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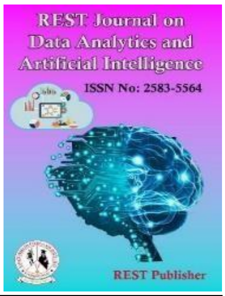

Nexus-an Enhanced Network Coverage Routing Protocol in 6g Networks

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***Abstract:** Cellular networks experience the participation of multiple devices every day. Sixth Generation (6G) technology is considered to be the most challenging future generation communication technology, in which new methods for data exchange and communication can be incorporated. 6G brings new ideologies to share information without relying on communication with a fixed Base Station (BS). In case of a post catastrophic situation, the devices need to create an ad-hoc network to communicate under 6G's requirements which includes communication frequency, latency, data rate etc. Generally, Routing in 6G networks is significant for meeting the diverse requirements of ultra-low latency, high throughput, heterogeneous network architectures and energy efficiency. Effective routing protocols and algorithms enable seamless operation of advanced applications and services envisioned for the 6G era. In order to recompense these requirements an enhanced coverage 6G routing protocol, Network Extension and Security Routing Protocol (NEXUS) for 6G networks is proposed. This routing protocol implements efficient AI based approaches namely Supervised Learning (SL), Reinforcement Learning (RL) and Graph Neural Network (GNN) in order to extend the network coverage area. NEXUS also provides a high data rate with acceptable latency, low energy and storage costs.*
***Keywords:** Network Extension and Security (NEXUS) - Supervised Learning (SL), Reinforcement Learning (RL) and Graph Neural Network (GNN) – Optimized Routing – Increased Network Coverage.*

1. INTRODUCTION

With the rapid evolution of wireless communication technologies, the occurrence of 6G networks promises to revolutionize the way we connect, communicate, and interact in the digital era [1]. The demand for ubiquitous connectivity, ultra-low latency and massive data transmission continues to increase rapidly. Thus the development of advanced routing protocols aiding 6G networks becomes mandatory. In general, traditional routing protocols act as the support system for communication networks. Its effectiveness in meeting the demanding requirements of 6G environment is limited. The ultra-dense deployment of devices, the increase in Internet of Things (IoT) devices and the emergence of latency-sensitive applications facilitates novel routing solutions which are capable of optimizing resource utilization, ensuring reliable communication and minimizing latency [2,3,4].

In this paper, a novel routing protocol is designed exclusively for 6G networks. It leverages advanced machine learning techniques and network intelligence to manage network resources, optimize routing paths and reduce performance restrictions. The proposed routing protocol aims to address the challenges caused due to ultra-dense networks, dynamic traffic patterns, and diverse communication requirements that degrade the ability of the Sixth Generation technology. The advent of 6G technology introduces novel concepts for information sharing that circumvent the need for fixed Base Station (BS) communication. Additionally, there arises a necessity to establish ad-hoc networks in the aftermath of disasters, adhering to 6G's specifications such as communication frequency, latency, and data rate etc. [5,6]. In general Routing in 6G networks is significant for meeting the diverse requirements of ultra-low latency, high throughput, heterogeneous network architectures and energy efficiency [7]. The main objective of the paper is to provide an enhanced coverage with secured routing protocol in 6G networks. Effective routing protocols and algorithms enable seamless operation of advanced applications and services envisioned for the 6G era. In order to encounter these requirements an enhanced coverage routing protocol for 6G networks is proposed. The proposed 6G routing protocol Network Extension and Security Routing Protocol (NEXUS) also leverages Artificial Intelligence (AI) to extend the network coverage area. Integrating Supervised

Learning (SL), Reinforcement Learning (RL) and Graph Neural Network (GNN) an efficient AI-based approach is proposed. The proposed routing protocol provides an enhanced network coverage area with low energy and storage cost. The organization of the paper is as follows, Section 2 outlines the Related Work, Proposed Work is discussed in Section 3. The Results and Discussions are discussed in Section 4. Finally, the conclusion is highlighted in Section 5 with scope of future work.

2. RELATED WORKS

X. You et al. [4] discussed about the Fifth Generation (5GMN) Mobile Networks that are utilized globally from 2020. There are potentialities in the methodologies to be regulated, like global linkage, outstanding robustness, and assured minimal delay. Since 5G cannot meet all requirements of the future in 2030 and beyond and Sixth Generation (6G) wireless communication networks are expected to provide better intelligence level and security, enhanced Spectrum/energy/cost effectiveness, worldwide coverage. To fulfill these essentials, 6G networks will rely on Breakthrough technologies like, Wireless interface and transmission technologies, Innovative network structure, such as multiple access, Antenna array technologies, Segmented network, Non-cellular architecture, Modulation scheme development, channel coding schemes and cloud/fog/edge computing.

Pan Lu et al. [3] has proposed a Routing protocol in 6G named Graph SAGE – Path-diverse reliable routing algorithm for Wireless Mesh Networks. Graph SAGE creates a strategy to generate network labels for supervised training. Network labels and Graph SAGE learns graph features to obtain values of Optimization of shortest path performance. After assessing network conditions, the optimal route with the highest performance is chosen for data transmission. Thuy-Van T. Duong et al. [2] have proposed a Routing protocol in 6G named IRSML- AN Intelligent Routing Algorithm based on Machine Learning in software defined wireless networking. It is used in Software - Defined Wireless Networking (SDWN). Routing in Software - defined wireless networking is usually done by Integer Linear Programming Problem (ILP). It focuses on efficient routing standards by providing rejection ratio, minimized end –to end delay (EED), maximizing network throughput. IRSML is a combination of Reinforcement learning and Supervised Learning.

These two machine learning techniques are used to discover new route and to predict Quality of transmission and Packet Blocking Probability. ‘Q’ value is used in the fundamental equation of Reinforcement learning to store Packet Blocking Probability. Generally, SDWN nodes Interconnect wirelessly through mesh network architecture. Each node in SDWN is a wireless router. Some wireless routers are linked to the gateway through either wired or wireless connections for internet access. Ricardo Pagoto Marinho et al. [1] have proposed a Routing protocol in 6G named CAIN-Coverage Area Increased Network. It is a fusion of Reinforcement Learning techniques, Federated Learning and Deep Neural Network. In a wide spread network, the protocol allows the node optimizing neighbor selection to expand network coverage. Depending on the node’s connectivity to access point, CAIN can communicate via messages to nodes to reach the access point using neighboring nodes.

CAIN makes devices to convey information with Access Points minimizing energy consumption, storage usage, and latency. The CAIN routing protocol suggests certain techniques in order to extend the coverage area. Increasing the signal frequency to accomplish higher throughput of 1 Terabits per second, Increasing the frequency eventually leads to decreasing the Signal propagation range necessitating proximity to the source for reception. In the event of signal obstruction or coverage gaps, relay antennas serve as signal amplifiers and extenders.

3. THE PROPOSED NEXUS ALGORITHM

The proposed work presents an ad-hoc routing protocol, called Network Extension and Security (NEXUS), which uses an AI approach by integrating Supervised Learning (SL), Reinforcement learning (RL) and Graph Neural Network (GNN) with the aim of increasing the network coverage and providing secured routing in 6G networks.

An ML algorithm normally consists of three components namely; the states in which the nodes may be in; the actions they could carry out and finally the function to distinguish the best actions for a particular state [15]. Each time the node undertakes some action, a penalty or reward is given to them, impacting the end result of the function. In view of this, the RL algorithm consists of three states and two actions: (i) close distance/smaller hop number, (ii) middle distance/hop number and (iii) longer distance/greatest hop number, while the actions are sending the packet or not [16]. Meanwhile, the hop count technique requires data on the mean hop number that each device requires to reach a CH [18]. Upon receiving the message from the CH, the node computes the average hop count for the CHs and sends the data within the CH election message. The limit for each metric is the maximum distance and hop number a device can get from its neighbor.

2.1.1 RL metrics

To illustrate the RL-based algorithm, the details and choices made by the system are explained. Specifically, for the Euclidean distance metric's limit ($maxDist$) for each node, which represents the farthest distance between it and any of its neighbors is defined. The value is then split into three regions: closer, medium and farther, indicating the relative distance of a particular node from the others [19,20]. Similar to the Euclidean Distance metric, hop count metric also defines a threshold— The maximum hop count to reach a CH neighbor. This is also divided into 3 regions: lowest, medium and highest representing a particular node's relative positioning from its peers [21].

2.1.1.1 NEXUS-Euclidean distance

The Euclidean distance is used as a basis for calculating a node's spatial coordinates. Utilizing distance allows for potentially expanding the network coverage, increasing the likelihood that the selected route will widen the gap between the source and destination nodes. In a dynamic environment like 6G, however where the topology is rapidly changing, the distance might not remain stable and the route taken might not be the optimal one. The present node state is based on the distance to a neighbor. Every node receives either a reward or penalty upon being chosen to either get closer, medium or farther. If node 6 opts to transfer to a CH and chooses node 5 as the primary candidate, followed by node 7 as the secondary option and node 8 as the least favorable choice, node 5 will receive a reward for selecting node 6, but face a penalty if it fails to do so. However, Node 7 neither offers a reward nor incurs a penalty. Opting for node 8 and successfully transmitting the message yields a reward; failure to do so results in a penalty. At a moderate distance, node 5 receives a reward for selecting and transmitting the message to node 7. A minor reward or penalty is given for the other two nodes, depending on the chosen action.

changes in the transition matrix apply for each selected neighbor. For example, in Fig. 2, Selecting node 6 increases the probability $P55$ as it moves deeper into circle A. According to the policy, the Q-value is impacted by said probability either in a favorable or unfavorable way. It applies to the other two nodes as well. Specifically, when node 7 is selected, the probability $P67$ increases, whereas for node 4, it is $P76$if it's moving towards state 2 (circle B). Conversely, as one probability rises, the other two decline accordingly, e.g. when $P55$ increases for node 2, $P56$ and $P57$ decreases.

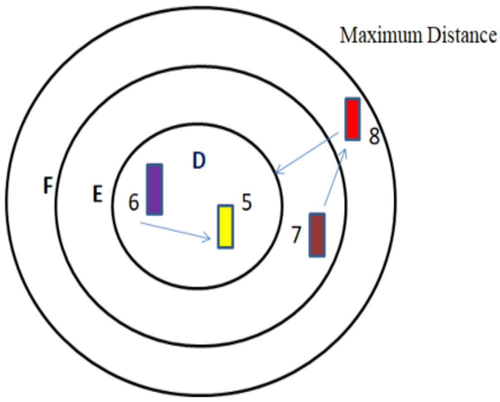

FIGURE 1. RL state example

2.1.1.2 NEXUS-Hop count

The hop count is used as a second metric. It includes a simple successive additive calculation when each time the packet moves through a hop. Nevertheless, the route need not be necessarily far away from the source and therefore needs adjustments to the coverage area. Thus the hop count from each neighbor node to CH is calculated. The hop count to reach the CH is also incremented. As a result, it is divided into three distinct states low, medium, and high hops.

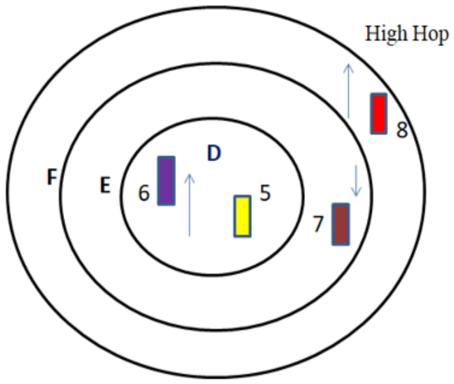

FIGURE 2. Hop RL algorithm state division

The three states are represented in Fig. 3 with inner circles. Circle A contains neighbours which require the least the hop distance to access a CH. Circle B contains those with a few more hops and Circle C requires the most the hop distance to access a CH. With every selection, the rewards and the punishments vary accordingly. As illustrated in Fig. 3, when node 1 elect's node 6, it receives a reward whereas, if it chooses node 7 or node 8, neither reward nor penalty is received. For node 7 and node 8, the reward is seen for negative decision-making i.e. the penalties are increased if it sends messages and decreased if it does not send messages. Additionally, the reward for node 7's medium hop count is higher than node 6 and 8. The transition of the node with the highest hop number determines the probability by comparing the node's hop number to the established threshold.

2.2 Modified Q-value:

The RL algorithm applies the modified Q-value equation (Eq.1) to determine the optimum decision. The equation is based on its reward/penalty vector of the node. It also utilizes the state transition matrix, computed with the measurement and the selected neighboring state to make its decision. Each time a node relays a message, the Q-value equation is run 100 times in order to determine the best course of action. After these 100 iterations, the node makes its selection and proceeds accordingly.

$$Ok+1(s, a)\ (1-a) * Qk\ (s, a) + a * \sum s'\ (s, a, s')\ [R\ (s, a, s') + \gamma .\ maxa'\ (s', a')]\ \forall\ (s, a)]\ (1)$$

Where, is the learning ratio < a < 1, The above equation (1) is a modified Q-value calculation used in reinforcement learning. It is used to adjust the Q-value associated with a specific state-action combination (s, a). The new Q- value $Qk+1(s, a)$ is calculated by combining the existing Q-value Qk (s, a) with a new value determined by the expected reward and the maximum Q-value of a possible next state [20]. The expected reward s determined by multiplying the transition probability of the transition $T\ (s, a, s')$ with the reward of the transition$R\ (s, a, s')$. The maximum Q-value is determined by taking the maximum of all possible next state action pairs$maxa'\ Qk\ (s', a')$. The learning rate (a) determines the relative importance between the existing Q-value and the new value. Gamma (γ) is a parameter that defines the significance of future rewards compared to immediate rewards. It is employed in Q-value computations to estimate the anticipated reward of a specific state-action pairing. Higher the gamma, greater the importance is given to long- term rewards over short-term rewards.

2.2.1.1 NEXUS_LSTM model for node and data analysis:

The LSTM network is depicted in Fig. 5. The network undergoes training using a set of traffic data denoted by D(k). Initially, D(i) is specified as D1(i)=1/n.

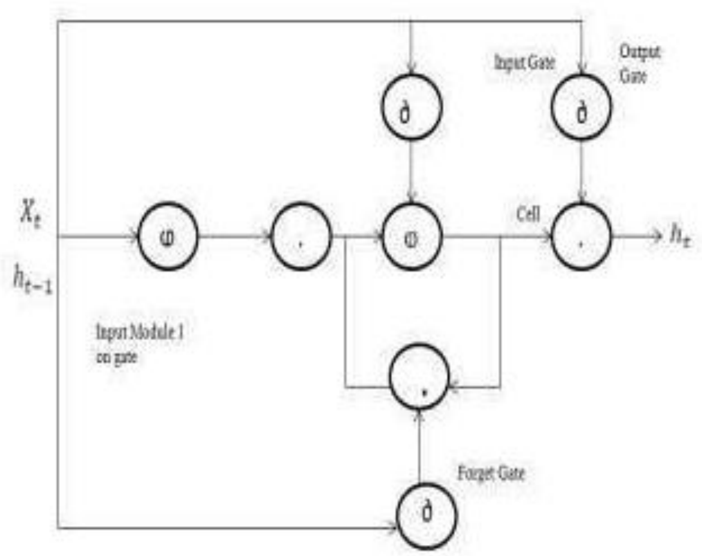

FIGURE 3. LSTM model for node and data analysis

The output of the LSTM network at every cycle k is denoted byTk, which is determined by the following equation [2]:

$$Tk = \sum_{k=0}^{n} [O\,(G0_k.\ Ok + G0_k.\ ek-1 + sk)] \qquad (2)$$

The predicted error value ek shown in equation [3] is calculated by subtracting the actual value $Tactual$ from the estimated value Tk

$$ek = Tactual - Tk \qquad (3)$$

The corresponding network coefficients αk are calculated by using equation [4] the following relation:

$$\alpha_k = 0.5\{\frac{\ln(1-e_k)}{e_k}\}$$

The model is deemed completely trained after all iterations are performed and generates $'k$ ' number of weak LSTM predictors [5]. These predictors are then combined into a single ensemble model to make predictions about 6g network traffic data.

$$Yk = \sum_{k=0}^{n} \frac{1}{\{\alpha_k.\ Tk\}}$$

Every device utilizes a Reinforcement Learning (RL) algorithm to determine the optimal set of internal weights. These weights are periodically sent to the Cluster Head (CH) for further processing. All devices in the network apply their own RL algorithm to identify the best weights for their respective operation [22]. Once the CH collects the individual devised weights, it performs an averaging process and sends the freshly aggregated weights back to the implicated devices [23]. The looping process allows continuous exploration and growth in the network, with the added challenge of trying to maintain a constant set of CH. Additionally, each node may periodically change its weights in order to find the most optimal solution.

Table 1: Simulation Parameters

Parameter	Value
Device Number	50, 100, 150, 200, 250
Area	1000 m x 1000 m
Communication Range (m)	50
Frequency	1 THz
Data Rate	1 Tbps
Number of repetitions	35
Protocols	NEXUS, CAIN and LAR

Table 1 represents the Simulation Parameters using NEXUS routing protocol. It includes the device number, area, communication range, frequency, data rate, number of repetitions and protocols involved during the routing process.

3. RESULTS AND DISCUSSIONS

The simulated graphs are in correspondence with network parameters like, Packet Loss, Packet Delivery Ratio, Average Delay, Network Lifetime, Communication Overhead and Average Throughput. The proposed work has been simulated in Network Simulator 3 (NS-3) environment. The simulated graphs have evidently proved that NEXUS an intelligent coverage area protocol enhances the required network parameters of Packet loss, Packet Delivery Ratio, Average delay, Network Lifetime, Communication Overhead and Average Throughput in a 6G environment with maximum node distribution with nearly 250 nodes.

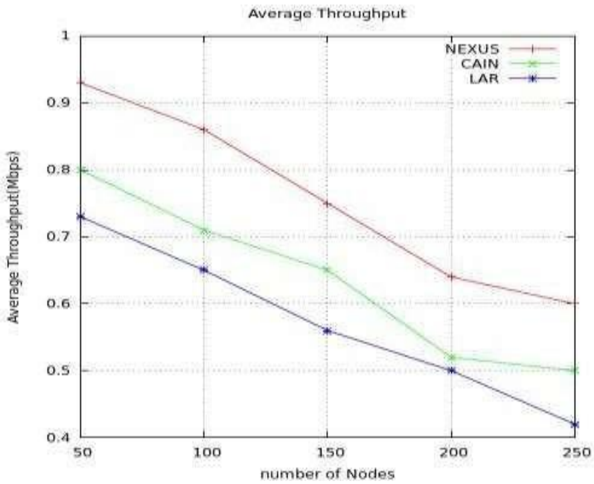

FIGURE 4. Average Throughput (Mbps)

Table 2. Comparison between the Existing and Proposed Routing Protocols

Parameters	Existing Routing Protocol		NEXUS (Proposed Routing Protocol)
	LAR	CAIN	
Network Lifetime (s)	84	87	92
Communication Overhead	24	17	10
Average Throughput (Mbps)	0.42	0.5	0.6
Energy Consumption (joules)	1.15	0.98	0.62

Table 2 depicts the comparison between the existing routing protocols CAIN and LAR with the proposed routing protocol NEXUS.

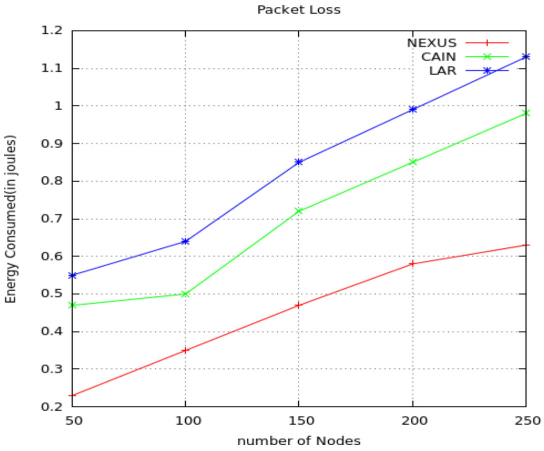

FIGURE 5. Energy Consumption (joules)

Figure 5 infers that for 250 nodes, the Energy Consumption is found to be 1.15 joules in the existing Location Aided Routing (LAR) and 0.98 in Coverage Area Increased Network (CAIN) protocols. Whereas for the proposed NEXUS- Network Extension and Security protocol the Energy Consumption is evidently decreased to 0.62 joules.

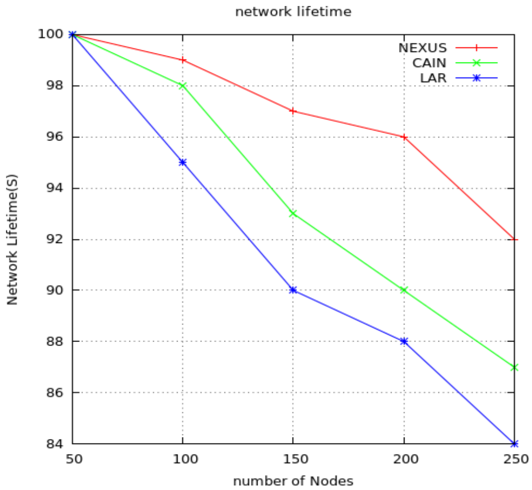

FIGURE 6. Network Lifetime (s)

Figure 6 it is infers that for number of deployed nodes being 250, the Network Lifetime in terms of seconds is found to be 84 s in the existing Location Aided Routing (LAR) and 87 s in Coverage Area Increased Network (CAIN) protocols. Whereas for the proposed NEXUS- Network Extension and Security protocol the Energy Consumption is evidently decreased to 92 s.

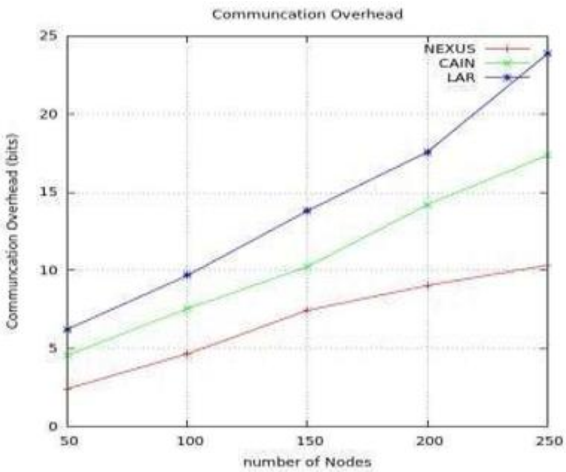

FIGURE 7. Communication Overhead (s)

From figure 7 it is inferred that for number of deployed nodes being 250, the Communication Overhead in terms of bits is found to be 24 s in the existing Location Aided Routing (LAR) and 17s in Coverage Area Increased Network (CAIN) protocols. Whereas for the proposed NEXUS- Network Extension and Security protocol the Energy Consumption in terms of Mbps is evidently decreased to 10 s.

4. CONCLUSION

The fundamental objective of any network is to facilitate communication between its devices by establishing routes until the message reaches its intended destination. Routing in 6G networks is crucial for meeting such diverse requirements of ultra-low latency, high throughput, heterogeneous network architectures, reliability and energy efficiency. The paper proposes an enhanced coverage area with secured routing protocol for 6G networks. The effectiveness of the proposed routing protocol in improving the network performance, enhanced security and meeting the necessary requirements of 6G environment is addressed. The research also makes reasonable key contributions in the field of 6G networking. Initially, a novel routing protocol for enhancing the coverage area is proposed. Secondly, the protocol integrates trust aware measures to prevent security threats in the routing scenario thereby ensuring the integrity and confidentiality of data transmission in 6G networks. In addition to these requirements, in order to provide an enhanced network coverage using a Machine Learning based routing technique, a novel routing protocol for 6G that uses Reinforcement Learning (RL), Supervised Learning (SL) and Graph Neural Network (GNN) is proposed.

NEXUS (Network Extension and Security Routing) stands out as an intelligent routing protocol designed to expand coverage area efficiently while requiring minimal storage resources. RL_NEXUS, which excludes Federated Learning (FL) algorithms, demonstrates superior performance, largely attributed to the replacement of FL algorithms with Long Short Term Memory (LSTM), an ML algorithm deployed for routing security. NEXUS distinguishes itself by facilitating communication among devices from Cluster Heads, a feature crucial for expanding network coverage. Notably, integrating RL, SL, and GNN techniques into NEXUS yields even better outcomes, further extending network coverage area. NEXUS exhibits a 3% reduction in communication overhead compared to alternative protocols, while also prolonging network uptime by 92% through efficient utilization of device battery power. Additionally, it achieves an average throughput of 0.95 Mbps, surpassing that of other protocols. Moving forward, enhancing reinforcement learning (RL) and federated learning (FL) with novel algorithms can further minimize network overhead. This enhancement promises to extend network coverage and can be tested across various scenarios, including simulations with different numbers of Base Stations. Furthermore, considering the proliferation of diverse device types in a 6G landscape, adapting NEXUS for evolving device ecosystems becomes imperative.

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