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Original Article

Exponential Tactical Unit Algorithm based Network Slicing and Resource Provisioning in 6G

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Abstract *- Network slicing and resource provisioning in 6G focus on creating multiple customized virtual networks over a shared infrastructure. However, these approaches also introduce challenges, like increased architectural complexity, higher implementation costs, security vulnerabilities between slices in resource optimization across highly dynamic and heterogeneous network environments. In this work, Exponentially Tactical Unit Algorithm (ETUA) is devised for network slicing in 6G. Initially, blockchain-enabled 6G network is simulated, and the set of features, like user device type, delay rate and packet loss rate are collected from various devices. Moreover, network slicing is done by ETUA that integrates Exponentially Weighted Moving Average (EWMA) and Tactical Unit Algorithm (TUA). Finally, resource allocation is performed using Attention High-order Deep Network (AHoNet) by considering the parameters that includes bit error probability, sum rate and trust. The efficacy of ETUA is examined by bit error probability, utility and latency with 0.012, 0.950 and 0.509 Sec.*

Keywords *- Network slicing, Resource provisioning, Exponentially Weighted Moving Average, Tactical Unit Algorithm, Attention High-order Deep Network.*

1. Introduction

Driven by an extraordinary surge in demand for ultra-fast and highly dependable statements, a transformative vision aims to redefine global connectivity and address the ambitious technological expectations of the 2030s and the years ahead. While 5G offers notable advancements, it still faces constraints in areas such as large-scale machine-type communication and efficient spectrum utilization. Addressing these gaps lead to integration of advanced technologies that include blockchain and Artificial Intelligence (AI), which together can realize the broader vision of hyper-connected intelligent ecosystems [1]. Within the 6G landscape, network slicing enables the creation of virtual network instances tailored to the diverse service requirements of applications operating in smart city infrastructures [2]. This approach enhances operational simplicity and flexibility by supporting many rational systems over a physical foundation. It further supports the deployment and coordination of dedicated end-to-end virtual networks for specific large-scale applications while ensuring strict adherence to their individual performance requirements [3]. Moreover, 6G is expected to deeply embed AI techniques, especially meta-learning that utilizes prior experience to address new but related tasks with minimal training data. By enabling deep neural models to perform effectively even with limited datasets, meta-learning mitigates the heavy data dependency of conventional Deep Learning (DL) methods by reducing the risk of unreliable outcomes.

Each network slice is configured with distinct resource demands and specific Key Performance Indicator (KPI) targets that depend on the service category it supports [1]. Conventional optimization approaches often struggle when addressing highly complex resource distribution challenges. In contrast, Deep Reinforcement Learning (DRL) has emerged as an effective solution, where an intelligent agent continuously interacts for a given state through iterative trial-and-error processes. Widely adopted DRL techniques include DQL and DDPG. Among these, DQL has been predominantly applied to resource allocation scenarios that involve discrete action spaces [4]. Resource optimization involves an iterative cycle of four core management phases that begins with resource selection and deployment [5]. Graph Convolutional Neural Network (GCN)-based allocation strategies have also been investigated to enhance the effectiveness of resource management mechanisms. Additionally, optimization strategies, such as Genetic Algorithms (GAs), are explored to address allocation challenges by reducing interference levels and improving spectral efficiency. Heuristic approaches, like Particle Swarm Optimization (PSO), contribute to refined resource coordination [17]. The incorporation of AI-based methods facilitates adaptive, real-time resource management aligned with fluctuating network dynamics and user requirements by substantially enhancing overall system performance and operational efficiency [6]. The emergence of data-intensive and delay-sensitive applications that include smart automation and large-scale IoT deployments demands a highly adaptable communication framework that surpasses current network capabilities [18]. Conventional fixed resource allocation methods cannot efficiently satisfy the heterogeneous performance demands and stringent reliability requirements anticipated in future 6G systems. Therefore, advanced network slicing combined with dynamic and intelligent resource provisioning is vital to optimize utilization, maintain service differentiation and support seamless operation across diverse 6G use cases.

The objective is to develop ETUA for network slicing in 6G environments. Initially, a blockchain-enabled 6G network model is simulated, and relevant parameters, that includes user device category, delay rate and packet loss rate, are gathered from several devices. Subsequently, network slicing is conducted by ETUA that combines EWMA with TUA. Finally, resource allocation is carried out utilizing AHoNet by considering metrics that includes bit error probability, aggregate sum rate and trust values.

1.1. Devised ETUA for network slicing in 6G environment

A novel ETUA framework is introduced to perform network slicing in 6G systems, where ETUA is the incorporation of EWMA with TUA.

The remaining sections of this paper is structured as follows: Problems and merits of preceding schemes are discussed in Section 2, the system model is explicated in Section 3, Section 4 describes the ETUA's method, Section 5 presents ETUA’s results, and Section 6 concludes the research.

2. Literature Review

S. B. Saad et al., [7] presented a Blockchain-based trust architecture for network slicing in 5G and beyond networks. This approach identified the most suitable resource provider for every sub-slice. However, it failed to consider continuous trust evaluation that was essential for maintaining a reliable trust management framework. M. Dalgitsis, et al., [8] designed a cloud-native Open Radio Access Network (O-RAN) for network slice federation across administrative domains. It enabled smooth coordination and administration of network slices among multiple operators and across diverse geographic regions, but did not assess the federation of Radio Access Network (RAN) slices by leaving that aspect unexamined.

S. Bukhari, et al., [1] introduced a dynamic fine-grained Service Level Agreement (SLA) for 6G enhanced Mobile Broadband (eMBB)-plus slice using mDNN and Smart Contracts. Though this scheme enhanced the Quality of Experience (QoE) for users and minimized service provider penalties, it was unable to identify recurring patterns due to a lack of a specialized training model. A. Gharehgoli, et al., [9] developed Deep Reinforcement Learning (DRL) for network slicing under demand and CSI uncertainties. Though this method responded effectively to demand fluctuations and variations in Channel State Information (CSI), it relied on large volumes of high-quality and representative data for training. Table 2 compares the traditional approaches based on Network Slicing and Resource Provisioning.

Table 1 depicts the comparison of the traditional approaches based on Network Slicing and Resource Provisioning.

Table 1. Comparison of traditional approaches based on Network slicing and resource provisioning

Ref	Author & Year	Problem Addressed	Methodology	Dataset	Key Results	Limitations
[1]	S. Bukhari et al. (2024)	SLA management in 6G network slicing	mDNN + Smart Contracts	Simulated 6G environment	Improved SLA compliance and automation	High computational complexity
[2]	M. Alwakeel et al. (2024)	Network slicing for IoT in smart cities	Conceptual framework	Not specified	Scalable architecture for IoT integration	Lack of experimental validation
[3]	Thantharate et al. (2020)	Security in 5G network slicing	Deep Learning framework	Simulated network data	Enhanced intrusion detection accuracy	Limited real-world deployment
[4]	Y. Wang et al. (2022)	End-to-end network slicing optimization	Deep Reinforcement Learning (DRL)	Simulation-based dataset	Improved resource utilization and latency	Training complexity and convergence issues
[5]	N. Salhab et al. (2018)	Optimization of 5G RAN slicing.	Mathematical optimization	Synthetic data	Efficient RAN resource allocation	Does not consider dynamic traffic patterns

[6]	D. C. Bikkasani et al. (2024)	AI-driven network optimization in 5G	Review of ML/DL techniques	Survey-based	Comprehensive insights on AI techniques	No implementation or experimental results
[7]	S. B. Saad et al. (2022)	Secure architecture for network slicing	Trust-based architecture	Conceptual model	Improved security and trust management	Lack of performance evaluation
[8]	M. Dalgitsis et al. (2024)	Slice federation across domains	Cloud-native orchestration framework	Simulated multi-domain setup	Efficient inter-domain slice management	Complexity in real-world deployment
[9]	Gharehgoli et al. (2023)	Resource allocation under uncertainty	AI-based optimization	Simulated dataset with CSI uncertainty	Improved allocation under dynamic conditions	High model complexity
[10]	K. Xiao et al. (2021)	SLA auditing in 5G slicing	Blockchain-based scheme	Not specified	Privacy-preserving SLA verification	Overhead due to blockchain operations
[11]	M. H. Abidi et al. (2021)	Optimal network slicing	ML and DL models	Simulated network dataset	Improved slicing efficiency and accuracy	Limited scalability analysis

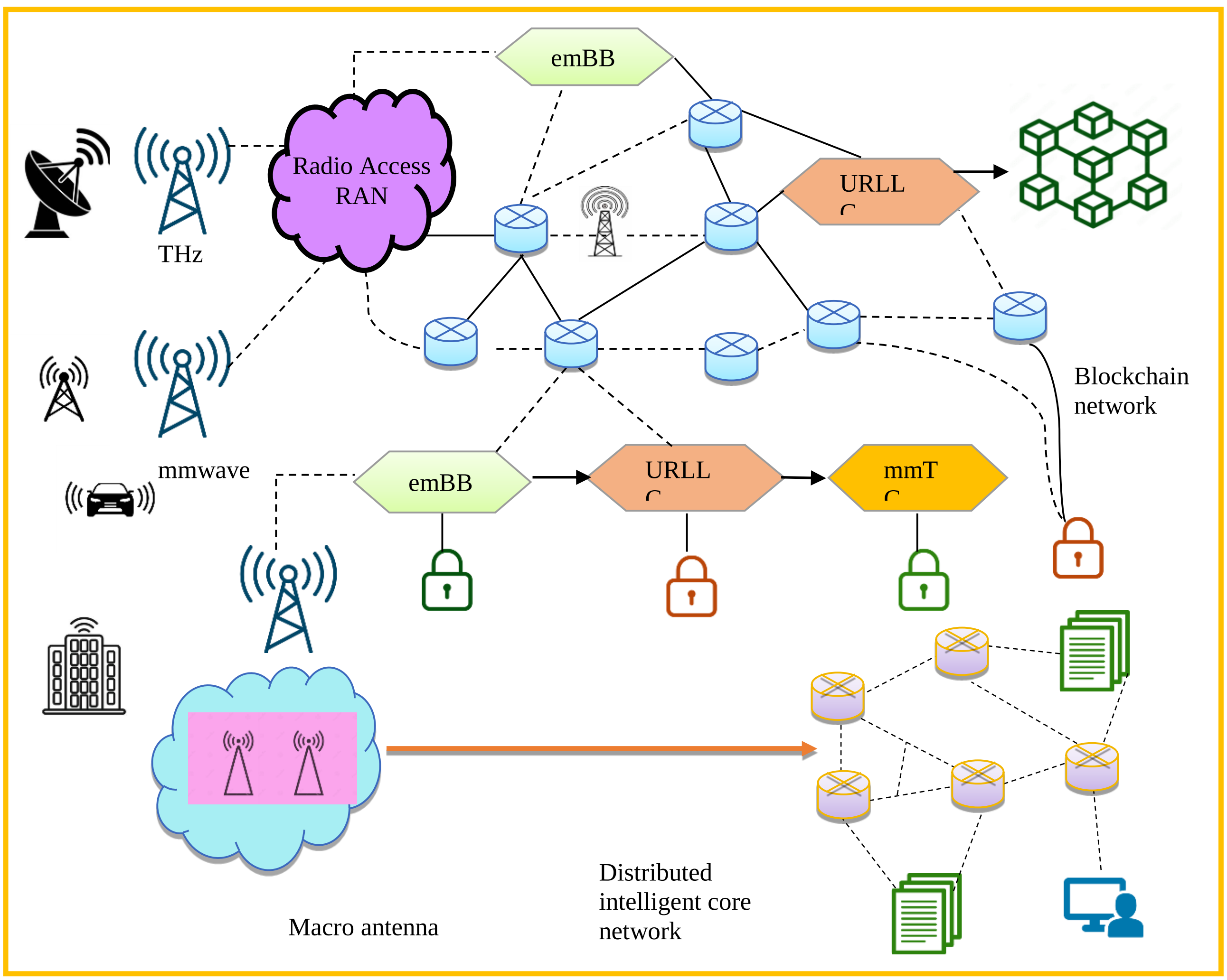


Fig. 1 System model for blockchain-enabled 6G network

2.1. Challenges

The problems encountered by preceding approaches are outlined below:

- The technique introduced in [8] focused on enhancing security during the federation process by enforcing authentication for orchestrator access and strengthening post-federation safeguards. Nonetheless, it lacked the capabilities to optimize service migration.
- In [1], the designed scheme was practical, dynamic and decentralized. Despite these advantages, it did not reduce execution time because it failed to group similar Service Level Objectives (SLOs) and forecast resource needs collectively.
- To face the diverse requirements of 6G networks, network slicing partitions the physical infrastructure into multiple logical networks. Nevertheless, challenges remain in managing multi-dimensional resources for end-to-end slices within dynamic and uncertain environments. Balancing revenue and cost while maintaining service quality for tenants is crucial that highlights the need for an effective hybrid algorithm for 6G network slicing.

3. System Model

The system model [10] shows different radio access technologies, like THz and mmwave, connected to the Radio Access Network (RAN), which manages multiple slices like emBB, Ultra-Reliable Low Latency Communication (URLLC) and massive Machine Type Communication (mmTC). These network slices are secured with different lock symbols that indicate security levels. The distributed intelligent core network manages data storage and processing through interconnected nodes. Macro antennas and other wireless nodes extend the coverage and connectivity that links end-user devices and infrastructure to the core network through this multi-layered setup. Figure 1 shows the system model.

4. Proposed Exponentially Tactical Unit Algorithm for network slicing in 6G

Network slicing is an innovative approach to allocate resources in future wireless networks. However, effectively allocating, managing, and controlling resources within these slices remains a complex and challenging task. Here, ETUA is proposed for network slicing in 6G. At first, the system model of blockchain-enabled 6G network is simulated, and set of features, including user device type, delay rate and packet loss rate [11] are collected from various devices. Next, network slicing is done utilizing ETUA that is combined by EWMA [12] and TUA [13]. At last, resource allocation is performed using AHoNet [14] by considering parameters, like bit error probability, sum rate [15] and trust [16]. Figure 2 shows the ETUA's structure for network slicing in 6G.

4.1. Network Slice Request

Network slice requests are divided into three categories, where each slice request is modeled as a logical network structure. It includes a collection of virtual nodes and the virtual links that interconnect them. Separate models are maintained for eMBB, mMTC, and uRLLC requests, with each type characterized by its own topology, resource needs and service duration.

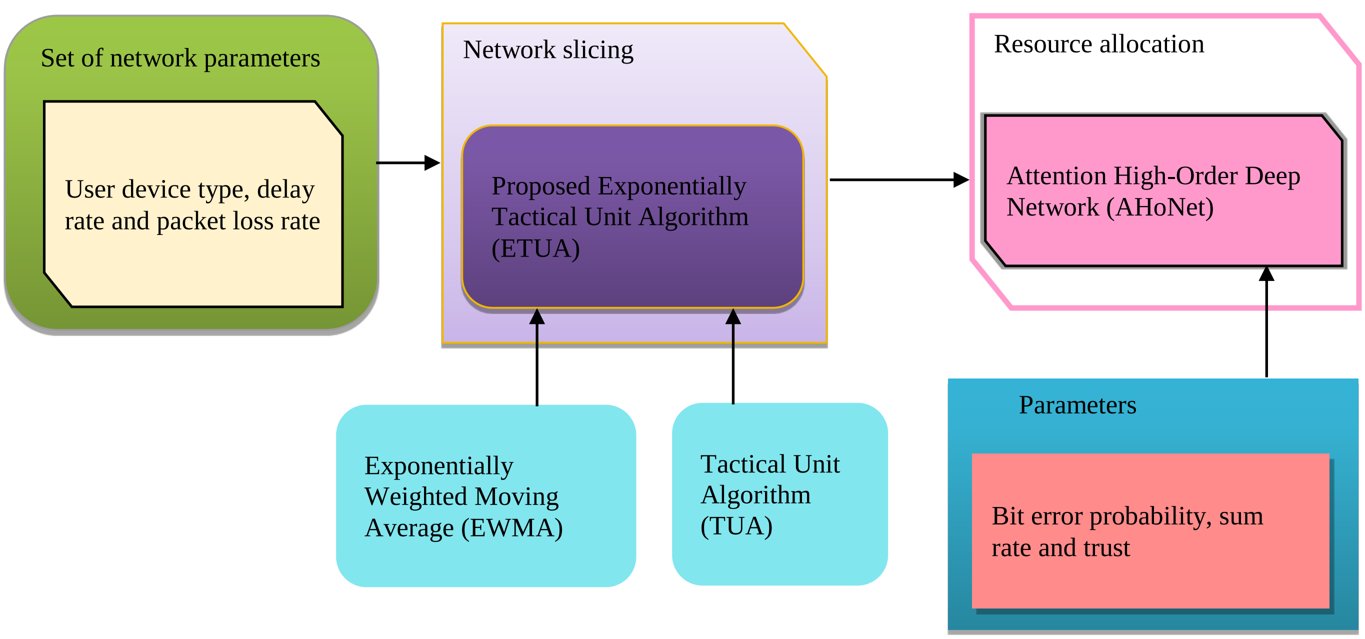


Fig. 2 Block diagram of ETUA for network slicing in 6G

4.2. Network Parameters

It represents essential attributes that determine how a network slice is structured and supported within the physical infrastructure. The network parameters include device type, delay rate and packet loss rate and is given below as,

4.2.1. Device Type

According to [11], device type refers to a collection of attributes that define the components and functional characteristics of a particular category of device.

4.2.2. Delay Rate

According to [11], the delay rate represents the time interval that must pass before a specific event occurs. This value indicates the waiting period associated with a process or action.

4.2.3. Packet Loss Rate

According to [11], packet loss occurs when one or more data packets traveling through a network fail to reach their intended destination.

4.3. Network slicing using AHoNet

AHoNet [14] ensures effective feature extraction while reducing the risk of overfitting. The network parameters N_p is passed as input for network slicing. The first convolutional layer is replaced with a kernel to capture finer and more detailed feature information. The outputs obtained are emBB, URLLC and mmTC.

4.4. Resource Allocation

Resource allocation is the process of distributing available network or computational resources efficiently among multiple tasks or users.

4.4.1. User parameters

A user parameter refers to a specific setting or characteristic that defines an individual's requirements or preferences within a system.

Utility of User

The utility of a user [15] measures how effectively a system meets the individual needs or preferences of that user. It is evaluated by,

$$S_1 = \partial \, log\left(k_i^{(e)} | L_i\right) \tag{1}$$

Where $\partial > 0$ is the sensitivity parameter $k_i^{(e)}$ implies bit rate, and delay is explicated as L_i.

Channel Capacity of User

Channel capacity [15] of a user refers to the maximum amount of data that can be transmitted reliably over the user's communication channel within a given time period and is estimated by

$$S_2 = (1-\lambda) \sum_{p \in \delta^i} r_{qp} N \, log_2\left(1 + j_{qp}\right) \tag{2}$$

Where N is the bandwidth, λ denotes the overhead factor and j implies SNR.

4.4.2. Slice Parameters

A slice parameter defines the specific resource and performance requirements allocated to a particular network slice.

Sum Rate

Sum rate [15] represents the total data transmission rate achieved by all users or slices in a network over a given period. It is evaluated as,

$$L_1 = \sum_{s=1}^{m} \sum_{t=1}^{n} T\left(f, SINR_{s,t,P}^{R}\right) \tag{3}$$

Where an unknown number of active devices is explicated as m, block length is implied as f and P is the bit error probability.

Bit Error Probability

Bit error probability [16] quantifies the frequency of errors occurring in transmitted data bits over a network or communication link and is expressed as,

$$L_2 = W\left(\sqrt{\frac{u}{h(s)}}(d(s) - l) \, log_e 2\right) \tag{4}$$

Where, u is the block length, channel capacity is denoted as $d(s)$, channel dispersion is indicated as $h(s)$ and l is the coding rate.

4.5. Network Slicing using ETUA

The network slicing is performed by ETUA that combines EWMA [12] with TUA [13]. This approach efficiently navigates the solution space to optimize resource allocation and slice management. EWMA contributes by providing smooth and responsive trend estimation for network metrics, while TUA ensures effective local adjustment through coordinated tactical updates.

4.5.1. Solution Encoding

Solution encoding is a way to represent the assignment of users to different network slices by indicating which user is placed in each slice.

S_1	S_2	S_3
U_3	U_1	U_2

Fig. 3 Solution encoding

4.5.2. Fitness Function

A fitness function evaluates how well a given solution meets the desired objectives or criteria in an optimization problem. It is deliberated as,

$$F = \frac{S_1+S_2+L_1+(1-L_2)}{4} \tag{5}$$

Here, S_1 and S_2 is the utility and channel capacity of user, whereas L_1 and L_2 is the sum rate and bit error probability.

4.5.3. Algorithmic steps of TUA

The TUA [13] is based on the coordinated search tactics of specialized teams that simulate their iterative process of exploration, information exchange and adaptive movement toward target areas in complex environments.

Step 1: Initialization Phase

The TUA uses a search approach that acts as an agent exploring the solution space and can be represented as,

$$D = \begin{bmatrix} c_{1,1}\cdots c_{1,2}\cdots c_{1,e} \\ \cdots \\ \cdots \\ c_{2,1}\cdots c_{2,2}\cdots c_{2,e} \\ \cdots \\ \cdots \\ c_{d,1}\cdots c_{d,2}\cdots c_{d\times e} \end{bmatrix} \tag{6}$$

Where, d is the population size and the decision variable is depicted as e.

Step 2: Searcher Phase

Searchers explore the solution space and identify potential target locations by sharing their best discoveries, with their positions updated as

$$D_{w,x}^{v+1} = \begin{cases} D_{w,x}^{v}.\,exp\left(-\frac{w^2}{|2\delta-1|.I_{max}}()_1\right) \\ D_{w,x}^{v} + exp\left(-\frac{2w}{I_{max}}()_1\right)\{ \end{cases} \tag{7}$$

Where v is the current iteration.

Step 3: Executor Phase

Executors enhance the search process by adjusting their movements from the population by converging toward high-quality solutions with their positions updated as,

$$D_{w,x}^{v+1} = D_{bests}^{v+1} + J.\left(D_{w,x}^{v} - D_{bests}^{v+1}\right), w < popsize/2 \tag{8}$$

From EWMA [12],

$$D_{w,x}^{v}(Q) = \chi.D_{w,x}^{v} + (1-\chi)D_{w,x}^{v-1}(Q) \tag{9}$$

$$D_{w,x}^{v} = \frac{1}{\chi}\left[D_{w,x}^{v}(Q) - (1-\chi)D_{w,x}^{(v-1)}(Q)\right] \tag{10}$$

Substituting Equation (10) in Equation (8),

$$D_{w,x}^{v+1} = J \times \frac{1}{\chi}\left[D_{w,x}^{v}(Q) - (1-\chi)D_{w,x}^{(v-1)}(Q)\right] + D_{bestS}^{v+1}(1-J) \tag{11}$$

Where v depicts the recent iteration.

Step 4: Assessment Stage

Assessor tracks the progress by updating its position based on the best information, which is explicated as,

$$D_{w,x}^{v} = \frac{1}{3}.\left(D_{bestS}^{v+1} + D_{bestEE}^{v+1} + D_{w,x}^{v}\right) \tag{12}$$

Where D_{bestS}^{v+1} as well as D_{bestEE}^{v+1} is the best locations of searchers and executors.

Step 5: Re-Evaluation of Fitness

The steps are reiterated until the most effective solution is generated.

Step 6: Termination

Execution ends upon reaching the optimal outcome.

5. Results and Discussion

The results obtained from the ETUA-based network slicing framework demonstrate significant improvements in overall network performance and resource utilization. The proposed approach effectively enhances utility by optimizing resource allocation according to varying service requirements while maintaining reliable communication. Furthermore, the framework achieves a lower bit error probability, indicating improved transmission accuracy and robustness against channel impairments. The latency analysis shows reduced transmission delays, enabling faster data delivery and supporting latency-sensitive applications. Overall, the experimental results validate the effectiveness of ETUA in providing efficient, reliable, and high-performance network slicing.

5.1. Experimental Setup

The ETUA framework for network slicing has been implemented using Python.

5.2. Evaluation Metrics

The metrics are given as,

5.2.1. Bit Error Probability

It measures the likelihood of a transmitted bit being received incorrectly due to noise or interference in the communication channel and is expressed in Equation (4).

5.2.2. Utility

Utility quantifies the effectiveness or satisfaction of a user or system in achieving its performance goals under given conditions and is explicated in Equation (1).

5.2.3. Latency

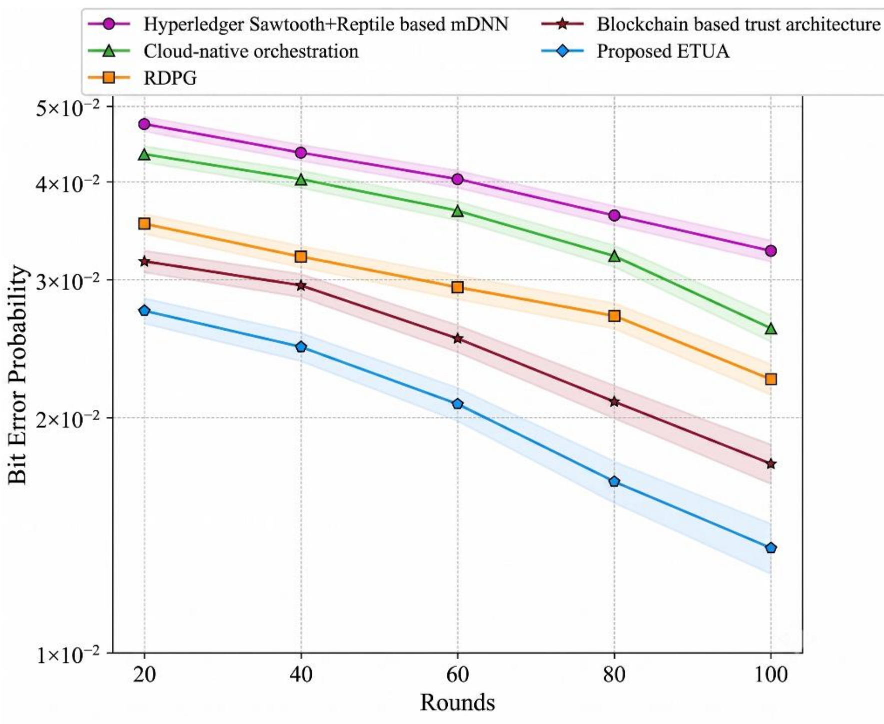
The time delay experienced for data to travel from source to destination in a network.

5.3. Comparative Methods

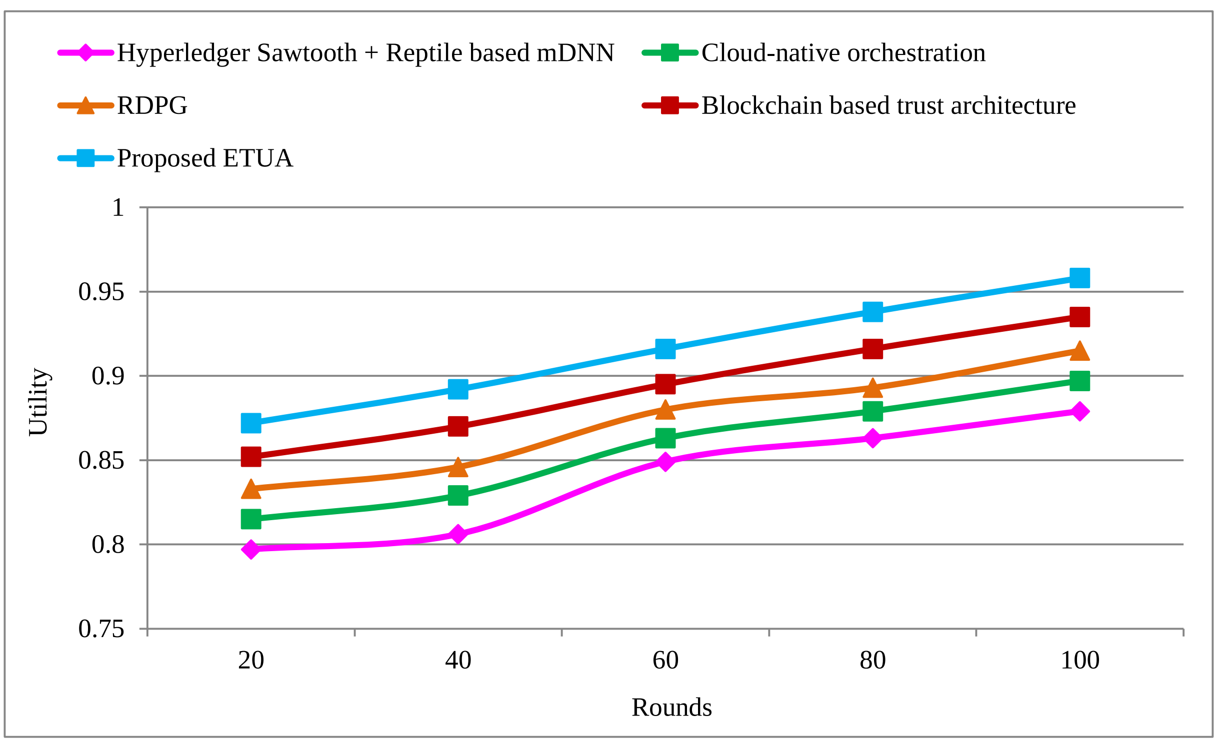
The prior models that include Hyperledger Sawtooth+Reptile based mDNN [1], Cloud-native orchestration [8], RDPG [9] and Blockchain-based trust architecture [7] are taken for proving ETUA's efficacy.

5.3.1. Comparative analysis based on the number of slice requests = 10

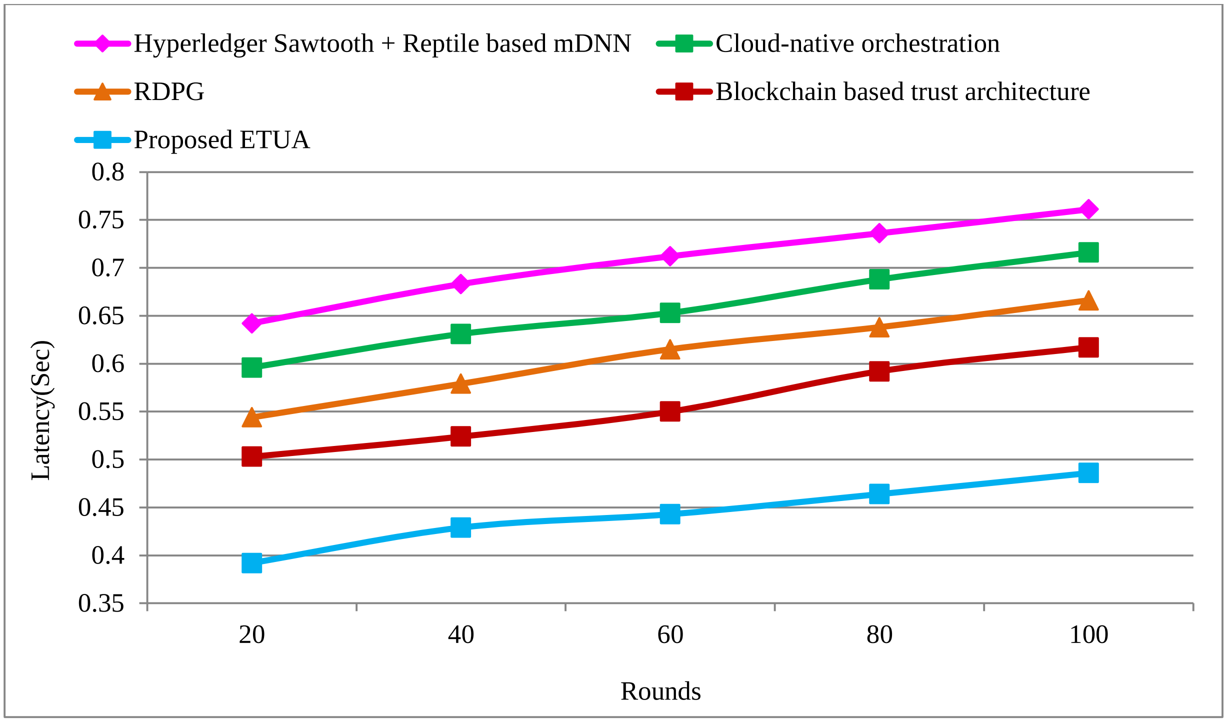
Figure 4 displays the comparative analysis. As shown in Figure 4 a), bit error probability attained by ETUA is 0.014, whereas preceding models yielded 0.033, 0.026, 0.022 and 0.017. The utility attained by prior schemes is 0.880, 0.898, 0.916 and 0.936, whereas ETUA gained 0.959 as shown in Figure 4 b). In Figure 4 c), ETUA yielded a latency of 0.486 Sec and conventional models yielded 0.762 Sec, 0.716 Sec, 0.667 Sec and 0.617 Sec.



(a)



(b)

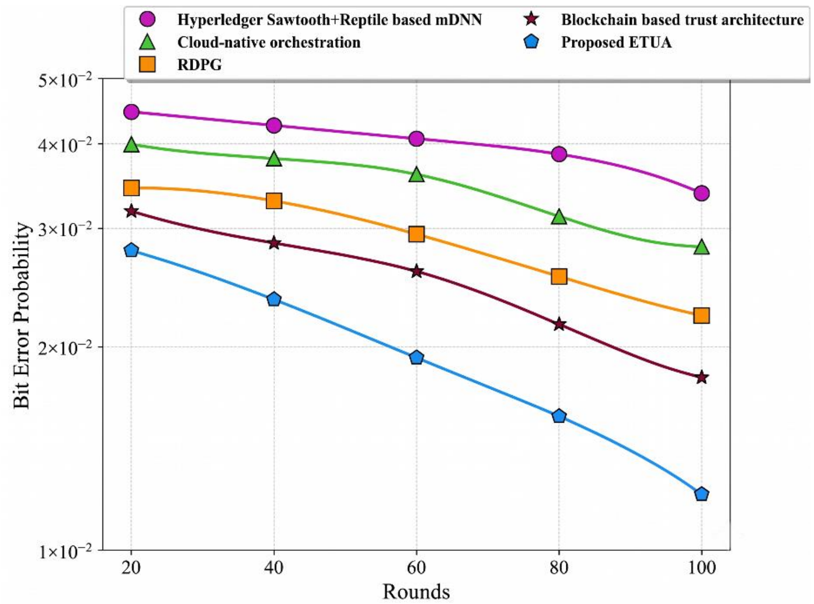


(c)

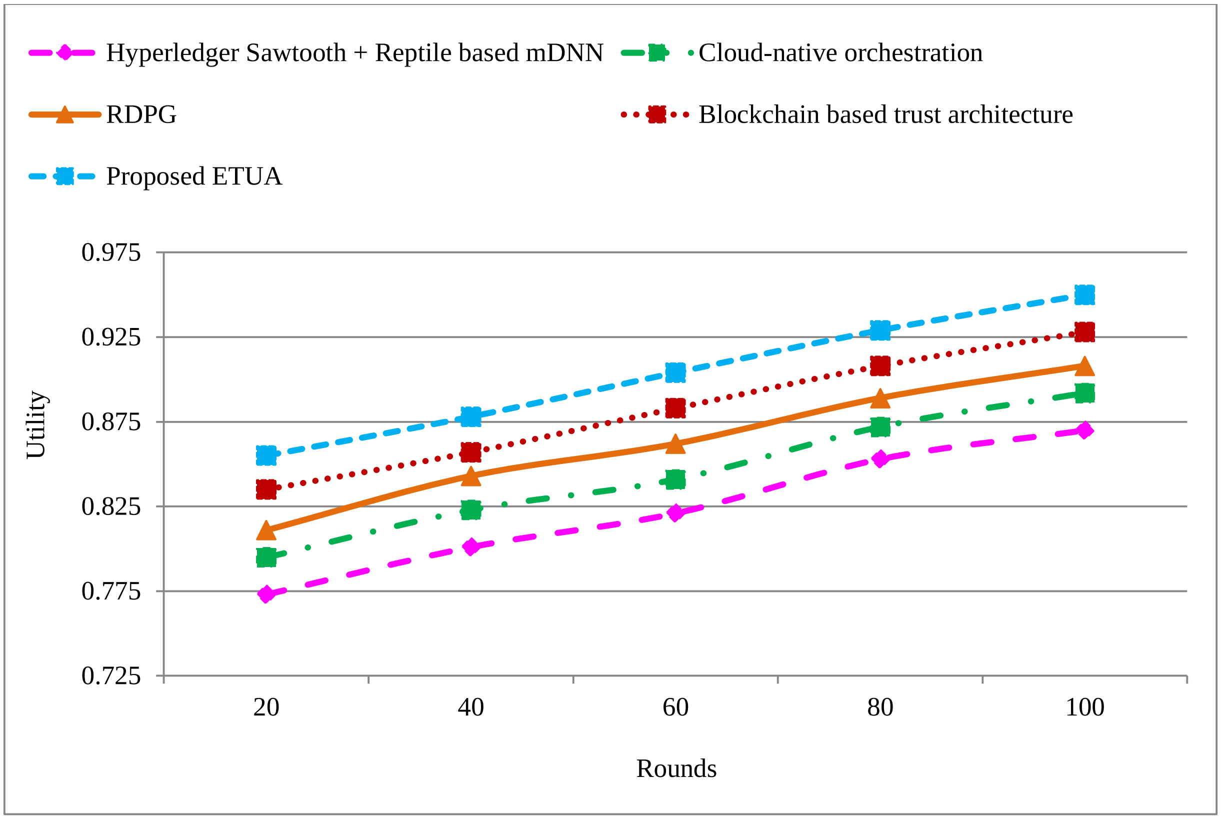
Fig. 4 Comparative analysis, a) Bit error probability, b) Utility, c) Latency (slice requests = 10).

5.3.2. Comparative analysis based on number of slice requests = 20

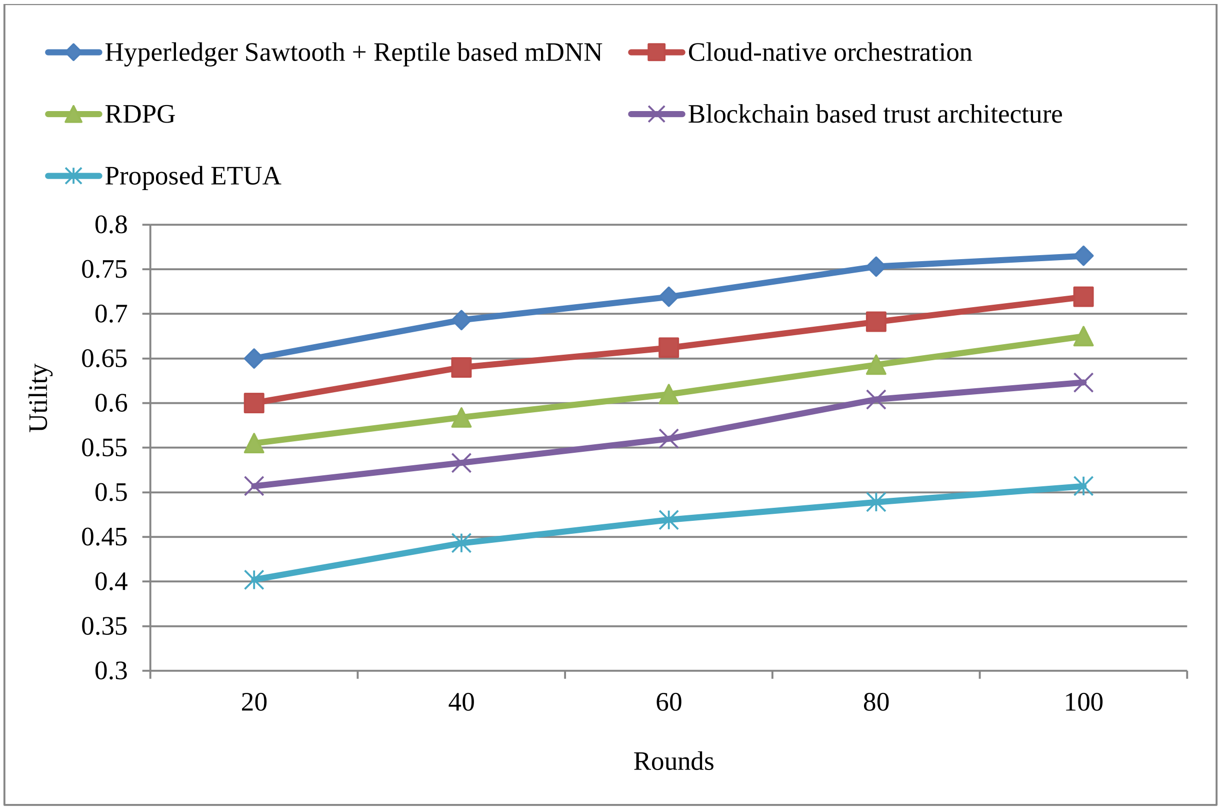
Figure 5 displays the comparative analysis. As shown in Figure 5 a), bit error probability attained by ETUA is 0.012, whereas preceding models yielded 0.034, 0.028, 0.022 and 0.018. The utility attained by prior schemes is 0.870, 0.891, 0.907 and 0.929, whereas ETUA gained 0.950 as shown in Figure 5 b). In Figure 5 c), ETUA yielded a latency of 0.509 Sec and conventional models yielded 0.769 Sec, 0.720 Sec, 0.675 Sec and 0.624 Sec.



(a)



(b)



(c)

Fig. 5 Comparative analysis, a) Bit error probability, b) Utility, c) Latency (slice requests = 20).

Table 2. Comparative discussion of ETUA

Analysis based upon	Metrics / Methods	Hyperledger Sawtooth + Reptile-based mDNN	Cloud-native orchestration	RDPG	Blockchain-based trust architecture	Proposed ETUA
Number of slice requests = 10	Bit error probability	0.033	0.026	0.022	0.017	0.014
	Utility	0.880	0.898	0.916	0.936	0.959
	Latency (Sec)	0.762	0.716	0.667	0.617	0.486
Number of slice requests = 20	Bit error probability	0.034	0.028	0.022	0.018	0.012
	Utility	0.870	0.891	0.907	0.929	0.950
	Latency (Sec)	0.769	0.720	0.675	0.624	0.509

5.4. Comparative Discussion

Table 2 shows the discussion of ETUA. For slice request=10, utility gained by ETUA is 0.959, whereas existing models attained 0.880, 0.898, 0.916 and 0.936. The latency gained by previous schemes and ETUA are 0.762 Sec, 0.716 Sec, 0.667 Sec, 0.617 Sec and 0.486 Sec. On the other hand, the bit error probability yielded by ETUA is 0.012 and conventional methods gained 0.034, 0.028, 0.022 and 0.018. Overall, ETUA obtained bit error probability, utility and latency with values of 0.012, 0.950 and 0.509 Sec, while assuming the number of slice requests = 20.

6. Conclusion

In a 6G environment, network slicing and resource allocation allow to generate several networks, where each is designed to meet different needs, like very low delay, connecting many devices or high-speed data. This also brings challenges, including more complicated network design, higher costs, security risks between slices and difficulty managing resources in constantly changing network conditions. In this work, ETUA is devised for network slicing in 6G. At first, simulation of blockchain-enabled 6G network takes place, and user device type, delay rate, as well as packet loss rate are collected from various devices. Moreover, ETUA performs network slicing, where ETUA combines EWMA and TUA. Finally, resource allocation is performed by AHoNet by considering the parameters that includes bit error probability, sum rate and trust. The efficacy of ETUA is examined by bit error probability, utility and latency with 0.012, 0.950 and 0.509 Sec. In future, the ETUA framework is extendable to incorporate energy-efficient network slicing strategies to reduce power consumption and improve sustainability in 6G networks.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Sunitha M K - Conceptualized the research, designed the methodology, and drafted the manuscript.

Brijesh Mishra - Assisted in data analysis, reviewing the manuscript, validation, and result interpretation.

All authors have read and agreed to the published version of the manuscript.

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