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Original Article

Adaptive Makeup Artist Optimization Based Hierarchical Scale Convolutional Neural Network for 5G Network Slicing

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***Abstract** - Fifth-Generation (5G) network slicing offers Network-as-a-Service (NaaS) for various use cases, permitting network operators to construct numerous virtual networks on distributed infrastructure. With a network slicing, the service providers can deploy their services and applications quickly as well as flexibly for accommodating certain requirements of various services. As a developing technology with many benefits, the network slicing has increased many problems for academia and industry. Some existing slicing techniques lack in capability to dynamically adapt to varying network conditions, decreasing their efficacy in highly changeable scenarios. In this research, Adaptive Makeup Artist Optimization based Hierarchical Scale Convolutional Neural Network (AMAO_HSNet) is introduced for the 5G network slicing. Initially, system model of secure 5G network is simulated. Whenever the network slicing requests arrive from User Equipment (UE), the set of parameters, namely delay rate, packet loss rate, device type and speed, are collected from different devices for network slicing. Lastly, network slicing is performed employing Hierarchical Scale Convolutional Neural Network (HSNet). The training process of HSNet is done using Adaptive Makeup Artist Optimization (AMAO). However, AMAO is derived by incorporating adaptive concept with Makeup Artist Optimization Algorithm (MAOA). The services provided by 5G network can be accessed by an Internet Service Provider (ISP) utilizing Virtual Network Function (VNF). Additionally, AMAO_HSNet has obtained high acceptance rate and resource efficiency of 0.910 and as well as low execution time of 0.172ssec.*

***Keywords** - 5G network, network slicing, network parameters, Hierarchical Scale Convolutional Neural Network, Makeup Artist Optimization Algorithm.*

1. Introduction

An evolution of the wireless communication has achieved a notable improvement with an emergence of 5G technology. Other than its predecessors, the 5G provides very less latency, ultra-high data rate, enhanced reliability and enormous device connections [1] [2]. These features expand its utilization far beyond commercial or civilian application, making it an important facilitator for modern military operations. The advance warfare progressively relies on real-world data interchange, independent systems as well as seamless cooperation amongst various assets and units. 5G offers a technological basis for supporting such complicated and dynamic military environment [3] [2]. Its minimum latency ability permits real-world remote controlling of the independent ground robots, clinical support system and Unmanned Aerial Vehicle (UAV) deployed in a hostile environment. An enhanced capacity and bandwidth enable rapid transfer of the higher-resolution satellite image, sensor data and surveillance videos to a decision-maker, thereby decreasing reaction time and improving circumstantial awareness [4] [5]. In addition, an energy-efficient state of the 5G expands functional time of a battery-powered device in specific field. Its ability to manage dense user environment and adaptability to the harsh scenarios make it a crucial asset in digital revolution of defense. Thus, 5G is not only an update in a mobile technology, but also the strategic facilitator that has an ability to redefine communications, command, surveillance, reconnaissance and control abilities in advanced military operations [6].

One amongst most effective features of the 5G that improves its suitability for military usage is referred as network slicing. In the military contexts, it means that diverse operational areas, like field communication, cyber defense, autonomous vehicle control and logistics management can independently operate on the customized slices without bandwidth competition or interference [7]. For instance, the less-latency slice can be kept for real-world drone operation while a higher-security slice can control encrypted communication. It not only assures Quality of Service (QoS), but also improves functional resilience as well as decreases a threat of system-wide failures. By including another layer of ability, Deep Learning (DL) schemes can be incorporated with a network slicing to intellectually forecast potential threats or failures, manage resources and identify anomalies in the real-time [4] [8]. DL methods, tuned on huge databases from the battlefield environment, can support in taking split-second decisions by assessing streaming data from several sources, namely radar, sensors and camera. Furthermore, edge computing driven by DL permits on-site data process, decreasing a dependency on the centralized data centers and assuring quick response time [9]. In the highly dynamic combat scenarios, the local intelligence refers to a variation amongst mission failure and success [10] [7].

The major aim is to present a novel approach termed AMAO_HSNet for 5G network slicing. A network slicing is intended as the collection of logical network operations as well as parameter configurations aimed to assist the necessities of specific service. In this research, secure 5G network's system model is initially simulated. Whenever network slicing requests arrive from UE, the set of parameters such as delay rate, packet loss rate, device type and speed are collected from different devices for network slicing. Finally, network slicing is done utilizing HSNet, which is tuned by AMAO. Moreover, AMAO is modelled by the combination of adaptive concept with MAOA. The services provided by 5G network can be accessed by an ISP utilizing VNF.

The significant contribution is presented beneath.

- Proposed AMAO_HSNet for 5G network slicing: A network slicing is considered as emerging and inventive concept for attaining various configurable slices from physical network. Here, network slicing is accomplished employing HSNet and it is trained by AMAO. However, AMAO is modelled by integrating adaptive concept and MAOA.

The arrangement of below sections is represented as follows: Section 2 explains existing works and their demerits for 5G network slicing, section 3 illustrates system model of the secure 5G network, section 4 interprets methodology of AMAO_HSNet, section 5 describes outcomes of AMAO_HSNet and section 6 elucidates conclusion of AMAO_HSNet.

2. Motivation

Network slicing has an important part in facilitating the multitude of 5G applications, services and use cases. 5G network demands as well as newer feature sets for supporting complex and ever-developing business requirements have made traditional schemes inadequate to network security. This motivates to introduce a network slicing method by collecting various conventional approaches. The existing method's advantages and disadvantages are described in this section.

2.1. Literature Survey

R. Dangi and P. Lalwani., [11] developed Harris Hawk Optimization-Convolution Neural Network+Long Short-Term Memory (HHO-CNN+LSTM) for effectual network slicing in 5G. It obtained exact prediction of proper network slices, thereby provided enhanced QoS. However, this method did not completely overcome an expansive challenge of designing a commonly intelligent and adaptive network slicing process for various network traffics. K. Suh, *et al*. [12] designed Deep Reinforcement Learning-based network slicing (DRL-NS) for beyond 5G network slicing. This scheme attained efficient maximization of longer-term throughput and also, it successfully managed a co-occurrence of various use cases in 5G environment. Nevertheless, it required further adaptation and development to bride a gap towards comprehensive application of DRL for network slicing. Z. Z. Saleh, *et al*. [13] presented Double Deep Q-Network with Prioritized Experience Replay with Pointer Network-based Long Short-Term Memory (DDQN-PER with PtrNet-LSTM) for network slicing in 5G. This technique had stronger scalability as well as capacity in dynamic wireless network environments, even though it did not completely examine its resilience and thus, further experiments under load intensities and altering network conditions were essential. S. B. Saad, *et al*. [14] introduced Blockchain-based trust architecture for 5G network slicing. This scheme eliminated the necessary for third-party contribution, but still, it did not overcome crucial challenge of trust monitoring that remained important to strengthen overall trust model.

2.2. Challenges

The challenges faced by traditional methods reviewed for 5G network slicing are described below:

- In [11], HHO-CNN+LSTM had scalability and computational complexity problems as total users as well as slices increased. Also, this method was heavily dependent on quality of the training data.
- DRL-NS was presented in [12] with enhanced convergence speed and optimum resource allocation decision. However, this model had an inability to interpret accurate network slicing and also, it did not reduce the computational complexity.
- 5G network slicing confront some challenges, such as maintaining security and QoS, assuring dynamic adaptability as well as managing resource efficiently. Owing to these challenges, an optimization-enabled DL model is necessary for managing 5G network slicing in real-time, thereby assuring higher performance.

3. System model of secure 5G network

The structure of 5G cellular networks [15] is derived by a demand for higher data rates. The ultra-dense structure of network comprises numerous tiers, such as pico-cells, femto-cells and macro-cells. Femto-cells are highly appropriate for interior use and it is designed to decrease load as well as congestion at macro-cell base station (BS). Various applications in 5G are accessed with Cloud Radio Access network (C-RAN). This network supports the user-centric connectivity scheme by direct device-to-device (D2D) communication. This leads to maximum data rates and minimum end-to-end delays. Moreover, devising of full-duplex transceiver directs to increase of data rate. Figure 1 delineates the system model of secure 5G network.

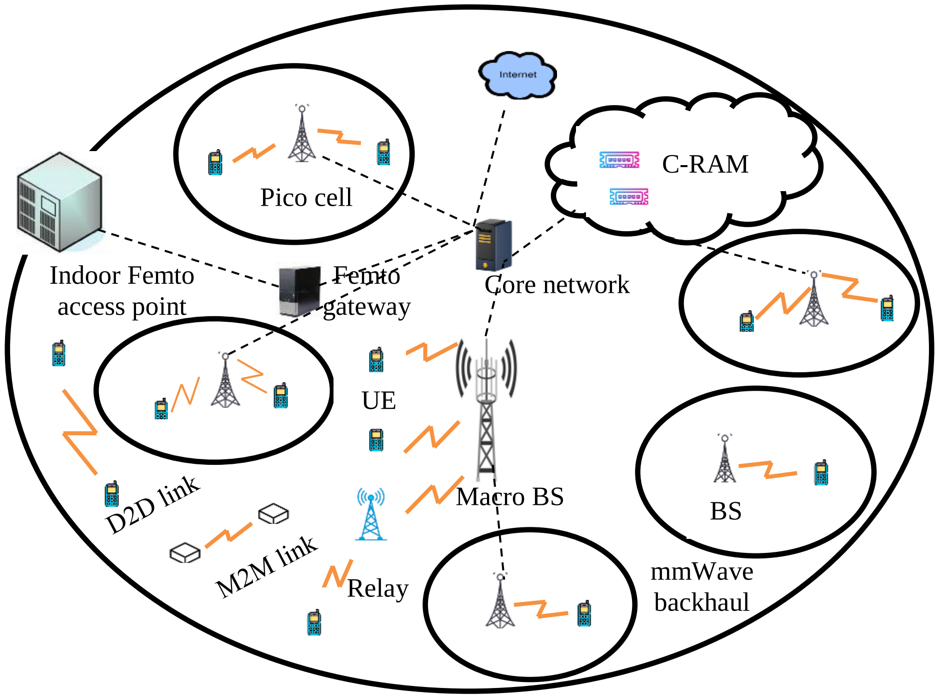

Fig 1: System Model of Secure 5G Network

4. Proposed Adaptive Makeup Artist Optimization Based Hierarchical Scale Convolutional Neural Network for 5G Network Slicing

Network slicing is one amongst vital technologies in 5G structure that has a capability to partition physical network into numerous logical networks with diverse network attributes. Here, AMAO_HSNet is newly introduced in this research for the 5G network slicing. Firstly, system model of secure 5G network is simulated. Whenever network slicing requests arrive from UE, the delay rate, packet loss rate, device type and speed parameters are collected from different devices for network slicing. Lastly, network slicing is conducted employing HSNet that is tuned by AMAO. However, AMAO is derived by an integration of adaptive concept with MAOA. The services provided by 5G network can be accessed by an ISP utilizing VNF. Figure 2 specifies visual illustration of AMAO_HSNet for the 5G network slicing.

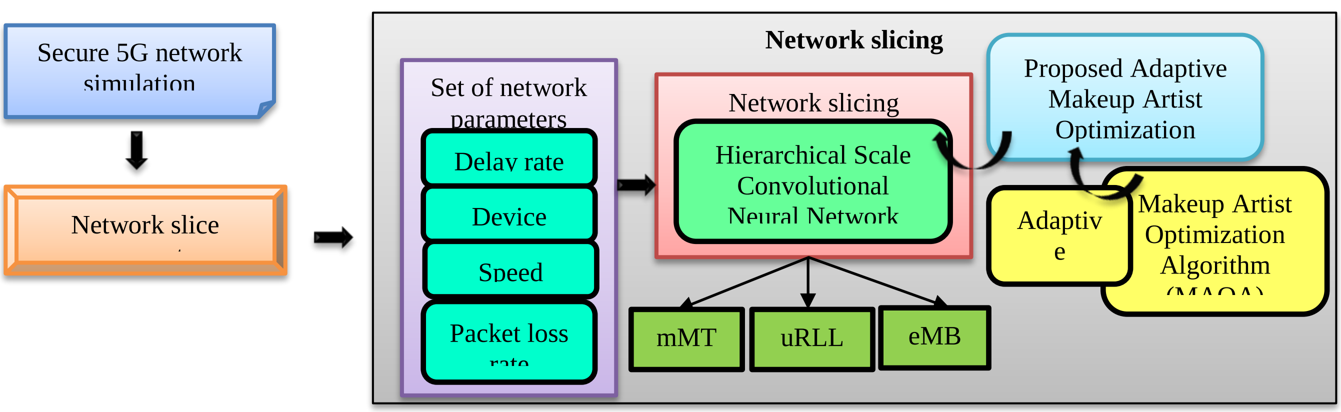

Fig 2: Visual Illustration of AMAO_HSNET for 5G Network Slicing

4.1. Network Slicing Request

Network slicing request [16] outlines the requirements and parameters necessary to form specific slice for assisting particular service or use case. A group of network slicing requests contain three slices for the three use case families that is represented as $Q_{NC}, Q_{NC} = Q_{\varepsilon} \cup Q_{\mu} \cup Q_{\upsilon}$. Q_{ε} implies eMBB slice, Q_{μ} signifies mMTC slice whereas Q_{υ} mentions uRLLC slice. An individual request is considered as $D_Q = (V_Q, W_Q, K_Q, A_Q, R_Q)$, wherein V_Q specifies nodes of the network slices, W_Q depicts links, K_Q illustrates capacity, R_Q symbolizes remaining network slicing request duration in a network and A_Q represents bandwidth. Therefore, $D_{Q_\varepsilon} = (V_{Q_\varepsilon}, W_{Q_\varepsilon}, K_{Q_\varepsilon}, A_{Q_\varepsilon}, R_{Q_\varepsilon})$ is for the request Q_ε and correspondingly D_{Q_μ} and D_{Q_υ} are for the requests Q_μ and Q_υ.

4.2. Network Parameters

Based on the request, various group of features are collected from various devices. The parameters include delay rate, packet loss rate, device type and speed.

4.2.1. Device type

The device type [17] refers to set of properties that specifies several characters and parts of a kind of device such as IoT devices and smartphones. It can be represented by a term E_1.

4.2.2. Delay rate

Delay rate [17] is defined as a time duration before the event occurs and it is illustrated by E_2.

4.2.3. Speed

Speed [17] is stated as a size of position change and it describes the scalar quantity. The speed feature can be mentioned as E_3.

4.2.4. Packet loss rate

Packet loss rate [17] is computed as the percentage of vanished packets with respect to transmitted packets. It occurs during transmission of one or several data packets across the network crash to reach an end-point. The packet loss rate can be symbolized as E_4.

The overall network parameters can be depicted as E, such that,

$$E = \{E_1, E_2, E_3, E_4\} \tag{1}$$

4.3. Network slicing utilizing HSNet

The network slicing specifies to a method of dividing single 5G network into numerous virtual, end-to-end networks termed slices. Each slice is intended to meet definite requirements of diverse applications or services. Here, network slicing into massive machine-type communication (mMTC), enhanced mobile broadband (eMBB) and ultra-reliable and low-latency communication (uRLLC) is accomplished utilizing HSNet, which is tuned by combining adaptive concept with MAOA. An input given to HSNet is network parameters E.

4.3.1. Structure of HSNet

HSNet [18] is the specialized DL structure developed to effectively optimize and manage numerous virtual network slices within 5G infrastructure. This network consists of Dilated Inception Block (DIB), Feature Guided Auxiliary Learning (FGAL) and Knowledge Transfer Learning (KTL).

1. Kernel-scale improvement: DIB

DIB comprises of standard dilation Inception block (SDIB) as well as residual dilated Inception block (RDIB) for enhancing kernel scale data extraction, Moreover, these blocks extract the features utilizing kernels with diverse receptive fields. An outcome feature map can be illustrated as,

$$J^k = J^{k-1} + B^k \tag{2}$$

Here, J^{k-1} mentions input feature map and B^k reveals concatenated feature map.

2. Network-scale improvement: FGAL

FGAL is modelled to learn many discriminate features from the intermediate feature maps utilizing higher-level semantic feature maps. The output of model is given as,

$$\hat{G} = \hat{G}^X + \hat{G}^Y + \hat{G}^z \tag{3}$$

Here, $\hat{G}^X$, $\hat{G}^Y$ and $\hat{G}^z$ depicts outputs from three classifiers.

3. Knowledge-scale improvement: KTL

As human cognitive capacity can increasingly be enhanced by the learned knowledge, the network imitated such capability by KTL to utilize a knowledge learned from corresponding tasks.

$$F(\theta) = F(\theta_p, \theta_t)\Big|_{\theta_p \leftarrow \theta_{recog};\, \theta_t \leftarrow \mathrm{H}(\theta_t)} \tag{4}$$

Here, HSNet's parameter θ contains two parts such as, θ_p for stem and θ_t for remaining parts. An output acquired from HSNet is denoted as N .

4.3.2. Training of HSNet using AMAO

Training process of HSNet aims to enable accurate and efficient resource management as well as service customization within 5G infrastructure. Here, HSNet is trained employing AMAO that is derived by an incorporation of adaptive concept with MAOA. A significant concept of MAOA [19] is modelled based on human characteristic of makeup artists while applying makeup to the actors. MAOA is an effectual optimization method to handle various optimization applications. Therefore, AMAO is capable to manage larger-scale network scenarios with multiple users and slices. The algorithmic steps of AMAO to attain best solution are illustrated beneath.

Step 1: Solution initialization

In the beginning of this algorithm, a location of all MAOA members in search space is initialized randomly and it can be specified by,

$$M = \{M_1, M_2, ..., M_a, ..., M_i\} \tag{5}$$

Here, M_a represents a^{th} candidate solution and M_i implies overall variables in population M ,

Step 2: Computation of objective measure

Based on individual member as candidate solution to a problem, an objective measure is estimated as follows.

$$\Im = \begin{bmatrix} \Im_1 \\ \vdots \\ \Im_a \\ \vdots \\ \Im_i \end{bmatrix}_{i\times 1} = \begin{bmatrix} \Im(M_1) \\ \vdots \\ \Im(M_a) \\ \vdots \\ \Im(M_i) \end{bmatrix}_{i\times 1} \tag{6}$$

Here, $\Im$ symbolizes fitness measure vector whereas $\Im_a$ depicts certain objective measure value related with a^{th} member of MAOA.

Step 3: Applying makeup

In MAOA, it is considered that individual actor is assigned the makeup and a pattern of makeup can be formulated as,

$$P_a = M_a + \Re.(M_\beta - M_a) \tag{7}$$

Here, P_a depicts pattern of makeup considered for a^{th} member, M_β denotes finest member of population whereas $\Re$ mentions random number with normal distribution amongst 0 and 1. In MAOA, based on deriving of makeup applications stated for individual actor by makeup artist, the newer location is computed for corresponding population in accordance to below expression.

$$M_a^{S1} = M_a + T.\Re.(P_a - T.M_a) \tag{8}$$

Let us consider,

$$M_a^{S1} = M_a(v+1) \tag{9}$$

$$M_a = M_a(v) \tag{10}$$

Substitute Eq. (9) and Eq. (10) in Eq. (8) and thus, an updated equation of AMAO is given by,

$$M_a(v+1) = M_a(v) + T.\Re.\left(P_a - T.M_a(v)\right) \tag{11}$$

where, v signifies iteration count, T illustrates randomly selected from the set $\{1,2\}$, M_a indicates makeup pattern considered for a^{th} member whereas $\Re$ is made adaptive and it can be modelled as,

$$\Re = (i-\pi)\left(\frac{v}{U-L}\right) \tag{12}$$

Here, $\Re$ ranges from 0 to 9, i signifies overall population members whereas U and L symbolizes upper as well as lower bounds. The newer location replaces prior location in accordance to below equation, if it enhances objective measure value.

$$M_a = \begin{cases} M_a^{S1}, & \Im_a^{S1} = \Im_a \\ M_a \;, & else \end{cases} \tag{13}$$

Here, M_a^{S1} describes an updated position of a^{th} population member during the initial stage and $\Im_a^{S1}$ refer to its objective measure value.

Step 4: Takes care of the makeup particulars

In MAOA, based on deriving of makeup artist's characteristic to handle fine particulars of makeup patterns, the newer location is estimated for related population member in accordance to Eq. (14). This newer location substitutes a prior location based in Eq, (15) if it enhances objective measure value.

$$M_a^{S2} = M_a + (1-2.\Re).\frac{U-T.L}{v} \tag{14}$$

$$M_a = \begin{cases} M_a^{S2}, & \Im_a^{S2} = \Im_a \\ M_a \;, & else \end{cases} \tag{15}$$

where, M_a^{S2} signifies an updated position of a^{th} population member in final phase whereas $\Im_a^{S2}$ reveals its objective measure value.

Step 5: Reevaluation of fitness measure

A fitness measure estimated using Eq. (6) is reevaluated until superior value is obtained.

Step 6: Termination

The steps of AMAOA are repeatedly done till optimum solution is acquired and then, terminated.

5. Results and Discussion

The outcomes of AMAO_HSNet for 5G network slicing are illustrated in this section.

5.1. Experiment setup

The experimentation of AMAO_HSNet is implemented in PYTHON tool using simulation.

5.2. Evaluation metrics

The considered metrics to analyze AMAO_HSNet are acceptance rate, execution time and resource efficiency.

5.2.1 Acceptance Rate

Acceptance rate is defined as a proportion of network slice requests that are approved successfully by the network out of overall received requests.

5.2.2. Execution Time

Execution time refers to a duration required for certain network slice or service to complete or process the given task from initiation to an end.

5.2.3. Resource efficiency

Resource efficiency specifies to an optimum utilization and management of the network resources across numerous virtualized network slices.

5.3. Comparative Techniques

The traditional methods considered to compare with AMAO_HSNet are HHO-CNN+LSTM [11], DRL-NS [12], DDQN-PER with PtrNet-LSTM [13] and Blockchain-based trust architecture [14].

5.4. Comparative Evaluation

The comparative assessment of AMAO_HSNet is done based on setups, such as number of slice requests=10 and number of slice requests=20.

5.4.1. Analysis Based On Number of Slice Requests=10

Figure 3 represents evaluation of AMAO_HSNet by varying rounds. In this section, values obtained by AMAO_HSNet and other conventional approaches are explained for rounds=100. Figure 3 a) delineates analysis of AMAO_HSNet in terms of acceptance rate. AMAO_HSNet attained acceptance rate of 0.908 whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture achieved 0.869, 0.879, 0.890 and 0.890 of acceptance rate. Estimation of AMAO_HSNet with respect to execution time is displayed in figure 3 b). Execution time obtained by AMAO_HSNet is 0.168sec whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture acquired execution time of 0.251sec, 0.248sec, 0.199sec and 0.180sec. Figure 3 c) mentions assessment of AMAO_HSNet in terms of resource efficiency. HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture attained resource efficiency of 0.835, 0.846, 0.858 and 0.869 whereas AMAO_HSNet attained 0.889 of resource efficiency.

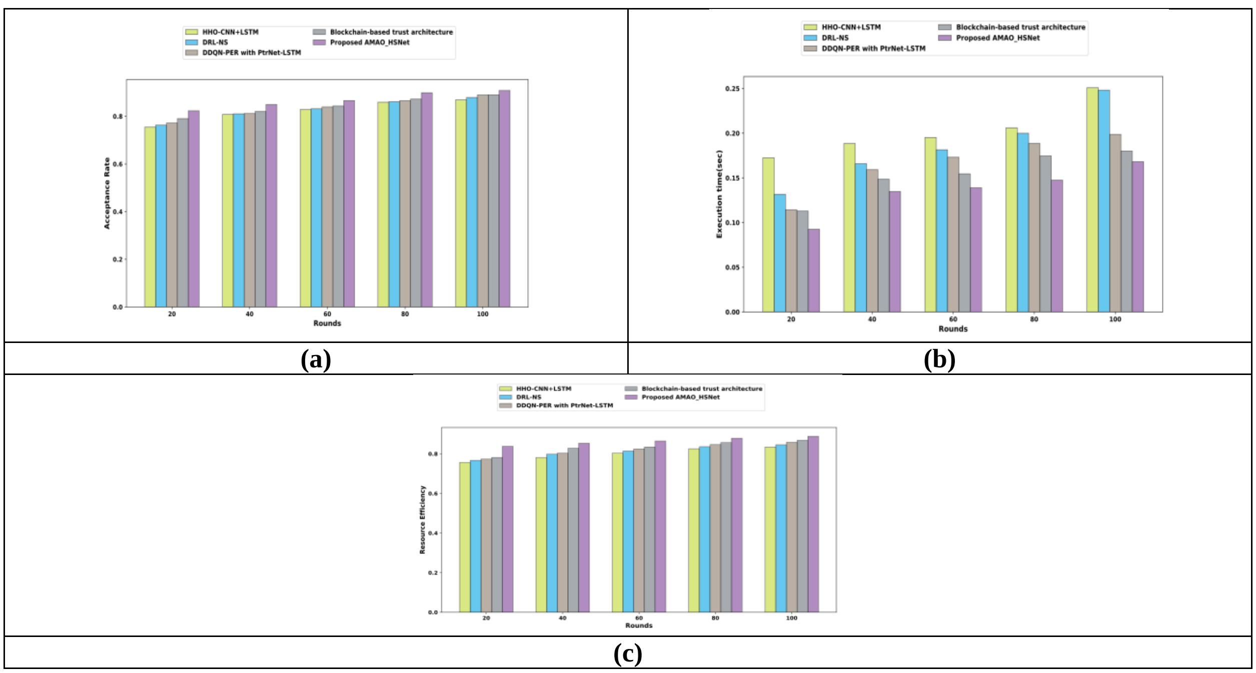

Fig 3: Evaluation of AMAO_HSNET for Number of Slice Requests=10, A) Acceptance Rate, B) Execution Time, C) Resource Efficiency

5.4.2. Analysis based on number of slice requests=20

Estimation of AMAO_HSNet by changing rounds is demonstrated in figure 4. The values of comparative methods and AMAO_HSNet are described in this section while considering number of rounds=100. Assessment of AMAO_HSNet regarding acceptance rate is shown in figure 4 a). Acceptance rate acquired by AMAO_HSNet is 0.910 whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture attained acceptance rate of 0.846, 0.856, 0.864 and 0.881. Figure 4 b) depicts analysis of AMAO_HSNet based on execution time. HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture obtained execution time of 0.241sec, 0.213sec, 0.194sec and 0.188sec whereas AMAO_HSNet achieved 0.172sec. Evaluation of AMAO_HSNet with respect to resource efficiency is specified in figure

4 c). AMAO_HSNet acquired resource efficiency of 0.898 whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture attained resource efficiency of 0.827, 0.837, 0.848 and 0.869.

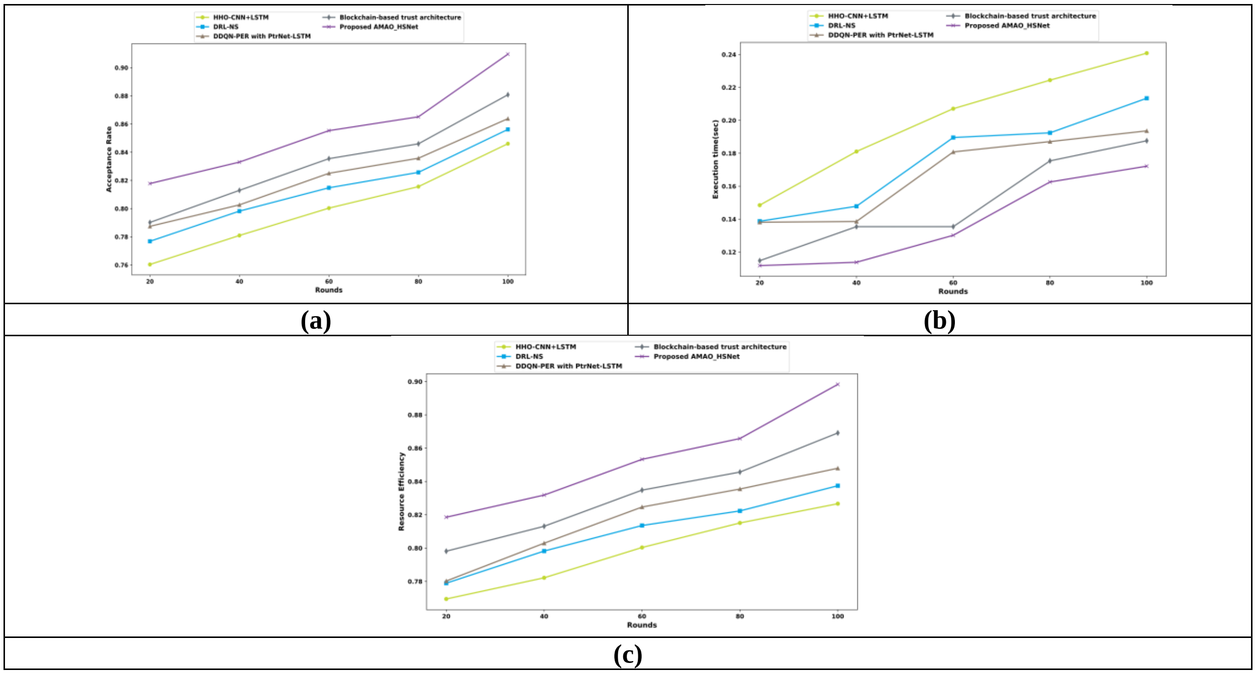

Fig 4: Evaluation of AMAO_HSNet for Number of Slice Requests=20, A) Acceptance Rate, B) Execution Time, C) Resource Efficiency

5.5. Comparative Discussion

Table 1: Comparative discussion of AMAO_HSNet

Setups	Metrics/ Methods	HHO-CNN+LSTM	DRL-NS	DDQN-PER with PtrNet-LSTM	Blockchain-based trust architecture	Proposed AMAO_HSNet
Number of slice requests =10	Acceptance rate	0.869	0.879	0.890	0.890	0.908
	Execution time (sec)	0.251	0.248	0.199	0.180	0.168
	Resource efficiency	0.835	0.846	0.858	0.869	0.889
Number of slice requests =20	Acceptance rate	0.846	0.856	0.864	0.881	**0.910**
	Execution time (sec)	0.241	0.213	0.194	0.188	**0.172**
	Resource efficiency	0.827	0.837	0.848	0.869	**0.898**

Table 1 represents the values attained by AMAO_HSNet and other schemes for 5G network slicing. When rounds=100, acceptance rate attained by AMAO_HSNet is 0.910 whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture acquired 0.846, 0.856, 0.864 and 0.881 of acceptance rate. A high acceptance rate of AMAO_HSNet specifies its better resource availability as well as flexibility in assisting diverse slices. HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture achieved execution time of 0.241sec, 0.213sec, 0.194sec and 0.188sec for rounds=100 whereas AMAO_HSNet obtained 0.172sec. The minimum execution time illustrates that AMAO_HSNet had better efficiency and responsiveness in delivering its designated services. AMAO_HSNet attained resource efficiency of 0.898 while considering rounds as 100 whereas HHO-CNN+LSTM, DRL-NS, DDQN-PER with PtrNet-LSTM and Blockchain-based trust architecture acquired resource efficiency of 0.827, 0.837, 0.848 and 0.869. The maximal resource efficiency reveals that AMAO_HSNet improved performance and QoS for various application requirements. It can be accepted that, AMAO_HSNet is the best method for 5G network slicing. Furthermore, AMAO_HSNet attained maximum acceptance rate and resource efficiency of 0.910 and as well as minimum execution time of 0.172ssec for number of slice requests=20 while considering rounds as 100.

6. Conclusion

5G is intended to assist several newer use cases from the vertical industries. These newer scenarios bring different and challengeable requirements, like expansive range of cost, performance, mobility management and security protection. The slicing of single physical network into various logical networks adapted to different distinctive necessities has emerged as an advantageous technique for satisfying such disparate requirements in the sustainable manner. The management of multiple slices with diverse networks led the traditional methods to high configuration errors and operational costs. In this research, AMAO_HSNet is newly presented for the 5G network slicing. Firstly, system model of secure 5G network is simulated. Whenever the network slicing requests arrive from UE, the set of parameters are collected from various devices for network slicing. The set of parameters include delay rate, packet loss rate, device type and speed parameters. At last, network slicing is carried out utilizing HSNet, which is tuned by AMAO. Furthermore, AMAO is modelled by integrating adaptive concept and MAOA. The services provided by 5G network can be accessed by an ISP utilizing VNF. In addition, AMAO_HSNet has achieved maximal acceptance rate and resource efficiency of 0.910 and as well as minimal execution time of 0.172ssec. In future, sharing and allocation of physical resources to various slices will be considered.

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