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RLIS: Resource Limited Improved Security Beyond Fifth-Generation Networks Using Deep Learning Algorithms

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ABSTRACT This study explores the feasibility of allocating finite resources beyond fifth generation networks for extended reality applications through the implementation of enhanced security measures via offloading analysis (RLIS). The quantification of resources is facilitated through the utilization of parameters, namely energy, capacity, and power, which are equipped with proximity constraints. These constraints are then integrated with activation functions in both multilayer perceptron and long short term memory models. Furthermore, the system model has been developed using vision-based computing, which involves managing data queues in terms of waiting periods to minimize congestion for data transmission with limited resources. The major significance of the proposed method is to utilize allocated spectrums for future generation networks by allocating necessary resources and therefore high usage of resources by all users can be avoided. In addition the advantage of the proposed method is secure the networks that operate beyond 5G where more number of users will try to share the allocated resources that needs to be provided with high security conditions.

INDEX TERMS Deep learning algorithm, extended reality applications, fifth generation networks, limited resource, visual systems.

I. INTRODUCTION

The contemporary communication network comprises a network of interconnected servers, clients, switches, routers, and other components, which operate in a loop by allocating suitable resources. The allocation of appropriate resources can be a challenging task when operating communication networks on a large scale. Consequently, it is imperative to verify the quantity of assigned resources, encompassing bandwidth, energy, power, and capacity, for all communication networks. It is widely recognized that resource constraints and limited data operation speeds are characteristic of first to third generation networks. While fourth and current fifth generation networks are in operation, the quantity of bandwidth allocated to end users continues to be a crucial parameter. Should the issue remain unresolved in fifth generation networks, subsequent generations beyond the fifth would pose significant challenges in achieving optimal performance with limited resources. The operational

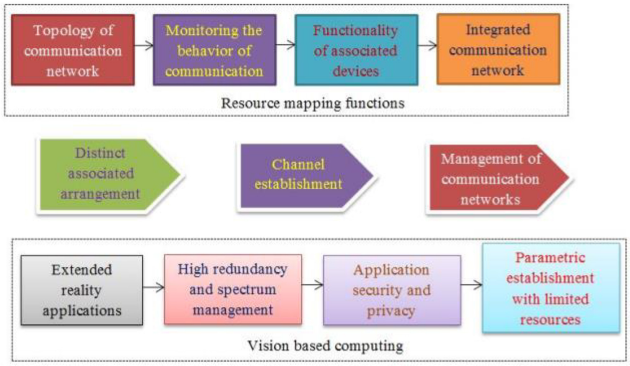

FIGURE 1. Block diagram of limited resource interconnection for extended reality.

limitations, however, are contingent upon diverse applications, with present advancements primarily directed towards extended reality applications. Therefore, the proposed approach investigates the significance of constrained resource allocation in extended reality (XR) applications, where all communication requirements are decoded.

The integration of optimization algorithms is necessary to ensure effective operation of the application mode, given the limited resource constraint imposed by various parameters. The aforementioned integrated process is commonly referred to as collaborative design, wherein a greater number of activities are executed in the process of resource allocation. The process of resource allocation scheme in 6G networks is illustrated in Figure 1. The allocation of resources (RLIS) for extended reality in networks beyond the fifth generation involves the establishment of a resource mapping function that encompasses multiple network topologies. These topologies are interconnected to facilitate the monitoring of the precise behavior of the connected systems. Furthermore, the mapping procedures involve monitoring the functionality of all interconnected devices in addition to the behavior of transmitted data, thereby establishing an integrated communication network. Once the arrangement is established in a distinct manner, channels are created and communication networks are effectively managed. Consequently, a vision-based methodology has been developed, incorporating management strategies for communication spectrum allocation. Additionally, parametric variations have been implemented to accommodate limited resource constraints in the context of extended reality. In the proposed method the resources are considered according to real time experiments that are described in results and discussions section. In order to analyze the conditions of various devices beyond 6G networks the spectrum range of 1THz is considered with input power allocation of 2075.5 respectively. If more number of devices is added then the resources will remain higher but the spectrum ranges remains at persistent ranges.

A. BACKGROUND AND RELATED WORKS

This section provides a comprehensive overview of the literature pertaining to the analysis of resource allocation techniques across various generations of wireless systems. The communication process within various reality systems typically occurs under stringent security protocols, necessitating the allocation of finite resources. In the context of fourth and fifth generation networks, the data transfer speed is consistently high, resulting in an unrestricted flow of data. Consequently, it is not feasible to allocate the same level of resources as in other network generations. Nevertheless, certain superfluous resources may be disregarded or repurposed as valuable assets during specific time intervals. The authors of [1] have presented a novel approach to resource allocation in which a reconfigurable intelligent surface is utilised in conjunction with a non-orthogonal multiple access technique. Intelligent surface systems of this nature primarily execute midair operations, however, additional operations such as output computations in applied areas require a significant amount of spectrum and energy. The achievement of maximum energy local outputs is challenging, resulting in limited resources and subsequent impacts on operational outcomes. A multi-access cloud computing approach is utilized [2] to ascertain time-sensitive data points for the purpose of facilitating efficient energy provision. The organization of multiple data centers can be achieved through the utilization of cloud computing operations that extend beyond fifth generation networks, resulting in resource limitations. If resources are allocated to different centers, they can be shared among them. However, it is not feasible to perform identical operations simultaneously due to the creation of resource demand. An alternative approach to segregating the quantity of assigned resources involves the implementation of a mode of operation that facilitates the offloading of analysis tasks with restricted communication capability, as stated in [3]. The creation of end tasks in reality applications during offloading analysis can be achieved by minimizing power allocation and energy consumption. However, reducing the capacity of offloading is not feasible due to the introduction of pipeline-based issues in the system.

The examination of requirements, targets, and challenges in fifth generation networks is conducted to address capacity issues in real-world applications [4]. By optimizing available resources, it is feasible to develop a commercially viable solution for extended reality applications. Furthermore, contemporary technologies rely on certain technological progressions, whereby each communication platform is scrutinized for enhanced convergence in contrast to inferior latency outputs. Additionally, the potential applications of fifth generation networks have been expanded to include the learning process, whereby the high demands that arise in the field of learning can be addressed through the utilization of low latency communication resources [5]. Despite the resolution of latency concerns, it is imperative to examine other pertinent factors that contribute to the critical path of the data transmission process. Consequently, the optical fog layer has been introduced. The implementation of a fog layer has enabled the regulation of bandwidth consumption. However, the demand for high bandwidth remains a significant limitation in various educational materials. The majority of scholars have investigated the impact of optimal bandwidth conditions on educational materials through the implementation of module placement tactics, which involve real-time cloud-based integration. This approach is widely regarded as a fundamental means of accessing learning-related resources. An additional approach to performing analysis offloading involves the utilization of multimode features, which aligns with the collaborative learning technique while minimizing energy resources, as described in [6]. In the context of collaborative learning, a significant proportion of edge computing nodes are subject to high levels of converging overflow processes, which ensure the provision of quality of service. Nevertheless, the primary limitation of the multimode feature is that the substantial quantity of data samples results in the allocated energy remaining in demand mode, thereby determining the maximum amount of energy required for the computational process.

The aforementioned probabilities are implemented in real-time for applications of the Internet of Things, and a technique for task computation is executed [7]. During the computation of tasks, certain mapping approaches are employed, resulting in the attainment of viable solutions in each of the three-tier processes. The generation of probability-based extended reality values is a challenging task to achieve in real-time when utilizing mapping approaches. A workload balance scheme is proposed to ensure equitable distribution of resources among designated applications. It is noted that even with optimal network speed, the allocation of resources cannot be altered. This is discussed in [8]. Edge computing models are incorporated into the workload sharing process to execute operations with reduced power consumption and latency. However, the trust conditions within the communication network for extended reality applications remain unchanged, thereby rendering the determination of latency inappropriate. One plausible approach to accessing resources in extended reality is contingent upon content sharing protocols, which are commonly executed in fifth generation networks [9]. In the context of extended reality operations, the sharing of content facilitates direct communication with high throughput and gain. Additionally, the aforementioned mode of communication can be implemented in extensive systems, resulting in a reduction of energy consumption and an overall network operation of 50% and 20%, respectively. Table 1 presents an overview of the techniques and goals employed in both current and proposed methodologies.

TABLE 1. Existing vs proposed.

Ref.	Methods/ Proposed Algorithm	Main characteristics	Objectives			
			A	B	C	D
[10]	Particle swarm optimization and Grey wolf optimization	Mobile edge computing with energy efficient utilizations	✓			
[11]	Deep learning and multiple input multiple output realities	Computer vision analysis for resource allocation problems	✓		✓	
[12]	Wideband cognitive radio networks	A trajectory design based radio in allocation of resources	✓	✓		
[13]	Information centric network and machine learning	Mobile edge computing with 360 degree bandwidth reduction	✓			✓
[14]	Collaborative learning process	Pre-programming at level 0 for resource allocation	✓		✓	✓
[15]	Deep learning limited platforms	Pervasive computing with embedded design during resource allocation		✓		✓
[16]	Federated learning beyond fifth generation	Radio source enhanced network connectivity with limited resources	✓			✓
Proposed	Deep learning algorithm with limited resources beyond fifth generation	Reduction of congestion with maximized capacity at reduced time complexities	✓	✓	✓	✓

A: Proximity measures; B: Network congestion; C: Energy and security; D: Power consumption and capacity determination

B. RESEARCH GAP AND MOTIVATION

Numerous techniques have been proposed for resource allocation in fifth generation networks. Given the prevailing operational circumstances, it is imperative to verify that requisite applications are allocated adequate bandwidth, capacity, power, and energy. All of the aforementioned parameters exemplify favorable attributes of communication networks, enabling the operation of various applications within their respective threshold limits. Nevertheless, prior studies that extend beyond fifth-generation networks have not established suitable operational parameters in the presence of limited resource availability. Therefore, it is imperative to verify the fundamental depiction of communication networks for extended reality security. Subsequently, it is imperative that the allocation of capacity and other relevant parameters adhere to a certain degree of proximity.

The current methods available for resource allocation lack efficacy in cases where a resource exceeds its designated limit due to direct updates of network parameters. This issue is compounded by a lack of tactful handling. The proposed methodology effectively addresses the aforementioned limitations through optimized resource allocation, ensuring that proximity constraints are maintained within the specified range. It is imperative to decrease the queue for autonomous data in order to regulate network congestion. Furthermore, the proposed approach involves conducting an offloading analysis, resulting in a reduction of energy consumption while simultaneously maximizing data capacity for information processing and storage. Furthermore, the incorporation of parametric design with multilayer perceptron and long short term memory enhances the efficacy of data transmission beyond the capabilities of fifth generation networks.

C. MAJOR CONTRIBUTIONS

The major contribution of proposed method on extended reality applications that is operated beyond fifth generation networks focuses on the following aspects.

- To limit the amount of resources for the connected networks during data transmission within the allocated time period.
- To reduce the amount of congestion in communication network that is carried out with offloading technique.
- To maximize the security and privacy of high speed data operations at maximized energy and reduced capacities.

D. PAPER ORGANIZATION

The rest of the paper is organized as follows: Section II formulates the design model for allocating resources with supporting parametric analysis. Section III integrates the optimization algorithm with designed system model with loop functions. Sections IV and V examines the real time outcomes and performance analysis of integrated system model and optimization algorithms. Section VI concludes the paper with directions on future work.

II. PROPOSED SYSTEM MODEL

This section offers a comprehensive analysis of the mathematical models utilized in fifth generation networks and beyond. The models incorporate limited resources, such as energy and bandwidth, as fundamental variables. The primary objective of incorporating a system model in high-speed networks that operate beyond fifth-generation networks is to address the persistent challenge of data constraints and bandwidth utilization that arise with increasing network speeds.

A. PROXIMITY FOR EXTENDED REALITY

Equation (1) has been derived by utilizing several proximity measures that are suitable for the proposed application in the realm of extended reality. Let us examine two distinct networks denoted as (*i,n*), wherein the process of interconnection can be depicted as follows.

$$P_i = min \sum_{i=1}^{n} \frac{D_t(i,n)}{I_t(i,n)} \tag{1}$$

If proximity measures are adhered to in networks beyond the fifth generation, it becomes more feasible to transmit data with reduced resources within the designated timeframe.

B. PROXIMITY CONSTRAINT

The data transmission boundaries for extended reality in a connected fifth generation network are defined as 0 and 1. In order to adhere to the specified constraint outlined in Equation (2), the proximity measure must be implemented accordingly [17].

$$constraint_p = \begin{cases} 1 \ if \ \ P_i = i + n \\ 0 \ otherwise \end{cases} \tag{2}$$

If Equation (2) is met, it signifies that two extended networks utilizing fifth generation technology are transmitting data within restricted or designated resources. If the networks are not operated with restricted resources, the duration of extended reality in the fifth generation will be prolonged, leading to resource wastage or increased demand. Therefore, it is necessary to analyze the mean waiting duration for transmission, as denoted by Equation (3).

C. RESOURCE ALLOCATION QUEUE

The current epoch of extended reality operation commences at time t, assuming an absence of network congestion in high-speed networks. Once data transmission has commenced, it is observed that all packets in extended reality beyond fifth generation networks will experience collisions. Consequently, the prevention of congestion in the interconnected network can be achieved through the following measures [18].

$$cong_i = min \sum_{i=1}^{n} \left(t_{i,n} - \omega_t(i,n)\right) \tag{3}$$

The third equation serves as a primary means of denoting the presence of restricted resources within the transmission area, whereby the allocation of excessive resources results in a lack of data transmission. Likewise, in the event of limited resources being allocated, the transmission of data will similarly adhere to a disconnection pathway between two networks. An alternative approach to mitigating congestion in extended reality for 5G networks involves the provision of an optimal amount of energy, as denoted by Equation (4).

D. ENERGY CONSUMPTION

The proposed methodology investigates three distinct forms of energy that exist at the network layer, as the implementation of extended reality and operation beyond fifth generation networks necessitates the utilization of the fog computing model.

$$Energy_i = max \sum_{i=1}^{n} \delta_{ed} + \delta_{on} + \delta_{ce} \tag{4}$$

According to Equation (4), it is necessary to allocate the highest possible amount of energy to extended reality, which operates beyond fifth generation networks, due to the heterogeneous environmental operations that are involved in every data transmission.

E. OFFLOADING PRIVACY AND SECURITY

In the heterogeneous environment of data transmission, extended reality applications beyond fifth generation networks operate under offloading conditions, wherein the maximization of network security and privacy is imperative. Hence the formulation of Equation (5) involves the consideration of the transmitted signal $\{\alpha_1..\alpha_n\}$ and a zero variance factor $\{\aleph_1..\aleph_i\}$ in order to preserve the integrity of security and privacy.

$$OS_i = max \sum_{i=1}^{n} d_l(i \rightarrow n) + d_c(i \rightarrow n). \tag{5}$$

F. CAPACITY ALLOCATION

In the context of extended reality and fifth generation networks, it is expected that each local user will transmit at least one unit of data at each newly introduced node within the system. Therefore, it is imperative to reduce the data allocation capacity by taking into account the present load $\{\beta_i\}$ and the preceding load $\{\beta_{i-1}\}$.

$$AC_i = min \sum_{i=1}^{n} (task_i + \beta_i) - \beta_{i-1} \tag{6}$$

Equation (6) describes that the current load $\{\beta_{i+1}\}$ can be achieved only if computational tasks are implemented at end of every local user.

G. POWER ALLOCATION

The minimization of capacity is contingent upon the allocation of power and bandwidth, which scrutinizes the beneficial attributes of networks beyond the fifth generation. Consider a set of bandwidth values $\{b_1..b_n\}$ that pertain to the transmission of data in extended reality operations. In this context, the interconnected channel characteristics, which account for attenuation, can be mathematically represented using Equation (7) in the following manner [19].

$$\Delta_p = min \sum_{i=1}^{n} b_{i,n} \times \sigma_i. \tag{7}$$

H. OBJECTIVE FUNCTION

The system models discussed for extended reality applications beyond fifth generation networks prioritise limited resource operation. The main Objective functions are established in the form of min-max parametric functions, as demonstrated in Equations (8) and (9).

$$obj_1 = min \sum_{i=1}^{n} P_i, cong_i, AC_i \tag{8}$$

$$obj_2 = max \sum_{i=1}^{n} Energy_i, OS_i \tag{9}$$

In the minimization objective function due to minimal power allocation the equation constraint is not represented however all 6G networks in proposed method are operated with low power supply in order to minimize the amount of resources. Both the min-max objective functions is examined by integrating it deep learning algorithm as efficiency of data transmission beyond fifth generation networks can be improved as described in Section III.

III. DEEP LEARNING ALGORITHM

In the present state of network operations, where the requirements of the fifth generation are utilized for extended reality, it is imperative to consider networks beyond the fifth generation that meet the criteria of high latency, reliability, and low power consumption. Therefore, it is imperative to incorporate deep learning algorithms beyond the fifth generation to achieve comprehensive offloading with enhanced security capabilities in comparison to the present operational state. Furthermore, beyond fifth-generation operation, a significant portion of extended reality operations are conducted for the purpose of big data operations that are sustained over time. One significant benefit of utilizing deep learning techniques beyond the fifth generation is the potential to decrease the occurrence of training and testing errors. As a result, the convergence of extended reality applications may be expedited. The physical layer information processing procedure exhibits a notably superior level of precision when compared to alternative algorithms currently utilized in fifth generation networks [17], [18], [19], [20], [21], [22]. When there is efficient connectivity established between the end user and reality devices, deep learning facilitates a significant interaction, resulting in the clear visualization of all structures or data patterns at a high speed. Moreover, the memory capacity of deep learning algorithms is greater, allowing for the storage of larger amounts of data without experiencing congestion, ultimately leading to expedited solutions within the designated timeframe. The proposed methodology involves the integration of two distinct types of deep learning algorithms with a system model that has been specifically designed for this purpose [21], [22], [23], [24]. A comprehensive description of this approach is provided below.

A. FEED FORWARD NEURAL NETWORK

In order to effectively process the relevant data in extended reality applications that surpass fifth generation networks, it is imperative to implement multiple layers for data processing. The multilayer perceptron has been introduced in the context of a designed system model, wherein a threshold activation function is denoted at each stage. This particular configuration involves exclusively utilizing non-linear activation functions and restricting the number of hidden layers to one in order to optimize security. The multilayer perceptron is capable of operating effectively on fifth generation networks, regardless of the size of the input data. This is achieved through the utilization of mapping functions, which enable the resolution of complex problems. One significant benefit of utilizing the multilayer process is the reduced time required for learning, training, and testing at each layer, including input, hidden, and output layers. This advantage is particularly noteworthy when compared to other deep learning algorithms that lack mapping functions. In the context of multiple layers, it is possible to expedite task operations, thereby allowing for the efficient allocation of low computational resources across all designated layers. The multilayer perceptron has demonstrated the ability to make rapid and accurate decisions with limited resources, surpassing other neural networks due to its streamlined data transmission process. The multilayer perceptron has the ability to adapt to a wide range of smooth nonlinear functions, even in the event of a sudden increase in input data size. Furthermore, in order to uphold stringent flexibility constraints in multilayer perceptron, the training samples are accorded relatively lower significance, resulting in a reduction in the overall number of perceptron's. One of the benefits of utilizing a multilayer perceptron is the potential reduction of over fitting, which can be achieved by maximizing the flexibility of data in real-world applications. During the learning phase, the weights are adjusted to minimize the total errors at the output stage, which enables the possibility of performing inverse operations. The mode of inverse operation in multilayer perceptron typically refers to the back propagation networks' operation, which is integrated with the feed forward mechanism. Equation (10) can be utilized to formulate the activation function of a multilayer perceptron for extended reality beyond fifth generation.

$$act_i = \sum_{i=1}^{n} \frac{1}{1 + e^{-(w_1 + ..w_i)}} \tag{10}$$

According to Equation (10), it is imperative that the activation function incorporates weight functions of minimal magnitude to enable the extended reality functions to operate with a high degree of flexibility. Equation (11) demonstrates that the learning rate fluctuates correspondingly with any modifications made to the weights in the aforementioned equation.

$$l_i^n = min \sum_{i=1}^{n} \frac{error_i^2}{2} \tag{11}$$

According to Equation (11), the reduction of the error rate to 50% of its original value is contingent upon the selection of suitable weight functions. The error functions in the aforementioned equation can be approximated in the following manner.

$$error_i = min \sum_{i=1}^{n} \tau_i - v_p(i) \tag{12}$$

According to Equation (12), the total error function will remain at zero percent if the difference between the target values and output resources is minimized. The input data for the multilayer perceptron is presented in the following manner upon importation into the system.

import multilayer perceptron as mp

import numpy as np

from multilayer perceptron.keras.models import Activation

from multilayer perceptron.keras.layers import Learning rate

from multilayer perceptron.keras.layers import Target values

from multilayer perceptron.keras.layers import Output resources.

The block flow determinations of multilayer perceptron are illustrated in Figure 2 and the pseudo code representation of indicated data set is as follows. Figure 2 provides a clear view on block representations that is provided for operation of feed forward neural network where a set of weight functions that denotes maximum available resources in connected 6G networks are provided. With the available weight functions the proposed method chooses only the active resources that increase the efficiency of network is considered thereby avoiding network congestion. During these two weight functionality states if the network or user demands a change in resource then it is possible by forming a multi-layer functionality. In the process of multiple layer existence it is possible to learn the current state conditions with a target value that is related to minimization of resources. As a result of change in resources the error functionalities are observed at each output unit and decisions are taken to avoid such cases.

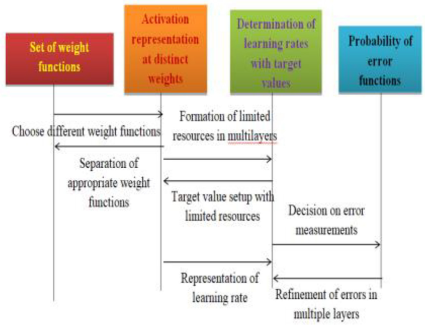

FIGURE 2. Resource allocations with multilayer perceptron for extended reality beyond fifth generation networks.

Algorithm 1: Multilayer Perceptron

Begin PROCEDURE MLP
 Given
 $w_1 + ..w_i$: Change in weight functions
 act_i: Activation functions
 for i=*1 : n* **do**
  1. l_i^n for measuring the learning rate in the operation beyond fifth generation networks
  2. τ_i for choosing appropriate resource target values
 end for
 else
 for all i=*1 : n* **do**
  1. $error_i$ for monitoring the error functions at output of multilayer perceptron
 end for all
end PROCEDURE

B. LONG SHORT TERM MEMORY

In order to effectively operate beyond fifth generation networks, it is imperative to regulate the volume of traffic at the application level. Certain deep learning algorithms are capable of regulating traffic volume, with long short-term memory being one such algorithm that can forecast traffic across an entire channel. Furthermore, Long Short-Term

Memory (LSTM) is employed to forecast the overall capacity required for allocating to a specific network. Therefore, a suitable allocation of resources will be provided to acquire knowledge of every aspect of the characteristics that exist in network operations. The primary benefit of long short-term memory lies in its ability to furnish feedback connections for extended reality, which can operate beyond fifth-generation networks, thereby enabling the processing of entire data sequences. The Long Short-Term Memory (LSTM) approach is comparatively more feasible for real-time implementation, as data processing takes place simultaneously, in contrast to the Multi-Layer Perceptron (MLP) method that processes each data point through multiple layers. Consequently, greater advantages can be attained through the processing of data during a specific period, which also coincides with data training. The bias and weight assigned to extended reality devices typically exhibit a range of values from 1 to n, akin to the multiple perceptron model. However, the activation functions do not undergo immediate changes due to the aforementioned variations. Instead, changes are made according to step variations. On the other hand, the transmission of long short-term memory data involves the utilization of three distinct types of gates, namely input gates, forget gates, and output gates. In the event of security-related data analysis, the incorporation of a forget gate is necessary to ensure the retention of only pertinent predictions. Moreover, Long Short-Term Memory (LSTM) refers to the capacity to swiftly process data in high-speed networks without altering the flow of the initial procedures. Equation (13) represents the various forms of long short-term memory that utilize the time step index in the following manner [25], [26].

$$act_{LSTM} = \sum_{i=1}^{n} \varphi_{out} \times h_c(i) \tag{13}$$

According to Equation (13), it is necessary to express the reproduction rate of output and cell functions as an element-wise function. This ensures that resources are allocated to each unit in a self-sufficient manner, without any external dependencies. The output units of long short term memory are contingent on the preceding cell units, thereby allowing for the representation of the learning rate through Equation (14) in the following manner [27], [28], [29], [30].

$$l_r(LSTM) = \sum_{i=1}^{n} I_1(\mathrm{ts}_i - 1) + .. + I_i(\mathrm{ts}_i - 1) \tag{14}$$

According to Equation (14), each input function is dependent on the preceding time step index, resulting in the computation of the subsequent step occurring solely at the specified time interval. Therefore, it is possible to express the output functions in relation to weight, as presented in Equation (15) [27], [31], [32], [33], [34], [35].

$$O_i = \sum_{i=1}^{n} \frac{\rho_i \times w_i}{b_i} \tag{15}$$

Algorithm 2: Long Short Term Memory

Begin PROCEDURE LSTM
  Given
  φ_{out}: Output data vector functions
  h_c: Cell vector data functions
  for *i=1 : n* **do**
    1. l_r(LSTM) for measuring the learning rate with time step index
    2. ρ_i for determining the learning rate of output functions
  end for
  else
  for all *i=1 : n* **do**
    1. O_i for monitoring the output functions for limited resource allocation
  end for all
end PROCEDURE

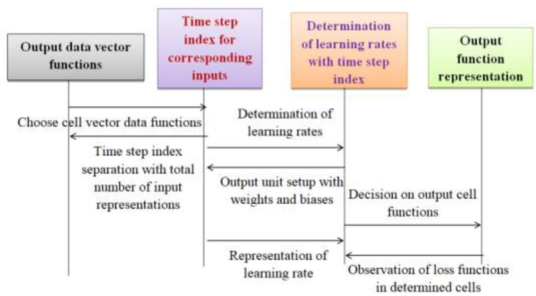

FIGURE 3. Resource allocations with long short term memory for extended reality beyond fifth generation networks.

Equation (15) delineates the dissociation between the learning rate of output functions and the determination of corresponding weights with bias functions. The input data for long short term memory is imported in the following manner.

```
from LSTM.models import Sequential
from LSTM.layers import input, forget, output
model = Sequential()
model.add(Masking(mask_value=0.0))
model.add(regularize(0.5))
model.compile(resource, loss, accuracy).
```

The block flow determinations of multilayer perceptron are illustrated in Figure 3 and the pseudo code representation of indicated data set is also indicated above. Also the indication of all variables in proposed system model is provided in Table 2.

The major advantage of implementing 5G and beyond 5G networks in deep learning algorithm is to enable high reliability in with the usage of high frequency spectrum thereby additional resources can be reduced. Additionally more amount of data can be carried as compared to other algorithms due to pre-defined training characteristics. Even it is possible to provide advanced computer vision techniques beyond 5G networks thereby reducing high traffic conditions in connected networks.

TABLE 2. Indication of variables.

Variables	Representation case
$D_t(i,n)$	Total duration of two different connected networks
$I_t(i,n)$	Increment in time periods during data transmission
$\omega_t(i,n)$	Appearance of transmitted packets
$\delta_{ed}, \delta_{on}, \delta_{ce}$	Energy of connected devices, visual networks and cloud storage systems
$d_l, d_c(i \rightarrow n)$	Direct connection must be established between two different users at channel and links
$task_i$	Total number of offloading task in extended reality
σ_i	Attenuation channel characteristics
$w_1+..w_i$	Total weight functions as limited resources are provided
$error_i$	Total number of errors that occurs during resource allocation
τ_i	Resource target values
v_p	Output resources at multilayer perceptron
φ_{out}	Output data vector function
h_c	Cell vector data function
$I_1+..+I_i$	Total number of inputs in determined cells
ts_i	Time step index
ρ_i	Learning rate of output functions

IV. RESULTS

This section presents an experimental analysis aimed at examining the resource requirements necessary for optimal operation under the strict constraints present in fifth-generation networks. The proposed system model incorporates both long short term memory and multilayer perceptron to facilitate real-time experiments. The activation functions are included with suitable data weights and cell functions. In the preliminary stage, a minimal allocation of resources is provided to each datum in order to facilitate the execution of operations for extended reality applications. It has been observed that the provision of a minimum amount of resources, such as bandwidth and capacity, in transmitting data to end users is inadequate beyond fifth generation networks. As a result, supplementary resources are incorporated. The present study involves the concurrent evaluation of two disparate systems characterized by distinct data measurements and features. The systems are initially introduced with minimal proximity, and subsequently, the time period is incrementally extended until maximum resources are allocated. In the proposed method, the quantity of resources remains consistent as time periods increase. However, modifications to data characteristics at both the transmitter and receiver will result in changes to the resources utilized. The proposed method incorporates supplementary security measures for extended reality applications that operate beyond the fifth generation, thereby enabling the prevention of unauthorized access to extended reality links. Additionally, offloading procedures are implemented in the event of data failures, owing to the consistent availability of resources. Furthermore, it has been observed that the offloading technique requires the establishment of direct connections between distinct networks. As a result, data processing beyond fifth generation networks is significantly faster, allowing each user to receive data without encountering any allocation queues. In order to investigate the allocation of resources in parametric terms for extended reality applications beyond the fifth generation, a set of scenarios have been devised. The respective significance of each scenario has been documented in Table 3.

TABLE 3. Importance of designed scenarios.

Scenario	Significance
Network proximity	To compute the resources based on increasing time periods
Allocation queues and energy consumption	To forward the data in case of congestion with individual queues at minimized energy
Offloading performance	Occurs in case of data failures with direct link connections
Data storage	To store all tasks that are performed for extended reality beyond fifth generation
Error measurements	To allocate limited resource to end user applications at low error rate

TABLE 4. Simulation parameters.

Bounds	Requirement
Operating systems	Windows 8 and above
Platform	MATLAB and Network simulator
Version (MATLAB)	2015 and above
Version (Network simulator)	3
Applications	Extended reality
Data sets	Multilayer perceptron and long short term memory activation functions

Scenario 1: Network proximity
Scenario 2: Allocation queues and energy consumption
Scenario 3: Offloading performance
Scenario 4: Data storage
Scenario 5: Error measurements.

A. DISCUSSIONS

The aforementioned situations are executed through the establishment of interconnected networks utilizing switches, routers, and other related equipment. The real-time outcomes are demonstrated by simulating the connected device directly in MATLAB, and a comparative case study is conducted with established methodologies. A three-dimensional representation is depicted for each simulation study, with suitable conversions from the network. The proposed method incorporates multilayer perceptron and long short term memory, and a comparison will be conducted with alternative optimization algorithms. Table 4 presents the simulation parameters relevant to extended reality applications.

The simulation environment employs a data set that is seamlessly integrated with activation functions, thereby optimizing the utilization of available resources without incurring any supplementary expenses. The following is a comprehensive account of the designed scenarios.

Scenario 1 (Network Proximity): This scenario entails the observation of proximity in diverse networks, wherein extended reality applications necessitate the alteration of resources, thereby necessitating the presence of interconnected networks. The evolution of cellular networks from first generation to fifth generation has resulted in a significant reduction in network proximity, with resource allocation undergoing changes only after the third generation

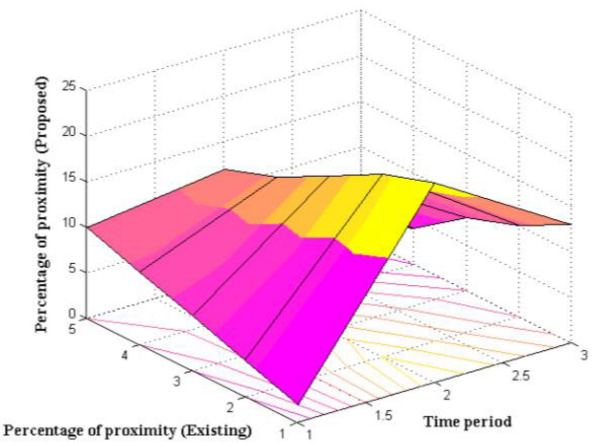

FIGURE 4. Proximity measures with two different networks.

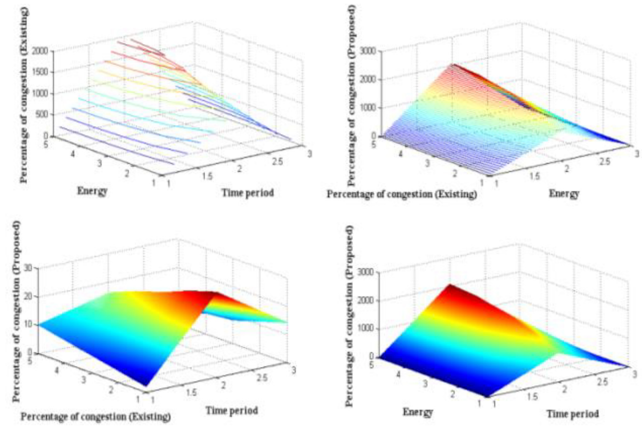

FIGURE 5. Observation of collision between data packets.

networks. In the context of networks beyond the fifth generation, it is imperative to provide one or more supplementary resources that adhere to specific limitations. The proximity parameter is calculated by considering two distinct networks that are directly connected, with emphasis on the initial time period. In the initial stages of data processing for extended reality applications, resources may be limited. However, as virtual data is generated, the proximity of the network tends to increase over time. The primary objective of this process is to minimize resource consumption over time. To achieve this, proximity constraints are established using binary indicators of 1 and 0. Figure 4 depicts the observed proximity between two distinct networks.

Figure 4 illustrates that the proposed approach achieves a reduction in proximity when compared to the existing method [5]. To establish a connection between simulation output and extended reality devices operating beyond fifth generation networks, a five-time period approach is employed within two-hour intervals. The percentage of proximity in connected networks that furnish requisite data to extended reality applications is limited across all five interval periods. The time interval ranges from 2 to 10 with varying increments in the proposed approach. Despite extending the time period to its maximum, the percentage of proximity remains below 5%. As the duration of time increases, the proximity of the network expands, resulting in a potential impact on the data connection for extended reality in the current approach. End users are capable of observing that either ‘0’ is transmitted throughout the entire time period or that the actual data is not fully visible in the connected networks.

Scenario 2 (Allocation Queues and Energy Consumption): This scenario outlines the methodology for determining queues in data transmission paths, with the aim of mitigating link breakage issues in networks beyond the fifth generation. Link breakage was a common occurrence in previous generation networks due to the transmission of data to extended reality applications at low data speeds within confined networks. In the context of networks beyond fifth generation, in the event of link breakage, each data transmission will be subject to an individual waiting period, resulting in the formation of a data queue. The formation of a data queue may compromise the security of data in extended reality applications due to potential collisions among the data. Therefore, in order to obtain real-time measurements, the likelihood of transmitted packets is reduced by their corresponding time intervals. Additionally, the issue of congestion arises as a result of reduced energy consumption, whereby the transmitting center endeavors to minimize energy wastage. Insufficient energy consumption by fifth generation networks for extended reality applications may lead to an increased number of transmitted packets with the same energy, thereby resulting in a higher collision rate.

Figure 5 illustrates the relationship between the likelihood of collision and the duration of time intervals, as well as the amount of energy supplied. The reduction of congestion is achieved through the conservation of energy resources. In order to assess the potential for congestion, a scenario was constructed consisting of five distinct time periods. The amount of supplied energy for each transmitted data point was recorded and found to be 1023.7, 1467.2, 1789.1, 1995.3, and 2075.5 for each subsequent time period. The existing approach [5] indicates a gradual decrease in congestion percentage over time, with values of 30%, 27%, 23%, 20%, and 16% observed for increasing time periods. The proposed method exhibits a lower collision rate for all packets, namely 14, 11, 8, 7, and 4, when supplied with equivalent amounts of energy and time period. The proposed method ensures that there is no wastage of resources, thereby preventing the possibility of congestion, owing to the provision of energy resources in a limited and appropriate form. In the current methodology, there are instances where energy fluctuates, resulting in some degree of inefficiency. Consequently, data packet congestion is more pronounced for extended reality applications beyond fifth-generation networks.

Scenario 3 (Offloading Performance): Most networks, spanning from the initial generation to the latest fifth generation, primarily provide operational methodologies without

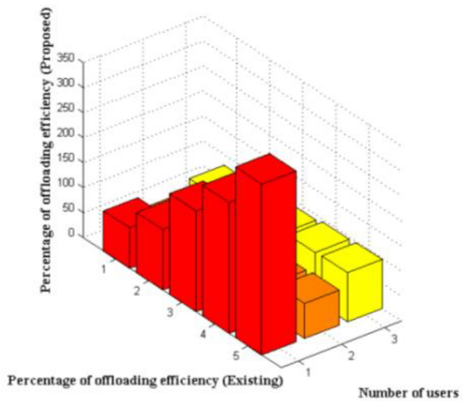

FIGURE 6. Offloading performance efficiency for varying users.

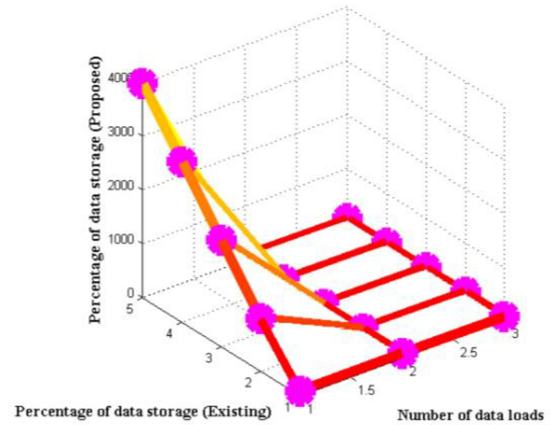

FIGURE 7. Minimized data storage with varying load conditions.

ensuring offloading analysis. In the realm of extended reality, it is common practice to transfer certain processes to external sources in order to avoid excessive depletion of available resources. In order to optimize offloading techniques within extended reality applications, it is crucial to establish a dedicated connection between two networks, whereby resources are specifically allocated for the pertinent links. The method under consideration incorporates the variables i and j, thereby facilitating direct connections between two channels. When two channels are interconnected, it is feasible to decrease two or more resources. Nevertheless, in computational procedures that do not entail the utilization of offloading techniques, the process of minimizing at least one resource can be considerably intricate. Hence, a considerable portion of extended reality (XR) applications will preserve data to carry out an offloading procedure, where channel interactions are performed with a notable level of accuracy. Figure 6 depicts the procedure of offloading for direct connection establishments.

As illustrated in Figure 6, the proposed methodology effectively reduces the necessary resources by eliminating the need for direct connection establishment, which stands in contrast to the current approach. This discovery is of a practical nature. Moreover, in the context of live observations, it is possible to distinguish distinctive attributes of two interlinked networks, thereby facilitating the autonomous establishment of transmission and reception connections. The optimization of connected links and channels in the context of offloading analysis is primarily concerned with cost maximization, whereas the optimization of throughput is given higher priority. The amalgamation of multilayer perceptron and long short term memory utilizing an offloading model yields a reduced error rate as opposed to computational operations. This study aims to examine the offloading technique through an analysis of user numbers in two established links, with a range of 80 to 340 users. The existing approach [5] has been observed to maintain efficiency percentages of 54, 58, 63, 66, and 70, respectively, when performing offload tasks. The method under consideration demonstrates diverse degrees of efficacy in distributing tasks among users who possess identical characteristics, with corresponding values of 78, 85, 89.94, and 97. The system model that was designed exhibits a noteworthy improvement in efficiency of approximately 8% when compared to the method mentioned earlier.

Scenario 4 (Data Storage): In this scenario, the determination of the data storage requirements for extended reality applications is contingent upon the completion of computing offloading tasks. The proposed methodology for extended reality operations primarily involves adhering to the offloading principle, whereby the existing operating load of networks is taken into account. If the network experiences a high load, computationally reserved resources may be utilized to process some of the data, resulting in a limitation of data storage to a specific unit. The primary rationale behind the implementation of such constraints in the proposed approach is to enhance the level of security for data transmissions in the context of fifth generation networks. Furthermore, it is imperative to compute the attenuation characteristics for all data transmission, particularly beyond the fifth generation, as high-powered data transmission may consume excessive storage space, which should be circumvented. When data storage is processed by a local user, it is possible to utilize some additional resources or share resources with a local medium. The outcomes of data storage in extended reality applications are presented in Figure 7 through simulation.

Figure 7 demonstrates that the proposed method minimizes data storage with computational load in comparison to the existing approach [5]. This finding is pragmatic in nature. In order to illustrate the storage mechanism, five data loads are examined at varying intervals of 1000, specifically at 100, 1000, 2000, 3000, and 4000. The focus is on the extreme loads and their corresponding outcomes. The aforementioned load was subjected to offloading analysis, resulting in a reduction of the percentage of data stored in the proposed method to 71%. In contrast, the current approach is limited to storing data at a maximum capacity of 87% under the same load. As a result, supplementary resources are required for both load computation and data storage. The proposed method provides minimized bandwidth for connected channels due to the significantly lower power allocated to computational operations, in addition

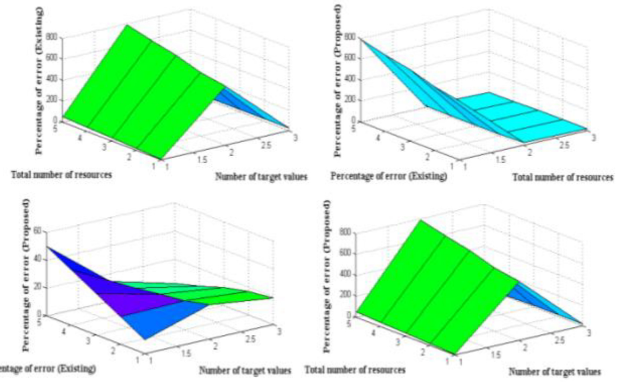

FIGURE 8. Error measurements with varying resources.

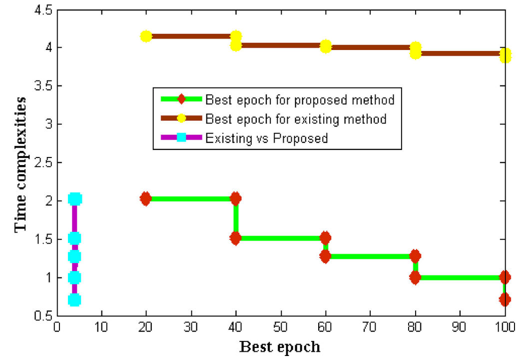

FIGURE 9. Comparison of time complexities with best epoch disparities.

to data storage. Consequently, it is feasible to enable the operation of augmented reality and virtual reality applications on networks beyond the fifth generation, while utilizing restricted bandwidth and data storage.

Scenario 5 (Error Measurements): As the data processing technique is utilized for executing offloading tasks, a greater number of errors may arise. Thus, for the entirety of the extended reality task, error measurements are obtained by taking into account both optimization algorithms. By incorporating appropriate weight functions for the corresponding data, the activation functions can significantly reduce the error resulting from data transmission. Major errors in function often arise from inadequate resource allocation, where the interdependence of various resources is not adequately established. In the event that extended reality applications beyond the fifth generation are not provided with necessary resources such as energy, bandwidth, and power, the resulting error functions will be significantly elevated and cannot be mitigated. The proposed methodology involves processing error measurements by computing the discrepancy between the output resource and the target values that are inherent in the system. The comparison between simulation results for error measurements and target values is depicted in Figure 8.

Figure 8 demonstrates a significant decrease in the total number of errors for both the multilayer perceptron and long short term memory models, following the activation of appropriate data weight functions. In contrast to alternative algorithms, the aforementioned optimizations are executed with constrained resources while targeting specific values and output responses. In order to validate the scenario in real-time, target values have been established within the range of 10 to 50, with incremental variations. The number of available resources is limited, with a total count of 567, 612, 683, 729, and 794, respectively. The proposed method aims to reduce the error values in the simulated outcomes to below 5%. This is achieved by calculating the percentage of error for each variation, which involves determining the difference between the output and target response. In the event that said measurements are conducted, the system will exhibit a greater number of stable points, thereby facilitating data operations that surpass those of fifth generation networks. In contrast to the current approach, it has been observed that the inadequate output response results in error measurements exceeding 10%, thereby precluding the attainment of stable points.

V. PERFORMANCE ANALYSIS WITH COMPLEXITY

6G networks are highly adaptable to changing time periods but due to low resource allocation there is a possibility that time complexity can arise. In order to overcome the complexities with differentiation in time periods the end users can be allocated with minimal amount of resource at one time period and it is possible to increase the amount of resource at another time period therefore time margins can be provided with a clear view. In addition as deep learning algorithms are integrated with proposed system model it is essential to discover the necessary time period for simulating the algorithmic pattern related to resources. During time complexities the amount of resources can be easily traced and a decision making system can be adapted in order to distinguish the necessary resources. If 6G users demands a particular resource then at reduced time complexity the resource can be allocated and in other case if the user neglects the resources continuously then it can be removed from all time system and can be used at later stage. Figure 9 demonstrates the time complexity in case of resource allocation to various users.

From Figure 9 it is realistic that time complexities are reduced for proposed method as compared to existing approach. In order to verify the consecutive time period of deep learning algorithm in 6G networks only best epoch periods are considered in variation of 20. Therefore with the best epoch the time complexity represents that at initial state minimum resources can be carried to all users and with another changing time period if the users demands additional resources then it can be changed for future use. Hence with best epoch the comparison case with existing approach provides time complexity of 4.15, 4.03, 4, 3.92 and 3.87 seconds whereas with same amount of resources the deep learning algorithm reduces the complexities to 2.02, 1.51, 1.27, 1 and 0.7 seconds respectively. Hence it is possible to utilize the allocated limited resources in an effective way in deep learning algorithms as compared to other algorithmic representations.

VI. CONCLUSION

Given the unlimited development of communication technologies across various applications, it is imperative to assess the attributes of evolving networks. The majority of contemporary network operations rely on updates that are inherent to third-generation networks, which incorporate advanced features and introduce data speed operations. Furthermore, the present network operation surpasses the fifth generation, thus prompting an examination of the attributes of the relevant networks in the suggested approach. The study with RLIS aims to analyze the attributes of extended reality applications beyond the fifth generation. This will be accomplished through fundamental parametric assessments that rely on the allocation of resources. In addition, a fundamental system model has been formulated, incorporating proximity constraints, and subsequently assessed for two distinct interconnected networks. The objective is to ensure that data packets pertaining to extended reality are transmitted seamlessly, without any instances of queuing. In addition, it is imperative to reduce the energy resource consumption during the data transmission phase, even in the context of networks beyond the fifth generation. By utilizing the available energy, it becomes feasible to conduct offloading analysis, thereby enhancing privacy and security in networks beyond the fifth generation. Optimization of network operations is necessary even when resources are allocated appropriately. This can be achieved through the use of activation functions to prevent errors in resource allocation. The proposed method involves the integration of deep learning algorithms, specifically multilayer perceptron and long short-term memory, along with their corresponding activation functions. A comparative study has been designed to investigate the outcomes of extended reality applications beyond fifth generation functions, with a focus on proximity limits and the avoidance of data queues. The study comprises five distinct scenarios. In addition, the energy allocation is fully utilized without any increase in demands. The comparative results is expressed by considering all five scenarios where foremost importance is given to offloading performance as it is necessary to utilize the resources in an effective way. The simulation outcome indicates that proposed method can able to perform offloading analysis in a better way than the compared identical working case studies in existing method at a rate of 97%. Similarly in offloading technique the errors are minimized to 2% as every limited resources are provided to users at appropriate time periods.

A. POLICY IMPLICATIONS AND FUTURE WORK

The limited resource constraint on 6G networks can be implemented in all network industries that support high operational resources. A combined network operation by using deep learning, artificial intelligence and machine learning algorithms can enhance the connectivity ranges of 6G networks thereby involving all edge computing classifications at high signal strength. In subsequent research, the suggested approach may be expanded to various use cases where modifications to features beyond those of fifth-generation networks are required through the utilization of integrated optimization algorithms.

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