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Efficient Slice Creation in Network Slicing using K-Prototype Clustering and Context-Aware Slice Selection for Service Provisioning

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***Abstract:** The advent of 5G technology has ushered in a new era of communication where the customization of network services is crucial to meet diverse user demands. Network slicing has emerged as a pivotal technology to achieve this customization. In this research, we present an innovative approach to optimize network slicing in 5G by employing K-Prototype Clustering for slice creation and Context-Aware Slice Selection for efficient resource allocation. In slice creation, we delve into the innovative application of the K-Prototype clustering algorithm. Recognizing that 5G networks encompass numerical and categorical attributes, the K-Prototype algorithm enables the creation of network slices that cater to diverse service requirements. By harnessing this clustering technique, our proposed method optimizes the creation of network slices, resulting in improved resource utilization and reduced network congestion. Furthermore, we introduce the concept of Context-Aware Slice Selection, which considers the dynamic and evolving nature of network demands. Context-awareness ensures that network slices are selected based on real-time contextual information, enabling a more adaptive and responsive network. This approach leads to the efficient allocation of resources and a higher quality of service for end-users. To evaluate the performance of our proposed methodology, we employ key performance metrics, including slice selection accuracy, slice selection delay, and radio link failure. Through comprehensive testing and analysis, our research demonstrates that our approach consistently outperforms existing methods in terms of these metrics.*

***Keywords:** Slice creation, K-Prototype Clustering, Slice selection, Context-Aware, Service Provisioning.*

I. INTRODUCTION

Slicing in the context of wireless communication refers to the concept of network slicing, which is a technique used to partition a single physical network infrastructure into multiple virtual networks. Each virtual network, known as a "slice," can have its own unique set of resources, configurations, and rules to cater to the specific needs and requirements of different users, applications, or services.

Network slicing is a pivotal concept in modern telecommunications, especially in the context of 5G networks, and it addresses the need for efficient utilization of network resources based on the specific requirements of users and applications. In the ever-evolving landscape of telecommunications, the advent of 5G has ushered in a new era of connectivity, promising unprecedented speed, low latency, and a plethora of innovative applications. At the heart of this transformative shift lies a groundbreaking concept - "slicing." 5G network slicing is not just an incremental improvement. It's a revolution that empowers service providers to tailor their networks to meet the diverse and dynamic demands of various industries and applications.

This introduction delves into the concept of network slicing, shedding light on what it is, how it works, and the remarkable impact it is poised to have on our connected world. We will explore how network slicing enables the creation of customized, virtualized networks within the overarching network infrastructure, allowing for the seamless coexistence of applications with vastly different requirements, from ultra-reliable low-latency communications (URLLC) for mission-critical applications to enhanced mobile broadband (eMBB) for high-speed data transfer and massive machine-type communications (mMTC) for the Internet of Things (IoT).

As we journey through this exploration, we will also consider the critical role of slice selection, a pivotal process that ensures optimal resource allocation and quality of service (QoS) for each network slice. The dynamic nature of 5G slicing, with its ability to adapt to real-time demands and shifting priorities makes it a linchpin in the realization of a hyper-connected world where everything from autonomous vehicles to augmented reality hinges on seamless, reliable, and low-latency connectivity.

In the digital age, where connectivity underpins nearly every aspect of our lives, the efficient allocation of resources and the ability to tailor network services to specific needs have become paramount. This has given rise to two crucial concepts in networking: slice creation and slice selection. These concepts, while fundamental, are pivotal in shaping the performance, scalability, and adaptability of modern networking technologies.

In this introduction, we embark on a journey to explore the essence of slice creation and slice selection across common networking technologies. These concepts transcend specific protocols or platforms and are at the core of designing networks that meet the ever-growing demands of our interconnected world. Slice creation refers to the art of dividing a network into smaller, isolated segments, each optimized for distinct purposes.

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This approach allows network administrators to efficiently manage resources and tailor services to meet the unique requirements of various applications or user groups. Whether it's Quality of Service (QoS) guarantees for video streaming, ultra-low latency for real-time gaming, or robust security measures for sensitive data transfer, slice creation empowers network architects to design bespoke solutions.

But creating slices is just the beginning. Slice selection, the process of dynamically choosing the right slice for a given task or user is equally vital. In an era where the networking landscape constantly evolves to accommodate diverse devices, applications, and user expectations, the ability to select the most suitable slice on the fly is a game-changer. It ensures that resources are allocated efficiently, optimizing performance and responsiveness.

Our exploration will take us through various networking technologies, from traditional Local Area Networks (LANs) to the cutting-edge realms of 5G and beyond. We will delve into how slice creation and selection play out in each of these contexts, highlighting their significance in delivering seamless, reliable, and adaptable network experiences.

A. Research Objectives

- Enhance the efficiency and effectiveness of network resource management through the development of innovative slice creation and selection techniques that optimize resource allocation, improve network performance, and adapt to dynamic user and application demands across various networking technologies.
- This overarching research objective encompasses both aspects of slice creation and slice selection and highlights the core aim of improving the management of network resources to provide better connectivity, quality of service, and overall user experience in diverse network environments.

B. Contributions

- Advanced Slice Creation Methodology: This research contributes to a novel K-Prototype clustering approach for slice creation that addresses the challenge of accommodating both categorical and numerical network attributes. This innovation enhances the network's ability to adapt to varying demands and ensures efficient resource allocation.
- Context-Aware Slice Selection: The development of a context-aware, rule-based slice selection mechanism contributes to the adaptability and responsiveness of networking technologies. This ensures that network slices are selected based on real-time conditions, offering an enhanced user experience and resource utilization.

II. RELATED WORK

This review paper offers an exhaustive presentation of extant solutions, frameworks, and utilization scenarios for edge-enabled network slicing, along with the associated advantages. Additionally, they examine the current body of work that explores the fusion of Machine Learning (ML) techniques with these concepts [1][14][15][16][17][18]. The objective is to furnish research in this field with a comprehensive evaluation of the interplay between edge-enabled network slicing mechanisms and ML methodologies. Furthermore, recognizing the pivotal role that synchronization among slicing controllers plays in enhancing slicing decisions the Reinforcement Learning (RL)-based solution for controller synchronization is proposed.

This comprehensive survey seeks to bridge the gap between the realms of network slicing and machine learning in the context of 5G networks [2, 3]. It offers insights into the current landscape, identifies challenges, and presents potential directions for future research. By analyzing the integration of machine learning techniques into the management of network slicing, this survey aims to provide a valuable resource for researchers, network engineers, and industry professionals working on the cutting edge of 5G network optimization and management.

They demonstrated a prediction mechanism in this research study that uses both machine learning and deep learning algorithms, applied traditionally and progressively, to choose the best network slice depending on various user needs and device kinds [4]. Stochastic Gradient Descent (SGD), an incremental learning model, and a publicly accessible dataset were used to achieve a remarkable accuracy rate of 99.33% in classifying incoming user requests into the appropriate network slices. In this work, they present the idea of "intelligence slicing," which refers to the idea of developing and deploying AI modules as needed [5]. Slices of intelligence are intended to carry out different intelligent tasks while providing flexibility to support a variety of AI algorithms. They give two exemplary instances of these slices, involving anomaly detection for industrial network security and the other neural network-based channel prediction. These illustrations highlight the usefulness and versatility of this system. They developed a hybrid deep learning model throughout this study that combines an LSTM network and a convolutional neural network (CNN) [6]. CNN in this framework manages resource allocation, network reconfiguration, and slice selection, while the LSTM is used to gather statistical data on network slices, including load balancing and error rates. By placing this model through a variety of scenarios, such as several unknown devices, slice failures, and network overloads, they evaluate the efficacy of the model. The outcomes demonstrate the viability of the suggested methodology, which achieves an amazing total accuracy rate of 95.17 percent. The architecture of this technology, which includes data collecting, storage, processing, and analytics, is reviewed at the beginning of the essay [7]. It then emphasizes the complex interaction between these components and network-slicing ideas, highlighting the associated choices. The paper goes on to present a thorough methodology that enables dynamic resource provisioning of resources driven by big data while maintaining the integrity of service level agreements (SLAs). This framework includes models for resource allocation, the development of low-complexity traffic predictors for slices, and the implementation of SLAs using limited deep learning approaches. The presentation concludes by outlining the key difficulties and unexplored research directions in this developing area. In this study, they presented a network slicing method based on deep Q-learning that is intended to improve slice selection and resource allocation in 5G wireless networks [8]. They presented a unique quality-of-experience-based incentive system to improve the effectiveness of throughput, connection, and latency requirements for diverse services across a spectrum of Next Generation Mobile Network use cases.

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Three standard network service slices, identified as enhanced Mobile Broadband (eMBB), Ultra Reliable Low Latency Communication (uRLLC), and massive Machine Type Communication (mMTC), are used to distribute these services. Additionally, the deep Q-learning (DQN) agent's needed convergence time has been significantly decreased by the updated approach.

This study focuses on the security issues that arise across the whole lifespan of network slices [9]. The integrated solutions are built on machine learning and deep learning techniques for use in the planning, design, building, deployment, monitoring, fault detection, and security enforcement phases of the slice's life. the idea of 5G network slicing, outlining its layers and architectural framework, and clarifying the tactics for countering assaults, threats, and problems that highlight the impact of network slicing on the 5G network is examined. Additionally, they provide a comparative review of current taxonomies and surveys that show various machine-learning approaches suited for specific application parameters and network functions.

To create a Family Traffic Analysis System, this study integrates the Internet of Things (IoT) with the context of homes [10]. This system's objective is to give family members access to information about the household's internet traffic data. It can identify anomalies based on sensor data provided by household appliances, acting as a defence mechanism against malware incursions or assaults. It also solves the issue of network-wide traffic isolation. Especially noteworthy are the system's superior scalability, high pattern recognition accuracy, and seamless interaction with domestic settings. In this research, they provide a novel machine learning (ML)-based architecture to address the orchestration of network slices in 5G networks [11]. This method requires the development and deployment of four core components: the "Gatekeeper" in charge of categorization and marking, the "Decision Maker" with its many sub-modules, such as the "Forecast Aware Slicer" and "Admission Controller," the "Slice Scheduler," and the "Resource Manager." They used the OpenAirInterface (OAI) technology to integrate these parts into a 5G prototype.

In this study, they outline the key stages of resource management within the framework of network slicing [12]. To achieve autonomous resource management throughout each phase, they have thoroughly examined techniques using Deep Reinforcement Learning (DRL) and Reinforcement Learning (RL) algorithms. The optimization objective, network scope (including core, radio access, edge, and end-to-end networks), state and action spaces, algorithmic options, deep neural network architectures, exploration-exploitation strategies, and the wide range of use cases and vertical applications are just a few of the important aspects that the analysis takes into account. The use of artificial intelligence, in particular Machine Learning (ML) techniques, has emerged as a potential approach to deal with the complex issues involved in optimizing resource allocation across network slices. To deploy ML-assisted solutions for cross-slice radio resource optimization, this research aims to clarify useful implementation architecture [13]. According to this paradigm, the study also offers a thorough description and assessment of an ML-assisted solution that makes use of a Multi-Agent Reinforcement Learning (MARL) strategy and the Deep Q-Network (DQN) technology. This approach smoothly fits into the suggested implementation architecture and is a potential way to deal with the problems with resource allocation inside network slices.

III. METHODOLOGY

The network slicing architecture (Figure-1) ensures that each user gets an optimized experience based on their specific needs and the characteristics of the applications they are using. By dynamically selecting and allocating slices, the network can adapt to changing demands, optimizing resource utilization and enhancing overall network efficiency. Users benefit from improved quality of service (QoS) tailored to their requirements, resulting in a better overall experience.

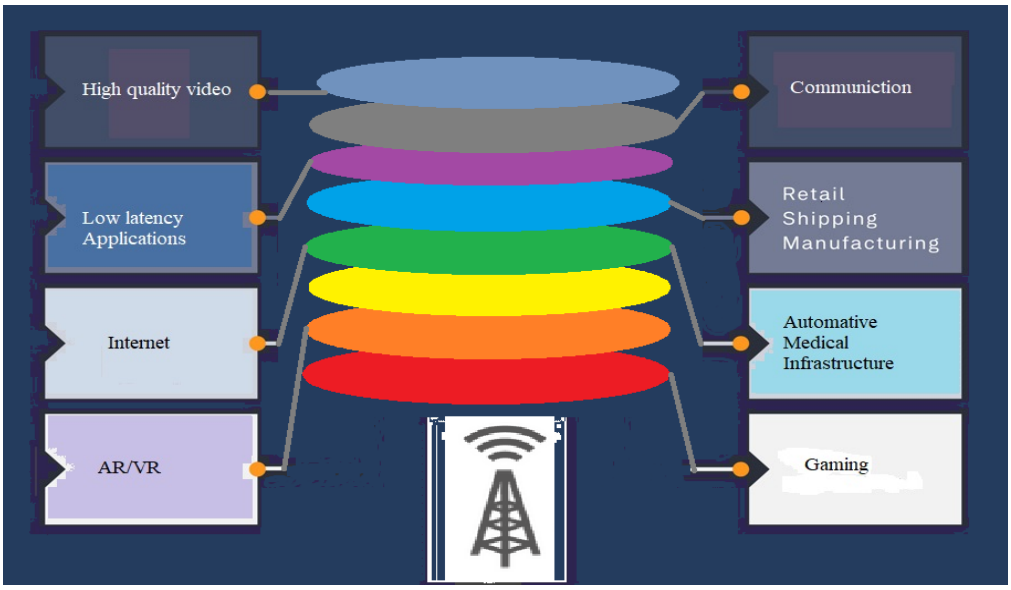

Figure 1. Network Slicing

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The first component of our proposed work focuses on efficient slice creation using the k-prototype clustering algorithm. Network slicing allows the simultaneous existence of multiple virtual networks on a shared infrastructure, each tailored to specific service requirements. To achieve this, we will employ the k-prototype clustering algorithm, an extension of the popular k-means algorithm, which can effectively handle both numerical and categorical features. The process of slice creation will involve the following steps:

A. Slice Creation

In the context of network slicing, ensuring that each user's unique needs are met is paramount. Collecting individualized user requirements is essential for creating tailored network slices that optimize the user experience. Here's how data collection from every user for individual applications can be conducted:

a. Application-Specific Data Collection

For each application, ask users to specify their Bandwidth Requirement (Mbps), Latency Tolerance (ms), Application Type, User Plan, Power Consumption, Security Level, Service level agreements, Data Volume, and QoS. This can be done through a simple interface during the setup process. Store this user-specific information in a network management system for future reference. The effectiveness of such a system relies on both user cooperation and the technical capabilities of the network infrastructure. Ensuring a balance between user preferences and network stability is key to providing a satisfactory user experience. Additionally, ongoing monitoring and adjustments will be necessary to meet changing demands and maintain optimal QoS.

b. K-Prototype Clustering

Clustering using the K-Prototype clustering algorithm can be a valuable step in the process of creating network slices based on application-specific datasets. The K-Prototype algorithm is an extension of the K-Means clustering algorithm that can handle datasets with both numerical and categorical features. In the context of network slice creation, this approach can help identify groups of similar applications or users with shared characteristics, which can inform the design of customized network slices. Here's how clustering with the K-Prototype algorithm can be applied:

- Apply the K-Prototype clustering algorithm to group similar applications based on their characteristics. The algorithm aims to minimize within-cluster variance for numerical features and the dissimilarity for categorical features.
- Defining appropriate distance metrics for numerical and categorical features is more important. For numerical features, Euclidean distance is used. For categorical features, a dissimilarity measure called the matching coefficient is employed.
- Iterate between Assigning Data Points and Updating Cluster Centroids:
  - The K-Prototype clustering algorithm operates iteratively. It alternates between two main steps: assigning data points to clusters and updating the cluster centroids.
  - During each iteration, data points are assigned to the nearest cluster centroid, taking into account both numerical and categorical features. This means that the algorithm considers the overall dissimilarity (distance) between a data point and each cluster centroid, considering the unique characteristics of numerical and categorical attributes.
- Assignment Step: Calculating Total Dissimilarity:
  - In the assignment step, the algorithm calculates the total dissimilarity between each data point and all cluster centroids. This dissimilarity is a measure of how different a data point is from each cluster centroid, taking into account both numerical and categorical features.
  - To calculate the total dissimilarity, the algorithm considers the following:
- For numerical features: It typically uses a distance metric like Euclidean distance to measure dissimilarity. This metric calculates the numerical distance between the data point and the centroid.
- For categorical features: It computes the dissimilarity using a metric appropriate for categorical data, such as matching distance. These metrics measure dissimilarity based on the differences in categorical attribute values.
  - The data point is assigned to the cluster with the lowest total dissimilarity, indicating that it is the most similar to that cluster.
- Update Step: Adjusting Cluster Centroids:
  - In the update step, the algorithm adjusts the cluster centroids based on the data points assigned to each cluster during the assignment step.
  - For numerical features, the algorithm recalculates the mean (average) values of the numerical attributes for all data points in the cluster. This new mean becomes the updated numerical centroid for that cluster.
  - For categorical features, the algorithm determines the mode (most common category) for each categorical attribute within the cluster. The combination of these modes forms the updated categorical centroid for that cluster.
  - The updated centroids represent the center or prototype of each cluster, reflecting the typical characteristics of the data points in that cluster.
- Iterative Process: The algorithm repeats the assignment and update steps iteratively until a convergence criterion is met. Common convergence criteria include a maximum number of iterations or when there is no significant change in the assignments or centroids between consecutive iterations.
- Slice Creation: Once the clustering algorithm has converged, the resulting clusters represent slices. Each data point is assigned to a specific cluster (slice) based on its proximity to the cluster centroid, considering both numerical and categorical features. The clusters define the boundaries and characteristics of the slices, allowing to creation of separate network slices based on the cluster assignments.

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- Slice Deployment: Deploy the customized network slices at the network to serve the applications or users within each cluster.

By applying the K-Prototype clustering algorithm, network operators and service providers can efficiently group applications or users with similar requirements and create customized network slices that enhance the overall network efficiency and the quality of service for different types of applications within a 5G network.

B. Context Aware Slice Selection

The second component of our proposed work focuses on dynamically selecting the most appropriate slice for each user based on their specific requirements and contextual conditions. The context-aware approach will take into account real-time factors, such as user location, network conditions, and application demands, to make informed and adaptive slice selection decisions. The slice selection process will involve the following steps:

C. Slice Selection and Resource Allocation

The algorithm represents a user's context and a list of available network slices as input and selects the most suitable slice for the user based on several matching criteria. The criteria include bandwidth, user plan, user location, and application type. The function calculates a score for each slice based on how well it matches the user's context and selects the slice with the highest score as the recommended slice.

- User-Required Bandwidth: Knowing the bandwidth requirements of individual applications and users enables the network to customize network slices to meet specific demands.
- Application type: A high-definition video streaming application may require more bandwidth than a simple messaging app.
- User Plans: User plans or subscription tiers may dictate the quality of service a user is entitled to. Contextual information about user plans helps in allocating resources and selecting network slices that align with plan-specific QoS expectations.
- User Location: User location refers to the geographical position of a mobile device or user within a network.

Algorithm

```
match_slice (user_context, available_slices)
selected_slice = None
max_score = 0
for slice in available_slices
score = 0
    if user_context [bandwidth] <=
slice[bandwidth_capacity]
      score += 1
    if user_context [user_plan] in slice [supported_plans]
      score += 1
    if user_context[user_location] in slice[coverage_areas]
      score += 1
    if user_context[application_type] in
slice[supported_applications]
      score +=1
    if score > max_score
      max_score = score
      selected_slice = slice
return selected_slice
```

- It initializes selected_slice as None and max_score as 0 to keep track of the best-matching slice and its score.
- It iterates through each available slice in the available_slices list.
- For each slice, it calculates a score based on how well the slice matches the user's context for bandwidth, user plan, user location, and application type.
- The function checks if the user's required bandwidth (user_context[bandwidth]) is less than or equal to the slice's available bandwidth capacity (slice[bandwidth_capacity]). If it is, it increments the score by 1.
- It checks if the user's plan (user_context[user_plan]) is in the list of supported plans for the slice (slice['supported_plans']). If it is, it increments the score by 1.
- It checks if the user's location (user_context[user_location]) is within the coverage areas of the slice (slice['coverage_areas']). If it is, it increments the score by 1.
- It checks if the user's application type (user_context[application_type]) is in the list of supported applications for the slice (slice[supported_applications]). If it is, it increments the score by 1.
- After calculating the score for each slice, it updates the selected_slice with the slice that has the highest score.
- Finally, it returns the selected_slice as the recommended network slice for the user.

The proposed work aims to achieve efficient slice management and selection, resulting in enhanced resource utilization, improved QoS, and an overall better user experience in network slicing environments. The effectiveness of the proposed approaches will be validated through extensive simulations and experiments, comparing their performance against existing methods and demonstrating their superiority in slice creation and selection.

IV. SIMULATION ENVIRONMENT

The work is implemented in NS3 and the parameters are displayed in Table 1. In the pursuit of advancing the understanding and optimization of network slicing in 5G the simulation environment plays a pivotal role in providing a controlled, scalable, and reproducible platform for experimentation and analysis. This section delineates the architecture, components, and key parameters of the simulation environment employed in this research, with a focus on evaluating slice selection accuracy, delay in slice selection, and radio link failure.

Table 1. Simulation Parameters

Parameter	Value
	Small cells
Number of cells	50
Cell radius (m)	100
Cell height (m)	15
Transmit Power (dBm)	26
Simulation area	8×8 km^2
Number of EUs	300
EU height (m)	1.5
Mobility model	Random Waypoint Model
Simulation time (s)	600
EU speed (meter/second)	20,40,60,80,100
Thermal noise density (dbm/Hz)	-174
Noise figure of EU (dB)	9
Time to trigger (ms)	Adaptive

V. PERFORMANCE EVALUATION

Performance evaluation is a critical aspect of any research work, as it provides a quantitative and qualitative assessment of the proposed methodology. In this study, we present an evaluation of our research work, which focuses on K-Prototype-Based Slice Creation and Context-Aware Slice Selection in comparison to existing methods such as CNN (Convolutional Neural Networks) [6] and Deep Q-Learning [8] based slicing techniques. The evaluation aims to demonstrate the effectiveness and superiority of our proposed approach over these established methods.

A. Slice Selection Accuracy

Network slicing is a key concept in 5G and beyond, enabling the creation of isolated virtual networks on a shared physical infrastructure. Slice selection accuracy is a crucial performance metric in network slicing, representing how effectively the network allocates resources and meets the quality of service (QoS) requirements of different slices. High slice selection accuracy ensures that the network delivers the expected QoS to each slice, leading to improved user experiences and efficient resource utilization.

- Formula for Slice Selection Accuracy

Slice Selection Accuracy (%) = (Number of Successfully Allocated Slices / Total Number of Slice Requests) * 100

Number of Successfully Allocated Slices: This represents the count of network slices that were allocated resources and configured to meet their QoS requirements satisfactorily. A "successful allocation" is one where the network resources effectively match the slice's demands.

Total Number of Slice Requests: This is the total count of requests made by users or applications to create network slices. Each request specifies the desired QoS parameters and resource requirements.

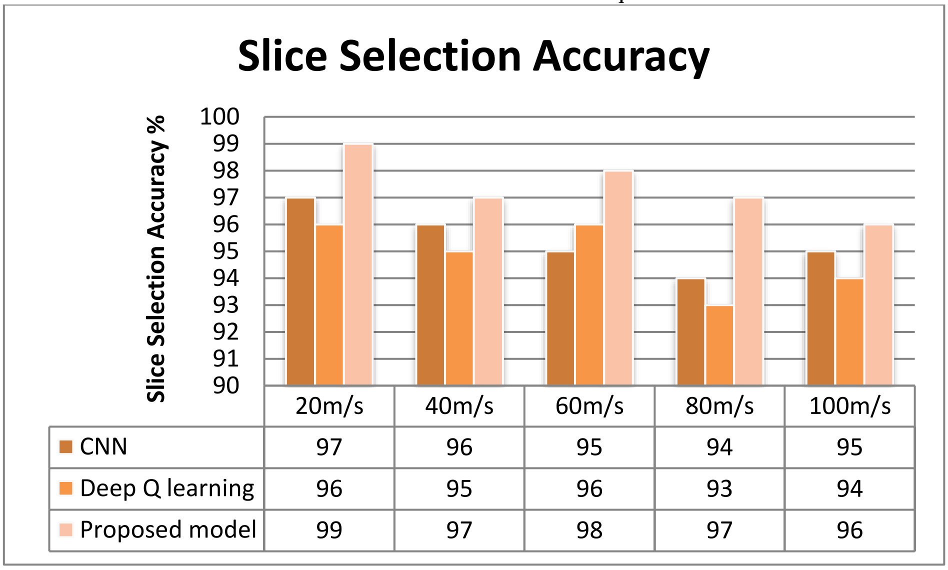

Figure 2. Slice Selection Accuracy

Figure 2 illustrates the efficiency of our proposed approach, which is a critical aspect of evaluating its performance. The results presented in this figure showcase the key advantages and improvements achieved through our research.

B. Slice Selection Delay

In the context of network slicing, "slice selection delay" refers to the time it takes for the network to make decisions and allocate resources to create a new network slice in response to a user or application request. This delay can have a significant impact on the user experience, especially for applications with stringent latency requirements. Reducing delay in slice selection is crucial to ensure the network's responsiveness and the timely provisioning of services within a slice.

- Formula for Slice Selection Delay

Slice Selection Delay = Time of Resource Allocation - Time of Slice Request Time of Resource Allocation: This is the timestamp when the network successfully allocates the required resources, configures the network slice, and makes it operational. Time of Slice Request: This is the timestamp when a user or application initiates a request for a specific network slice, specifying its QoS requirements and resource needs. In Figure 3, we present the results of the Slice Selection Delay under varying scenarios and conditions. These scenarios may include different workload levels and resource availability. The data clearly illustrates how our proposed system handles the dynamic allocation of slices efficiently.

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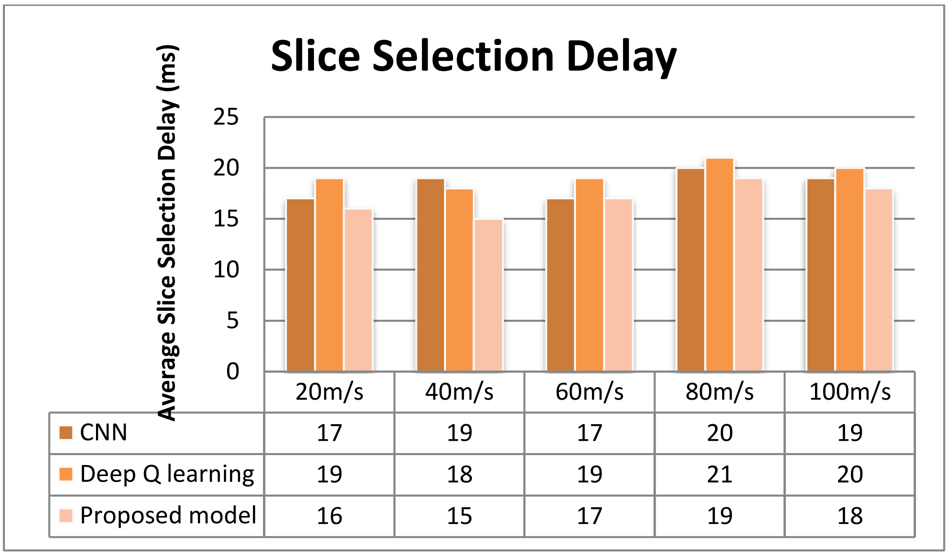

Figure-3. Slice Selection Delay

C. Radio Link Failure

Radio Link Failure (RLF) is a situation in wireless communication when the connection between a user's device and the base station gets disconnected or breaks down. This can happen when the signal strength or quality becomes too weak for the device to maintain a stable connection. RLF can be caused by factors like poor signal reception, interference, moving out of the coverage area, technical problems with the device or equipment, and environmental conditions. It can disrupt calls, data transmission, or internet access. When the signal strength or quality values fall below the thresholds for a specified duration (a certain number of consecutive measurements), that will be considered as an RLF event for that user in the simulation.

- Formula for RLF

RLF = Number of RLF / Number of Users

Number of RLF: This is the count of Radio Link Failure events that have occurred within a measurement period.

Number of Users: This is the total count of users or devices being considered during the same time frame.

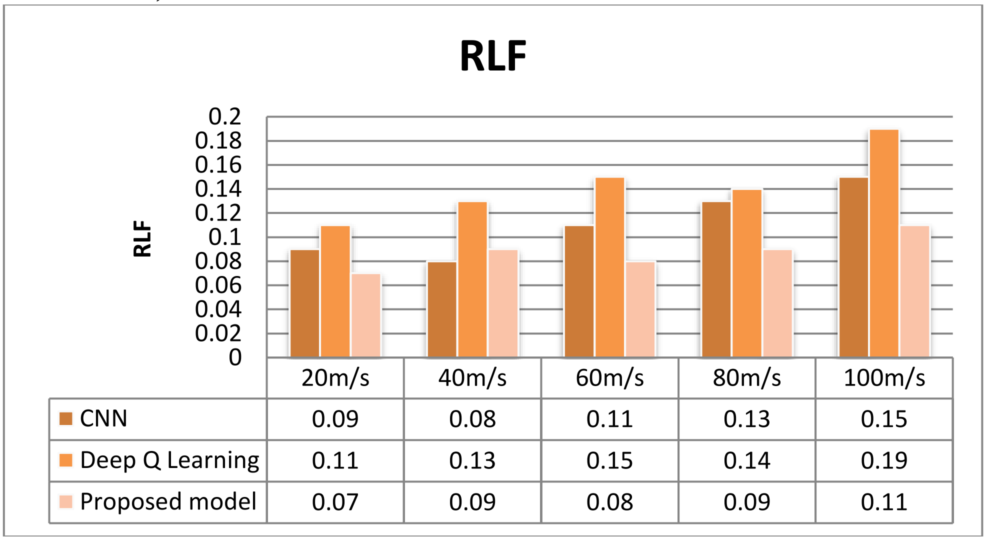

Figure 4. Radio Link Failure

In Figure 4, we depict the occurrences of RLF over time across different network conditions. These failures can result from various factors such as signal interference, network congestion, or hardware issues. The evaluation of Radio Link Failure is pivotal in understanding the system's ability to maintain stable and uninterrupted communication.

VI. CONCLUSION

In conclusion, this research work has explored the innovative approach of slice creation using K-Prototype clustering and slice selection aided by context-aware information in the context of 5G and beyond networks. The primary objective of this study was to enhance the efficiency and reliability of network slicing, addressing critical performance metrics such as slice selection accuracy, slice selection delay, and radio link failure. Through a comprehensive analysis and experimentation, it is evident that the proposed methodology offers several significant advantages. The use of K-Prototype clustering facilitates the creation of network slices that are tailored to the specific needs of diverse applications and services. This empowers network operators to allocate network resources more effectively and efficiently, thereby improving the overall network performance.

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The incorporation of context-aware information in the slice selection process adds another layer of intelligence to network management. By considering real-time context information the system can make more informed decisions when selecting slices. This leads to the highest slice selection accuracy and a reduction in the delay associated with slice selection, ensuring that the network can quickly adapt to changing demands. Furthermore, the research also addressed the critical issue of radio link failure. By optimizing slice creation and selection, the system can mitigate the risk of radio link failures and improve the overall robustness of the network.

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Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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