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RESEARCH ARTICLE

An LSTM-Based Network Slicing Classification Future Predictive Framework for Optimized Resource Allocation in C-V2X

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ABSTRACT With the advent of 5G communication networks, many novel areas of research have emerged and the spectrum of communicating objects has been diversified. Network Function Virtualization (NFV), and Software Defined Networking (SDN), are the two broader areas that are tremendously being explored to optimize the network performance parameters. Cellular Vehicle-to-Everything (C-V2X) is one such example of where end-to-end communication is developed with the aid of intervening network slices. Adoption of these technologies enables a shift towards Ultra-Reliable Low-Latency Communication (URLLC) across various domains including autonomous vehicles that demand a hundred percent Quality of Service (QoS) and extremely low latency rates. Due to the limitation of resources to ensure such communication requirements, telecom operators are profoundly researching software solutions for network resource allocation optimally. The concept of Network Slicing (NS) emerged from such end-to-end network resource allocation where connecting devices are routed toward the suitable resources to meet their requirements. Nevertheless, the bias, in terms of finding the best slice, observed in the network slices renders a non-optimal distribution of resources. To cater to such issues, a Deep Learning approach has been developed in this paper. The incoming traffic has been allocated network slices based on data-driven decisions as well as predictive network analysis for the future. A Long Short Term Memory (LSTM) time series prediction approach has been adopted that renders optimal resource utilization, lower latency rates, and high reliability across the network. The model will further ensure packet prioritization and will retain resource margin for crucial ones.

INDEX TERMS Cellular vehicles to everything (C-V2X), deep learning, latency, long short term memory (LSTM), machine learning, network slicing, optimization, reliability.

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I. INTRODUCTION

In the modern era of the Internet of Things, the spectrum of communication between objects is being diversified at a rapid pace. This mobility era has witnessed an increase in communication demands manifolds along with emerging requirements for high reliability and low latency rates. Vehicle to Everything (V2X) [1], [2], [3] is a relatively new rising concept that is seen as an important contour of making autonomous vehicles ubiquitous and also making the conditions of traffic more secure. Such a mode involves the establishment of communication between vehicles, pedestrians, road infrastructure, and other ad-hoc networks. To cater to such rising demands of communication where objects communicate with each other, an increase in network resources is becoming inevitable. The reliance on vehicular sensors or Direct Short Range Communication (DSRC) [4], [5] alone is insufficient for automated mobility where vehicles can work autonomously with the driver's intervention. The inclusion of cellular bands and technologies is essential to maintain perceptibility and enhanced capacity for staying abreast of the surroundings and ensuring highly secure maneuvering. This renders a non-line of sight cooperative driving and accurately detect the presence of objects in the surroundings. However, to ensure these factors, the limited recourses of the cellular networks are causing many challenges especially in terms of network resource allocation while keeping the latency low and higher reliability [6].

Software Defined Networking (SDN) has been seen as a key enabling technology in 5G communication networks [7]. Centralized resource management enables the division of network resources in an optimized manner while also ensuring accurate network monitoring and control. Some of the Key Performance Indicators (KPIs) ensure that the network conditions are kept at par with the service level agreements developed with the connecting objects. Nevertheless, the traditional approach involved in such networks makes use of the network address information in the form of IP and leads to the involvement of large overheads which renders poor dynamics, especially during the instances of URLLC requirements [8]. Thus, there is a need for a focus shift toward advanced tools having lower reliance on such overheads and instead allocating resources directly based on demand and network conditions.

Cellular Vehicle to Everything (C-V2X) is a pivotal and modern communication technology that allows vehicles to interact with each other as well as the infrastructure by leveraging the existing 4G or 5G network resources [1]. In this context, it is imperative to adopt mechanisms for efficient resource allocation. This is because the transmission of data in a real-time and reliable manner is essential to allow collision avoidance between vehicles. Stringent QoS shall be maintained to guarantee reliable data transmission to allow network congestion management under dense urban environments. Efficient resource allocation helps prevent the network from going into saturation and allows communication in a reliable manner. Therefore, scalability and spectrum efficiency are of paramount importance, which help accommodate the growing number of vehicles [9]. Finally, it plays a critical role in realizing the full potential of C-V2X for intelligent transportation systems and automated driving.

Under the influence of such costs and least optimized performance resources, a focus has been steered toward the network slicing concepts along with the inclusion of Machine Learning [10], [11], [12]. The higher heterogeneity of the service requirements including the enhanced mobile broadband (eMBB), massive Machine Type Communication (mMTC), and URLLC [13], [14] has all been made part of C-V2X as well to meet various service demands including higher packet delivery rate, lower retransmission requirements, and bandwidth allocation, etc. These differ in the data rate requirements, capacity, latency rates, and QoS. The vehicular communication following this approach reaches the 5G networks through different devices including smartphones, and Internet of Things (IoT) sensing devices to exchange packets of information ranging from being less critical to more. Thus, the one-size-fits-all architecture that is generally employed in LTE communication does not meet such diverse requirements set and a focus is on the segmentation of network elements into slices [14]. Instead of relying on address-centered division, the increased focus is on the dynamic slice allocation with the aid of Machine Learning tools, where resources for the slices are allocated depending upon the specific context or network conditions in general. Such tools are trained with large datasets representing the network conditions and correct sets of decisions and are later used for making predictions on the incoming sets of requests. For instance, based on the Packet Delivery Ratio (PDR) requirements, a suitable slice is allocated to the device based on the ML predictive analysis framework.

Although Machine Learning serves as the right tool for making predictive analyses on slice types, however, bias control remains an important consideration. In networks, objects demanding a singular slice category likely render overload in a certain area of the network while leaving poor utilization of other more optimized resources available. The use of ML for slice allocation ignores this factor and relies on the trained set of conditions for resource allocation. Thus, a need for predictive analysis of future network conditions emerges to re-route the traffic toward another set of slices and retain overall high-performing networks.

This study focuses on the employment of Artificial Neural Networks (ANN) and LSTM Deep learning models for making predictive and future analyses of the network conditions. In the existing ML-based network slicing, the algorithms focus on the existing network conditions to create slices [10], [15], [16], [17]. However, the models only make predictions based on the provided feature sets (bandwidth required by a particular application, etc.). Nevertheless, certain trends do exist in traffic conditions depending on the day and time of the day. This type of data can be predicted by an LSTM model in advance and thus optimize the network resources. For instance, URLLC network slices are the most reliable with low Packet Delay Budget (PDB). Therefore, if vacant slots are expected to remain available in a given timeframe, the application requested can be diverted toward it safely.

The model focuses on (1) making a predictive analysis of selecting the right network slice based on the service request requirements (2) analyzing the current network conditions and future predictive analysis using LSTM to analyze slice load conditions (3) rerouting traffic towards more optimized slices without depriving the existing network requests intended solely for those slices. The overall impact of this study will be the enhancement of reliability and latency conditions of networks and keeping the utilization at a better ratio.

The proposed Deep Learning model focuses primarily on predicting network conditions based on two key input features: the type of network slice (URLLC, mMTC, eMBB) and the anticipated number of devices that will demand these slices in the future. This approach allows the model to make predictions regarding resource allocation and network optimization by taking into account the critical factors of slice type and expected demand. By analyzing historical data and learning from patterns, the model can offer valuable insights into how to efficiently allocate resources, such as bandwidth and latency, to meet the forecasted demands of different network slices. While this approach simplifies the input features, it lays the foundation for optimizing network performance and improving the QoS for specific use cases.

This framework's applications and benefits in real-world scenarios include enhancing C-V2X communication. The model proposed as part of this simulation framework holds potential application in real-world scenarios. In the context of 5G networks and beyond, the model can serve as an enabler to optimize traffic management, cost-efficiency, and dynamic resource allocations based on the predicted demands. This can help reduce the latency rates, and packet loss rate, and improve the reliability of the network. Such adoptions make it well-suited for various sectors like transportation, healthcare, smart cities, industrial automation, etc. Such functionalities will help explore the full potential of the 5G networks. Thus creating a more sustainable and environmentally friendly C-V2X network infrastructure.

In Section II of this article, the theoretical framework of LSTM and ANN has been provided, Section III focuses on the model proposed for this study. Section IV focuses on the research findings and analysis. Section V concludes the work by providing future directions.

II. RELATED WORK

To fully realize the methodology and techniques that can be employed for network slicing in C-V2X communication, various research articles from 5G and beyond have been explored targeting similar scenarios. Reference [15] focuses on the abstraction of network resources to render virtual slices with the aid of SDN and Network Functional Virtualization (NFV) concepts. A theoretical framework leading toward high-speed communication has been developed under this frame of reference. Reference [16] makes virtualization in the network slicing using machine learning tools in a smart seaport environment. Although these articles serve as a good model for the employment of ML, however, the scope of the study is limited to the environment they have been tested. Reference [10] steps ahead by proposing deep learning tools for the accurate classification of an incoming request and allocation of the correct network slice as mMTC, eMBB, or URLLC. The predictions are based on the service requirements including the packet delay response and loss rate. The more effectively predicts the right slice for the network, however, does not incorporate a future network conditional prospect and thus can be subject to limitations. Reference [17] devises the network slicing techniques based on the operational managem-ent, control management, and constructional management. Later a set of machine learning operations are applied to infer useful characteristics and classifications. A comprehensive review of intelligent network slicing techniques has been made in [3].

Having established some of the relevant approaches adopted in the 5G network slicing in general, these approaches can find they are based on CV2X communication as well. Reference [18] considers the end-to-end approach in vehicular communication across various applications and develops a resource-centric framework for slicing. Reference [19] establishes a virtualized framework for network slicing in Vehicular ad hoc networks (VANETs) by considering a guaranteed QoS framework. Reference [20] provides an elaborate view of various machine learning and AI techniques that can be employed in VANETs across various domains of applications and performance architectures. For instance, the network requirements for infotainment and security applications, etc. Reference [21] provide the general requirements for SDN and virtualization in VANETs in the context of LTE, 5G, and beyond. In article [22], the concept of cross-network slicing has been introduced which somehow serves as a base framework for the idea proposed in this model. The cross-framing has been proposed in the domains of the internet of vehicles.

The spectrum of machine learning in the domain of V2X is diverse and many problems have been addressed through it. Although this paper focuses on network slicing and resource allocation, however, some other mediums of ML and their convergence toward the slicing problem can be found and made. For instance, [23] provides a novel terminology based on machine learning to serve multi-hop searching and enhanced reachability in the domain of CV2X and DSRC. The framework proposed loosely relates to the Channel State Information or Network Slices future predictive analysis. Reference [24] adopts another view of predicting QoS based on the traffic and other conditions in the network using machine learning. This article directly can relate to the proposed frame of work where future classification and object request predictions have been made.

Before delving into the actual details of the proposed design parameters, the use of LSTM and its applicability to the current model shall be explored. Across the various uses of this novel deep learning unsupervised scheme including the autocorrelation for anomaly detection or time series predictive analysis. Although the spectrum is highly diverse including the stock exchange predictive analysis or indoor localization [25], etc. this method can directly be employed for the current problem under review.

Article [26] proposes a deep learning network slicing based on the dataset using the data generated for a week where 7-8 different devices send communication requests and are allocated network slices based on the predictive settings using ANN. The study further makes use of a main slice to avoid network disbalance and congestion of slices. However, the consideration of network optimization has been ignored. The slices having lower connection requests can be configured for the devices biased towards a single type, thus the overall network conditions can be optimized. However, this demands a future predictive approach to stay abreast of the expected network conditions to keep the overall approach pragmatic. This work is a direct continuation of the said model using the same dataset and making network-level enhancements that will be rendered suitable for CV2X and 5G in general.

III. PROPOSED SYSTEM MODEL

The model under consideration is based on future predictions and classification norms. Artificial Neural Networks have been employed to make predictions on the network slice classification (eMBB, mMTC, or URLLC) based on the service requirement request demand, while a future predictive model based on LSTM keeps analyzing the upcoming network conditions, slice utilization, and thus overall network optimization by rerouting traffic towards the underutilized nodes.

The frequency of this learning process can be adapted to the specific operational needs of the network. Typically, the learning phase will occur periodically or based on the arrival of new data, depending on the network's dynamic nature and requirements. The system that feeds data to the model is part of the network's infrastructure for data collection and analytics. It collects historical network performance data, including traffic patterns, latency, packet loss rates, and other relevant metrics. This data is then preprocessed and used to train the LSTM model. Additionally, the model can receive real-time input data to make predictions for future demands. This system operates at both the network and operational levels. At the network level, the model is deemed to be integrated into the core network infrastructure and works with network performance data to make predictions for resource allocation. It helps optimize network resources based on predicted demand, improving overall network conditions. At the operational level, the model provides insights and recommendations to network administrators and operators. It guides resource allocation decisions, such as rerouting traffic from lower-resource slices (e.g., mMTC) to higher-resource slices (e.g., URLLC) during periods of low predicted demand. This operational aspect allows for real-time adjustments to optimize network performance.

A. DATASET

The dataset employed in this study has been taken from [27] and offers a comprehensive insight into the QoS within cellular networks, encompassing LTE and 5G technologies, across a wide array of use cases. The dataset comprises several crucial input features and an output feature that collectively shed light on network performance, reliability, and latency characteristics across diverse scenarios. These input features encompass the type of use case or application, LTE/5G User Equipment (UE) categories, supported cellular technologies, days of the week, times of data collection, and the differentiation between Guaranteed Bit Rate (GBR) and non-GBR services. Moreover, the dataset captures essential metrics for assessing network reliability, such as Packet Loss Rate (PLR), as well as latency metrics, notably the Packet Delay Budget (PDB), specifying acceptable latency thresholds in milliseconds. The output feature denotes the network slice type corresponding to each use case, with categories encompassing Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communic-ation (URLLC), and Massive Machine Type Communication (mMTC). This dataset proves invaluable for the evaluation and optimization of cellular network performance, especially in the context of diverse use cases and their specific QoS requirements.

TABLE 1. Dataset features and description.

Feature	Description	Example
Use Case Type	Application category	AR/VR/Gaming, Healthcar Industry 4.0, IoT Device Public Safety/E911, Smart Ci & Home, Smart Transportation
LTE/5G UE Category	UE category	-
Technology Supported	Cellular technology	LTE, 5G
Day	Day of the week for data collection	Monday to Sunday
Time	The time interval for data collection	24 Hours
PLR	Packet loss rate	0.001, 0.000001
PDB	Packet delay budget	50ms, 100ms, 10ms, 300ms
Slice Type	Network slice type	eMBB, URLLC, mMTC
GBR	Guaranteed Bit Rate (GBR) or non-GBR service	-
QCI	Quality of Service Class Identifier	-

B. CLASSIFICATION FRAMEWORK

The classification of network frames is based on the service requirement requests that involve the use of the QoS class, Packet delay budget, and PLR. The models take the data as the input at a given time frame and render two parallel operations: future predictive analysis to predict upcoming network conditions and predictive load on slices, and the classification of the incoming request into the desired slice class. The sampling rate of the rata is recorded at approximately 338 requests per second, and the LSTM model has been trained to predict the upcoming 10,000 requests which constitute around 30 seconds of data. The slice classification has been based on the similar norms presented in this dataset and reference article [26], however, the use of the main slice has been discarded and all routing is based on the network conditions and load preferences.

The network requirements along the individual slices and incoming data requests have been taken from Table 2 in [26]. The allocation is based on the PLR, PDB, and QoS class and category of the device. Devices mimic the general spectrum of 5G communication devices, however, also serve as founding blocks in V2X communication for different services including infotainment, security data exchange, etc. The proposed scheme and network architecture have been illustrated in Figure 1.

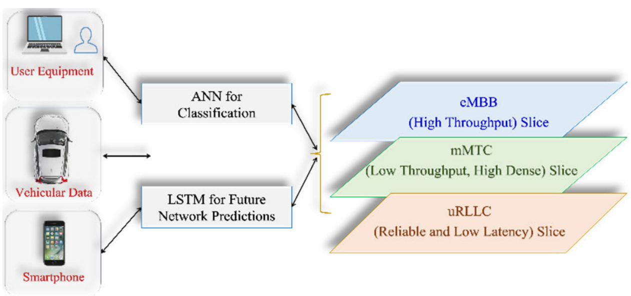

FIGURE 1. Network Slice Allocation based on Proposed Scheme.

The algorithm of the underlying approach is given as follows:

Algorithm 1 Predictive and Classification Analysis for Slicing and Network Optimization

Inputs: User Request Equipment, PDB, PLR, QCI, Slice, D (data)

Outputs: Network Slice Allocation

Process Starts:

Learning Phase

D ← train_test_split()
train_ANN (D)
train_LSTM ← linear split(), loss_func, learning_rate
model_fit ← validation_loss(), training_loss()
make_predictions()

Prediction Phase

Incoming Request()
ANN_predict()
LSTM_predict() → 30 seconds future predictions
Analysis of slice congestion level
Allocation and Reallocation of network slices

Network Efficiency Measures

Network Latency Rate
Network Reliability Comparison

Thus, the overall efficacy of the model has been illustrated in the form of network performance measures including the impact on latency rate, and the reliability enhancements during the processing of the packets.

The algorithm presented above entails two main parts. The first part involves predictive modeling of the network to analyze the future demands of the slice type. This can mathematically be modeled as:

$$D_{i,t+1} = f(Sl_i, H_i(t)) \tag{1}$$

Here $D_{i,t+1}$ represents the depicted demand for the network slice i at time $t+1, f$ is the deep learning model that predicts the future demands based on the slice type Sl and historical data $H_i(t)$.

The second aspect is resource allocation, where network resources like bandwidth, PLR, etc. associated with each slice are allocated based on the predictive demands. This has been modeled as below:

$$R_i(t+1) = \frac{D_{i,t+1}}{\sum_{i=1}^{N} D_{i,t+1}}.QoS_i.R_T(i+1) \tag{2}$$

Here $R_i(t+1)$ represents the resource allocation for the network slice i at time t+1. QoS_i represents the quality of service associated with slice i that influences the resource allocation, and R_T represents the total resources available.

The system level and data parameters adopted in this study are provided in Table 2.

TABLE 2. The simulation and dataset parameters.

Input Application	Technology	PLR	PDB (ms)
Smartphones	LTE/5G	Up to 10-2	Up to 300
IoT Sensors	IoT	10-2	Up to 300
Autonomous Vehicles	LTE/5G	10-6	10
Industry 4.0	LTE/5G	Up to 10-3	Up to 50
Healthcare	LTE/5G or IoT	10-6	10
Public Safety / E911	LTE/5G	10-6	10
Smarty Homes	LTE/5G or IoT	10-2	Up to 300

The architecture of the LSTM model employed in this study is designed for predictive purposes, specifically to forecast the future requirements of users for a particular network slice (URLLC, mMTC, eMBB) based on historical time series data. The model begins by preparing the training and testing datasets, to specify the number of past and future time steps considered in the prediction. The input layer implicitly takes sequences of historical data, with each sequence consisting of a certain number of past time steps and a single input feature, representing the type of network slice transformed into integer values. The model then comprises two LSTM layers, with the first having 64 units and the second having 32 units, both employing the 'relu' activation function. The first LSTM layer returns sequences as output, capturing temporal dependencies in the data, while the second LSTM layer produces a fixed-length output. To prevent overfitting, a dropout layer with a 0.2 dropout rate is introduced after the second LSTM layer. The model concludes with a dense output layer, which predicts a single integer value corresponding to one of the network slice types (e.g., 0 for eMBB, 1 for URLLC, and 2 for mMTC) for each input sequence, making it suitable for multi-class classification tasks. During training, the model minimizes the Mean

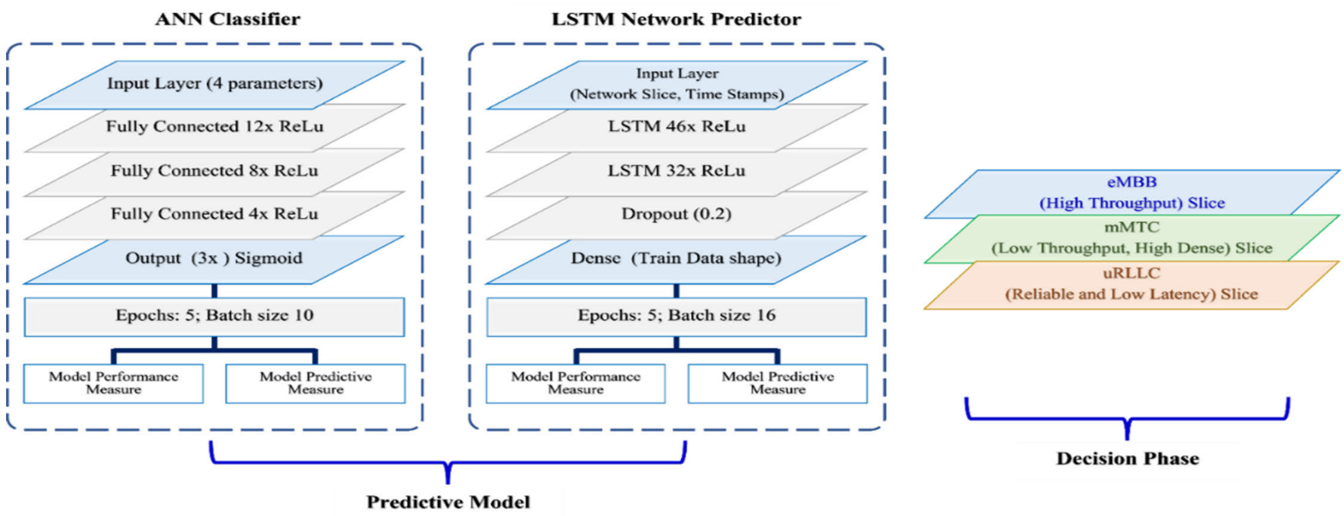

FIGURE 2. Network architecture of the proposed network slicing and predictive model.

Squared Error loss using the Adam optimizer. This architecture enables the model to learn from historical data and provide predictive information, facilitating resource reallocation decisions in the context of network management. By doing so, it empowers real-time optimization of resource allocation, ultimately improving the efficiency and performance of C-V2X communication networks. This architecture enables the model to learn from historical data and provide predictive information, facilitating resource reallocation decisions in the context of network management.

The LSTM model has been trained on 95 percent of the data while considering 30 past values and a single value for future validation during the training phase. Additionally, a further split of 10 percent has been made as validation incorporation. The details of model accuracy rates and suitability have been made part of the results section. The overall architecture that has been developed for both ANN and LSTM has been presented in Figure 2.

Within the context of 5G networks and the predictive system's role in re-routing, it's essential to elucidate several critical facets regarding identifier reassignment and re-routing strategies. In cases where devices rely on a 5G system employing identifiers such as Service Set Type (SST) and Service Data (SD), the process of reassigning identifiers to users is deemed to be facilitated through the network's control and management mechanisms. These mechanisms entail mapping user-profiles and their specific requirements to the relevant SST/SD identifiers. As for re-routing, it can occur between slices of the same type or between slices exhibiting compatibility in terms of characteristics and resource availability. The precise re-routing strategy hinges on network policies and optimization objectives; for example, if the anticipated demand for a lower-priority slice, such as mMTC, is low, the traffic can be redirected to a higher-priority slice like URLLC or eMBB, provided they share compatible attributes. Furthermore, the re-routing process is adaptable to both slices employing the 5G identifier system and internal slices managed by the network operator. Internal slices, which may not directly use the 5G identifier system, could be tailored to operator-specific services or optimization strategies. Thus, the re-routing decisions encompass both internal and standard 5G slices, contingent on the network's design and optimization objectives.

IV. RESULTS

This section illustrated the results generated across various stages of the model development and an overall impact on the network conditions.

A. SLICE CLASSIFICATION USING ANN

Slice classification using ANN has been performed by training a neural network having 3 dense layers to intrigue into the feature set of the network slicing data. The train and test datasets have been generated to identify the accuracy of the model which is found to be highly accurate as depicted in Table 3. The model fits perfectly with the data while bringing in a significant reduction in both the validation loss (10 percent of the training data) and training loss. 04 different performance metrics have been selected namely Precision, Recall, Accuracy, and F1 Score. Additionally, a confusion matrix has been generated to identify the probability of true and false predictive measures. The training accuracy and loss model for both Validation and Training sets has been depicted in Figures 3, and 4, respectively.

B. SLICE PREDICTIONS USING LSTM

Long Short-Term Memory (LSTM) has been trained on 95 percent of the dataset by tuning the past and future predictive parameters. The model has been trained on 30 past values constituting 0.625 seconds. The model performs an unsupervi-sed run on the complete training dataset and accuracy has been determined in terms of Training Loss,

TABLE 3. Accuracy parameters and performance metrics.

Parameter	Value
Training Accuracy	1.0
Validation Accuracy	1.0
Training Loss	0.000033
Validation Loss	0.0000078
Precision	1.0
Recall	1.0
Accuracy	1.0
F1 Score	1.0

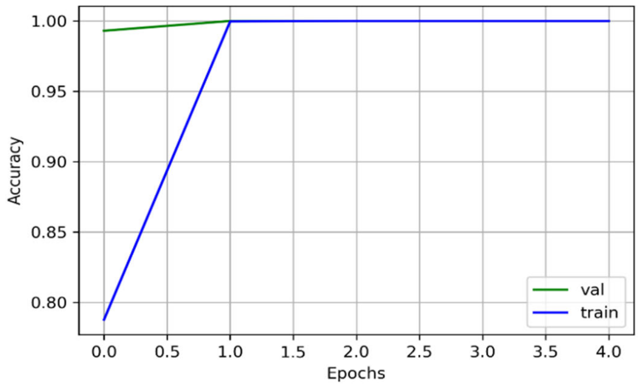

FIGURE 3. Training and validation accuracy of the ANN on deep slicing dataset.

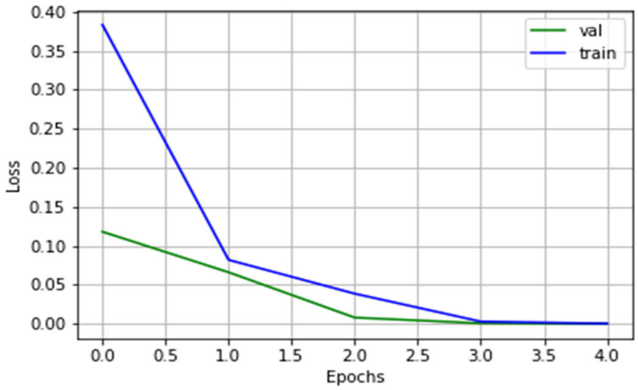

FIGURE 4. Training and validation loss of the ANN on deep slicing dataset.

Validation Loss during the epoch run. The test dataset is passed through a similar shaping model and is predicted using the trained model set. Similar performance metrics have been used as proposed in the case of ANN and their respective values are depicted in Table4.

TABLE 4. LSTM performance parameters.

Parameter	Value
Training Loss	0.0052
Validation Loss	0.0017
Precision	0.997
Recall	0.997
Accuracy	0.997
F1 Score	0.997

The model runs on 24,940 training parameters and predictive results are computed on 24 hours of data. The predictive class has been compared with the original class where numerical mapping has been made as follows:

TABLE 5. Integer mapping on network slicing class.

Slice	Map	Slice	Map	Slice	Map
URLLC	0	eMBB	1	mMTC	2

In Figure 5, the predictive results based on the LSTM model have been presented. The two lines reveal the original and predicted network slices against a chuck of time samples taken across the training dataset. A small bias of 0.1 has been added in the predicted class for ease of visualization. The model is found to accurately predict the future data network topology that has mainly been employed in this study to enhance the latency and reliability figures across the entire network.

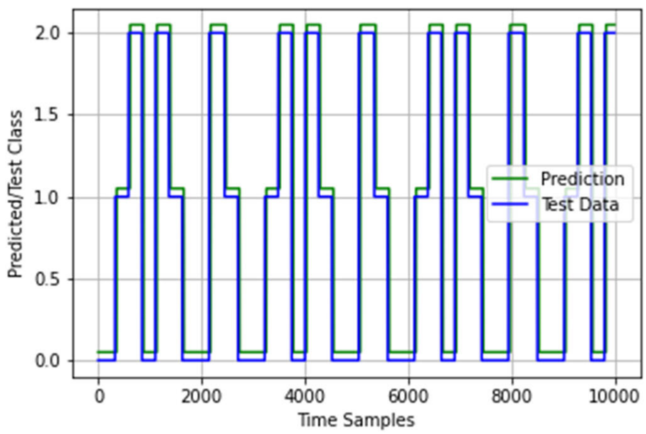

FIGURE 5. LSTM network slicing predictive results.

C. REALLOCATION OF NETWORK SLICES

The model involves predictive analysis for the set of network slices across the 24-hour chunk of data and analysis of the bias and available capacity across them. Based on the PDB, and PLR figure, slices have been ranked as URLLC > eMBB > mMTC, and ideally, when URLLC is vacant, most of the traffic shall be diverted towards this slice. This differs from a standard statistical or Bayesian model where predictions are made on a static set of conditions, while LSTM ensures future predictions using a data-centric approach that leaves less space for error predictabilities.

Mathematically, the factor of available capacity has been found, and based on that relevant traffic is diverted toward the higher slice. This has been modeled as below:

$$C_{NS_i} = \frac{\left(\sum_{t=1}^{T} C - L_t\right)}{T} \tag{3}$$

where i refers to the classes of network slices (0, 1, 2 in the present case), C depicts the total capacity of a network slice and is assumed to equal requests per minute to avoid congestion cases. L_t refers to the capacity occupancy in the given case that is computed across the given frame of reference. T is the total frame of time considered for the remapping process. The average factor across each slice i is multiplied by the fleeting capacity of the network slice to compute the new network factors including latency and reliability.

The concept of rerouting the packet requests across the network slices involves the allocation of packets using ANN and then routing some of the packets based on the capacity variable.

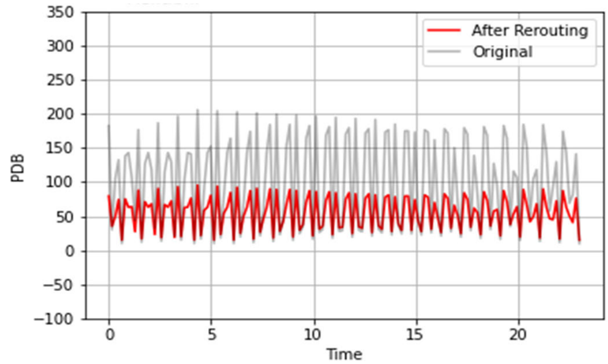

FIGURE 6. PDB reduction in the network slicing based on LSTM predictions and rerouting.

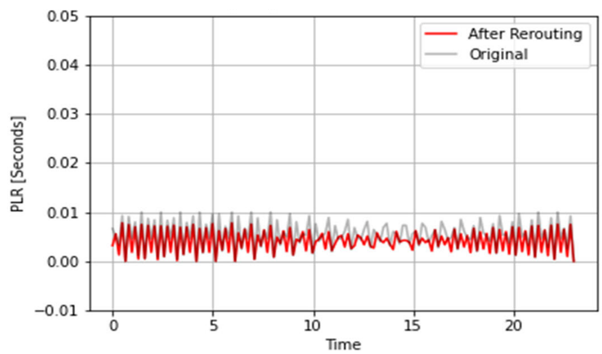

FIGURE 7. PLR in the network slicing based on LSTM predictions and rerouting.

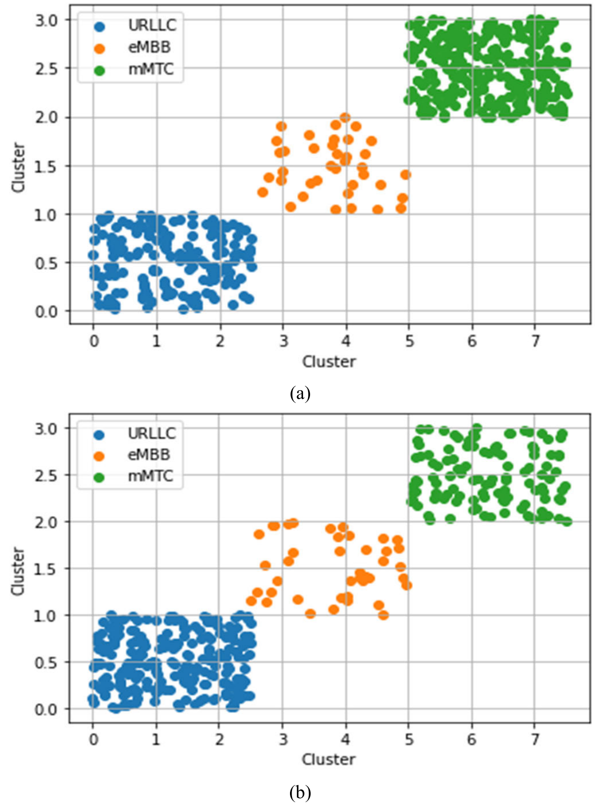

FIGURE 8. Network slices traffic conditions. a. Before rerouting. b. After rerouting.

D. EFFECTS ON NETWORK LATENCY CONDITIONS

The existing ANN model involves a standard set of rules based on which the PDB is settled and packets are transmitted. For example, a standard request coming from a smartphone under a given QCI is directly mapped to the eMBB slice where the PLR is kept close to 0.01 while packet delay is controlled to be less than 50 ms. However, the dynamics of the network are not incorporated into this while better resources are available and can be fairly assigned. In the above capacity model, the LSTM can infer this flexibility and make the network keep using higher resources until the capacity levels have been met. This renders better performance observation from the rerouted packets and the overall impact on the network-level performance can be analyzed.

As illustrated in Figure 6, the PDB constraints under standard predictive conditions are high. The average values recorded without incorporating the rerouting algorithm are found to be 102.26 ms, while the value falls at 55.23 ms after the application of the capacity factor. This is a tremendous improvement in the network conditions, especially in the context of CV2X. When the vehicles are moving at a high speed, re-transmissions and connectivity are required frequently and even those applications requiring less reliable conditions suffer from this factor. Utilization of the available source using these network parametrizations aids in the enhancement of the CV2X network conditions in general while ensuring the provision of URLLC frames to critical applications including autonomous driving.

E. EFFECTS ON NETWORK RELIABILITY CONDITIONS

The traditional approach employed in the previous studies involves slice allocation based on reliability thresholding. The under requests demanding a reliability factor of 0.01 are allocated to the relevant slices without consideration of the better slice availability. This renders non-optimized network conditions similar to the case of network latency conditions. To cater to this effect, similar modeling has been performed based on the LSTM approach. The incoming requests are facilitated to higher network slices where enhanced reliability can be met. This effect has been illustrated in Figure 7. The average threshold value becomes 0.0040 compared to 0.0054 observed in the non-routing case.

Better to analyze the results based on ratio format, Ex: Our proposed model reduces the End-End delay by 3% compared to the traditional method (better to name the method, traditional is not the accurate way in general).

F. EFFECTS ON NETWORK SLICES AFTER REROUTING

Since the method resides on the rerouting of some of the traffic towards URLLC and eMBB the reliability is higher and packet delay rates are lower. The effect of these conditions for one such network instance has been elaborated in Figure 7. Figure 8 (a) depicts the network conditions before rerouting took place, and Figure 8 (b) provides the network conditions after rerouting has been performed. It can be analyzed that URLLC and eMBB after rerouting become denser, while the mMTC becomes less dense.

V. CONCLUSION

The study involves the incorporation of deep learning models for the segmentation of the network into slices thus rendering accurate resource allocation. A provision LSTM for future predictive modeling has been incorporated that makes data-driven decisions to project future network conditions and performs slice-request rerouting based on that. The study served to enhance two performance parameters of C-V2X and 5G networks in general: Latency and Reliability. Without changing and altering the network conditions and infrastructure requirements, an overall positive trend has been analyzed and the network becomes more optimized. It has been found that the average packet delay rate across the network reduces to 55.23 ms instead of 102.26 ms. Also, the packet loss rate has been lowered to 0.0040 from the 0.0054 threshold value.

In the future, a similar predictive model based on LSTM can be used to cater to various attacks that cause the network to move into congestion. By employing the adopted LSTM approach towards an autoencoder mode, the network can make predictive analysis for attach detection and could route those attacks to a virtual node without affecting the existing network topology.

Additionally, the Deep Learning model's predictive capabilities can be enhanced by incorporating additional features and considerations. These include considering the specific application types or services running on network slices, accounting for different communication protocols used by devices, analyzing device characteristics such as category and mobility patterns, assessing the network's physical and logical topology for factors like congestion and routing, integrating service-level agreements (SLAs) to align with predefined quality commitments, and utilizing real-time data streams for dynamic predictions and rapid adjustments. These expanded features would enable the model to offer more context-aware, granular predictions, leading to improved network optimization and resource allocation strategies. This comprehensive approach would result in a more robust solution for enhancing network conditions and QOS in 5G networks.

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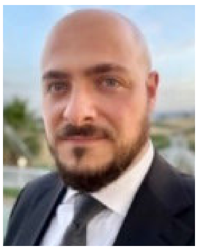

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