{3}RA and GRU-DNN are compared in Fig. 9. Using deep learning-based resource allocation and network slicing can result in a considerably higher slice acceptance ratio. In the former study, the best solution was not obtained using deep learning methods. Therefore, there were poor slice acceptance ratios. Particularly, limited parameters were considered by the problem for slice selection.

Therefore, better efficiency is obtained by the presented T-S^{3}RA compared to the GRU-DNN for all network slices. Moreover, security is ensured by the presented T-S^{3}RA while performing resource allocation and slicing the network.

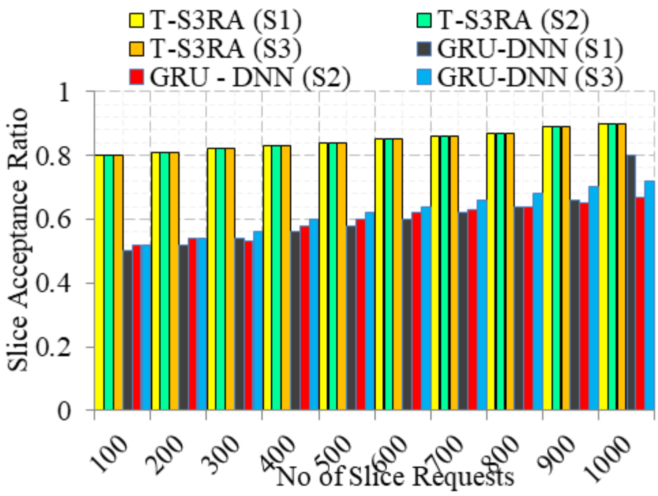

Fig. 9: The slice acceptance ratio against the number of slice requests.

5. CONCLUSION

In the present work, the QoS was enhanced in an SDN/NFV-permitted 5G network in terms of the presented architecture including T-S^{3}RA incorporating the service and SLA necessities for requests arriving from a user or device. There are four planes in the presented architecture including device, local controller, data, and global controller. The users or devices are authenticated through the VA via 5G AP utilizing PBKDF2. For secure communication, the VA is made and authenticated to the 5G AP reducing the communication overhead. Then, the traffic from the 5G AP is categorized into two HP and LP queues. It is held by the asymmetric queue model utilizing Bernoulli's theorem. Then, the HP request is forwarded to the LC for resource allocation and network slicing. SliceNet was proposed in this work for slicing, and resources were assigned utilizing HopFieldNet. Furthermore, to run dynamic flow offloading, *FωBG* was used. To prevent packet dropping and enrich the QoS, the flows were matched with underloaded switches. Furthermore, DDoS attackers were eliminated from the network through packet arrangement utilizing Renyi entropy. Ultimately, the system's performance was assessed in terms of QoS metrics like throughput, latency, response time, packet loss ratio, packet transmission ratio, bandwidth consumption, slice capacity, as well as slice acceptance ratio.

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