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OPTIMIZING NETWORK RADIO RESOURCE MANAGEMENT USING MACHINE LEARNING TECHNIQUE FOR TRAFFIC IMPROVEMENT

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Abstract

In the world of communication networks, which provide services to a variety of highly demanding applications, effective resource allocation is essential to guaranteeing maximum efficiency and user experience. This study presents the use of Long Short-Term Memory (LSTM)-based Radio Resource Management (RRM) approach for network optimization. Grid Search Optimization (GSO) is used to optimise the LSTM model's hyper parameter tuning, guaranteeing peak performance in dynamic network settings. The system uses guard interval insertion and frequency interleaving to reduce Inter-Symbol Interference (ISI) and burst errors. According to simulation results, the LSTM-RRM technique outperforms the Dynamic Radio Resource Management (DRRM) approach in terms of dual connectivity, throughput, and fairness. The effectiveness of the suggested approach in allocating resources was demonstrated by the up to 50% increase in User Equipment (UE) throughput and the 12% increase in dual connectivity for 30 UEs. The LSTM-RRM system, which was implemented with MATLAB, demonstrated scalability, robustness, and efficacy in mitigating congestion and enhancing Quality of Service (QoS) for communications between machines and humans. This study opens the door for more advancement in network performance optimisation by demonstrating the potential of LSTM and machine learning approaches for resource management optimisation in next-generation networks.

Keywords: Radio Resource Management; Resource Allocation; Machine Learning; LSTM; GSO; Inter-Symbol Interference (ISI)

1. INTRODUCTION

The advancement of the Long-Term Evolution (LTE) and upgraded cellular systems is the foundation of contemporary mobile broadband services. Low cost per bit, high spectrum efficiency, fast data rate, and high system capacity are the advantages offered by LTE (Condoluci et al., 2015; De La Fuente et al., 2017). The requirements of cellular networks are met by heterogeneous wireless networks (LTE) (Pramudito and Alsusa, 2013). The heterogeneous networks' small and macro cells are used to meet the need for broadband mobile traffic (Wang et al., 2016; Soret and Pedersen, 2014). LTE direct transmission is another name for device-to-device (D2D) communication (Belleschi et al., 2015).These D2D communication systems can reduce energy consumption and maximise the use of spectrum resources. Peer-to-peer and location-based services and apps are supported by D2D (Naqvi et al., 2018).

One node is installed between User Equipment (UE) and upgraded Node B (eNB) in the third generation collaboration project

LTE. According to Kaddour et al. (2014), the radio network controller in the eNB is capable of performing mobility, traffic balancing, and radio resource management (RRM). Additionally, in order to achieve appropriate performance, which is known as self-optimization in LTE, the eNB and UE are utilised to adjust the system parameters (Tiwana et al., 2014). In LTE-Advanced (LTE-A) systems, the reduced cell edge capabilities are thought to be the limitation. The LTE's capacity is impacted by user interference, which results in aggressive frequency. Complete isolation between various parallel services and signalling overhead have an impact on an LTE's random-access network (Elgendy et al., 2018; Tseliou et al., 2015). Cloud radio access networks, better interior coverage, machine-to-machine and human-to-human communications, reduced latency, lower energy consumption, and huge multiple input and multiple output are some of the emerging features and trends of 5G LTE-A (Saddoud et al., 2020).

The creation of 5th Generation (5G) mobile communication networks meets the anticipated needs of contemporary communication, including a large number of connected devices with different service needs, high traffic volumes, and enhanced user experience quality (Benzaid et al., 2020).In order to enhance the 5G network's performance, intelligent learning techniques are being developed. A model-free, data-driven method for reducing the complexity of available training inputs and outputs is called deep learning (DL). By training simulated data offline and providing the results utilising well-trained networks during online procedures, resource allocation difficulties are eliminated (Jo et al., 2021). One of the main problems with the RRM is thought to be the interdependency of the OSI stack levels. To get the best performance for the stack layer, a suitable cross-layer optimisation strategy is needed. Furthermore, several RRM components must be arranged in the same equipment for access methods with multiple interfaces (Cai et al., 2011).The following are examples of traditional RRM techniques: pathloss-threshold-based component carrier and cluster configuration algorithm (Wang et al., 2015), carrier aggregation-based RRM (Rostami et al., 2017), and hybrid approach (Haddad et al., 2011).

Optimisation is now possible at previously prohibitive levels of complexity because to recent developments in machine learning (ML). Significant performance gains have resulted from this, encouraging the application of ML methods like neural networks in a variety of domains. Using machine learning (ML) to improve wireless network performance began with 5G and will be crucial to advancing zero-touch setup and administration, which will allow 6G networks to self-optimize and self-configure (Zhang et al., 2019).

Many factors that are difficult to predict or infer and are not always known when decisions need to be made affect how a wireless network operates. Furthermore, because wireless networks are made up of several radio access technologies and modules that interact with one another, must meet a variety of changing needs, and must swiftly adjust to changes, they are becoming more complicated and heterogeneous. This makes the issue of optimising wireless systems' performance in real time unfeasible for conventional methods. On the other hand, ML tools can manage extremely dynamic wireless networks and make more intelligent judgements, such as based on anticipated future traffic patterns, because of their capacity to handle extremely complicated systems (Bui and Widmer, 2018).Based on these findings, this study proposed a modular Machine Learning (ML) architecture for wireless network optimisation that makes it possible to easily incorporate machine intelligence into both new and pre-existing network operations. In particular, we use ML to maximise network performance.

2. LITERATURE REVIEW

The Distributed RRM (DRRM) for 5G multi-RAT multi-connectivity networks was developed by Monteiro et al. (2018). Enabling strong interoperability between LTE and 5G supports the latter's extended range. The optimisation problem is used to raise the minimal UE throughput. Only a reduction in calculation effort and signalling overhead was accomplished by this technique. Rukmini (2020) introduced the LTE network over the QoS in conjunction with the RRM, and a greater transmission rate was not attained when the BS was alone taken into account as the reference signal received power Prasad. The LTE network's consumers were given the best possible resource allocation through the implementation of QoS with optimal confederation-aware technology, specifically QOC-RRM. The recurrent deep neural network was then used to prioritise the operators in the LTE network. Additionally, the chaotic weed optimisation method provided the queuing criterion information in order to complete the routing procedure required to transmit data. The priority value was then used to arrange the users' priorities for the resources that were available. However, only fourth-generation systems were used to analyse this RRM. The RRM was developed by Pramudito and Alsusa (2014) to improve soft-frequency reuse-based LTE's downlink performance. Dynamically assigning the RRM in a distributed and centralised way at the network improves the system's spectral efficiency. The network develops the confederation notion when the allocation is completed. This confederation idea is intended to minimise the overhead when a routing algorithm is paired with a confederation type network.

The predictive RRM (PRRM) system for next-generation wireless networks (NGWNs) was developed by Ali et al. (2018). Furthermore, mobility management and resource control difficulties are resolved while meeting Quality of Service (QoS) standards. To maximise performance over heterogeneous networks, the IEEE 802.21 Media Independent Handover (MIH) protocol is employed. The coordination between the two aforementioned network properties is provided by this MIH protocol. The handover procedure, which consists of three stages, resource allocation estimation, radio resource allocation decision, and allocation notification, is also integrated with the PRRM.

In order to carry out RRM in the Integrated Access and Backhaul (IAB) networks, Sande et al. (2021) introduced Deep Reinforcement Learning (DRL). The IAB network's access side congestion is reduced by using the developed DRL-based RRM. In order to give users adequate resources, the trans mission buffer is initialised to monitor the congestion rate of the IAB node. Furthermore, the restricted problem resulting from the power consumption issue is transformed through the application of Markov decision process and dynamic power management. Nonetheless, this developed DRL-based RRM's total complexity is comparable to that of the current method.

3. RESEARCH METHODOLOGY

The bandwidth and power allocation for the targeted UEs is done using the LSTM-based RRM. While hyperparameter tweaking is accomplished with GSO, the use of LSTM in the 5G context simplifies decision-making. In order to reduce burst faults across the network, frequency interleaving is also being researched in the context of 5G. In order to reduce Inter-Symbol Interference (ISI), guard level insertion is then activated prior to data transmission. Figure 1 displays the LSTM-RRM method's block diagram.

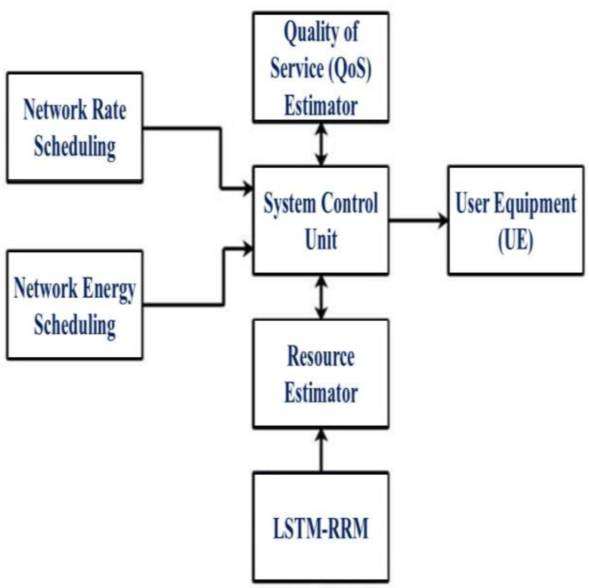

Figure 1. Block diagram of LSTM-RRM method

Radio access in a conventional LTE is primarily reliant on Orthogonal Frequency Division Multiple Access (OFDMA) in the downlink and Single-Carrier Frequency Division Multiple Access (SC-FDMA) in the uplink. The radio frame structure used by SC-FDMA and OFDMA is identical, which facilitates the usage of channel subdivision. Channels are often divided into radio resources that include domain time and frequency. In the frequency domain, the channel bandwidth is adjusted between 1 and 20 MHz. Sub-channels of 12 sub-carriers of 15 kHz make up the remaining 180 kHz of the total available bandwidth, which includes 1.4, 3, 5, 10, 15, and 20 MHz. A Resource Block (RB) is the smallest allocation unit for a radio resource.The single RB in this case has a frequency domain of 180 KHz and a time domain of 1 ms. In the time domain, radio resources are divided into Transmission Time Intervals (TTI), sometimes called sub-frames, which have a length of one millisecond. Ten TTI are used to create one frame. There are two 0.5 ms slots in each TTI, with seven symbols in each slot. The LTE-A taken into consideration in the 5G context is known as 5G LTE-A in this LSTM-RRM approach. A single cell with a single eNB and a collection of mobile UEs are included in this system architecture. As seen in Figure 2, the eNB is situated in the middle with UE.

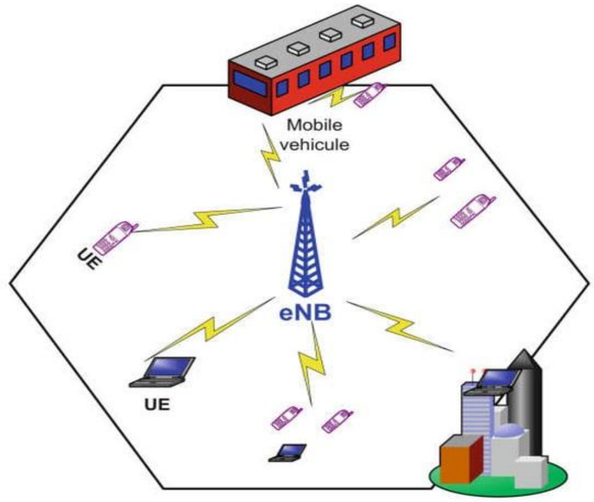

Figure 2: Model of eNodeB Network System (Balmuri et al., 2022)

There are two distinct user traffics on this 5G LTE-A network: human-to-human (H-H) and machine-to-machine (M-M) interactions. Numerous resource blocks designated by RBS are sent between M-M and H-H users via the eNB.

4. PROCESS OF LSTM-RRM

By examining the request queue, LSTM-based RRM determines the priority for assigning the resource to the intended UE. Consequently, a UE with a high priority is seen as such throughout the network. The UE from which the BS gets the most request queues is identified using a set of queues prior to the RRM. In this manner, the UE that sends more queues is given precedence. The matrixes utilised in the LSTM are prior values of bandwidth, power, and data rate. Additionally, GSO is used for LSTM hyperparameter adjustment. Two distinct resources are allotted in RRM according on data rate parameters like power and bandwidth.The UE with greater data transmission requirements receives high resources from the LSTM-based RRM. This lessens traffic in the 5G environment and the number of request queues that are sent across the network. The block design for the LSTM-based RRM is displayed in Figure 3.

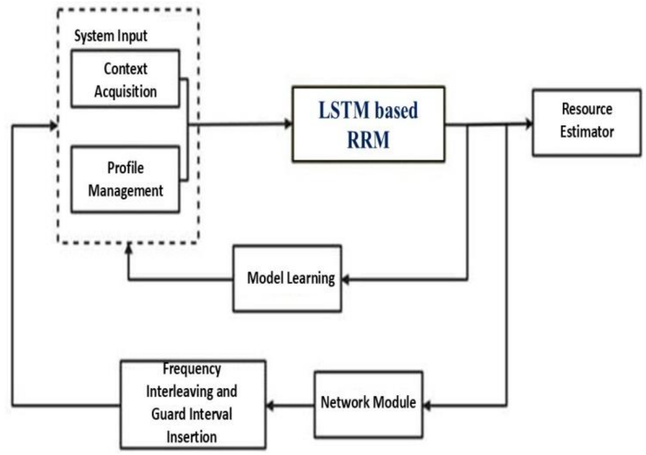

Figure 3: Block diagram of the LSTM-based RRM

This RRM approach takes input from two modules (profile management and context acquisition) and generates the output using the LSTM. In this instance, the RRM and the network are interfaced. The LSTM and input modules utilised for resource management are described as follows:

i. Context Acquisition: First, context acquisition is used to collect data about the UE and the network components. All of the 5G network's components employ the monitoring procedure to locate the data. Here, the monitoring procedure provides information on each component, a certain time period, request queues, and QoS levels. This context knowledge is used to address the UE problems that occur in the 5G network.

ii. Profile management: The profile management provides the segment terminal and element capabilities. Additionally, this profile management component offers details on the UE's needs, limitations, behaviour, and preferences (queues). This component specifically outlines the operational parameter sets that will be confirmed for the terminals and network components. To use LSTM to manage the UE's resources appropriately, this information is necessary.

iii. LSTM-based RRM: Utilising every network resource to achieve high bit rates with the highest feasible QoS level is the primary goal of the LSTM. In order to serve the UEs with a higher QoS level, the best resource management is found here using the LSTM. The section that follows provides a thorough explanation of an efficient RRM that makes use of LSTM.

iv. Learning: The learning rate of the LSTM, which was derived from GSO, is 0.9. The learning component of the LSTM contains information regarding context acquisition and profile management. This data aids in the identification and resolution of the problems using the LSTM-based RRM technique.

a. LSTM-Based Radio Resource Management

LSTM is utilised in this 5G network to get the best RRM in order to increase the communication process' bit rate. A particular kind of Recurrent Neural Network (RNN), the LSTM can often learn long-term dependencies and retain knowledge for extended periods of time. The LSTM network is made up of memory blocks called cells and is organised in a chain topology. The cell state and the hidden state are the two states that are transferred to the next cell in an LSTM. Here, the cell state is seen as a crucial chain of the data flow that permits the data to be sent unmodified during the decision-making process. However, the LSTM network may undergo some linear changes. As a result, the sigmoid gates may be used to add or delete data from the cell state. The series or layer of matrix operations with different individual weights is exactly the same as the LSTM's gates. Because LSTM uses gates to regulate the memorisation process, it avoids the long-term reliance issue. The architecture of LSTM is shown in Figure 4.

a. Grid Search Optimization (GSO)-Based Hyperparameter Tuning for LSTM

During this stage, the LSTM's hyperparameters are optimised using the GSO (Saleh et al., 2021). As indicated in Table 1, the collection of hyperparameters handled under hyperparameter tuning includes the number of neurones, learning rate, regression rate (reg_rate), batch size, and epochs. In situations when the hyperparameters are not relevant, this GSO is utilised to achieve the best outcomes. The range of values in the search space is represented by the values in Table 1, and the hyperparameter tuning is carried out in accordance with the power and bandwidth. Here, the ideal value within the specified range of hyperparameters is chosen using GSO with 10-fold cross-validation.

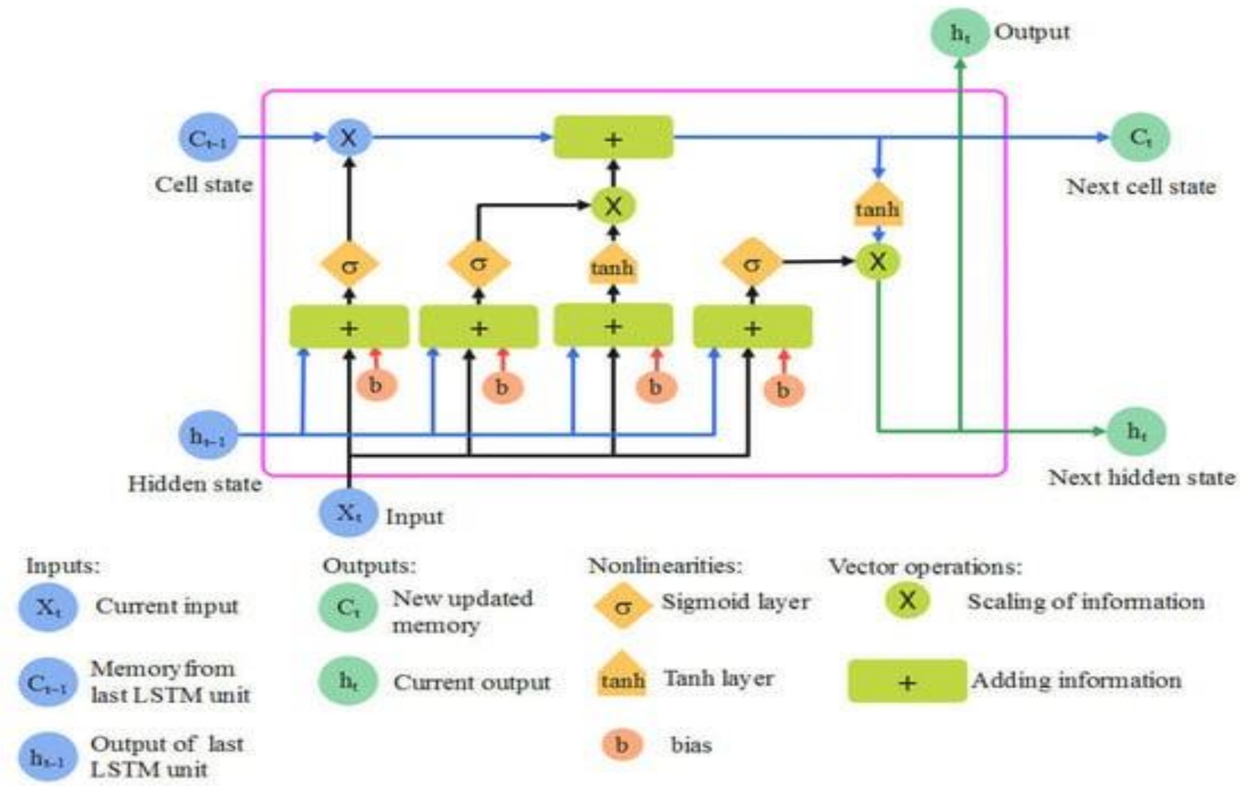

Figure 4: Architecture of LSTM cell (Balmuri et al., 2022)

Table 1. Parameters of LSTM (Balmuri et al., 2022).

Parameters	Range of Values
epochs	1–200
Neurons	10–200
reg_rate	0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5
learning rate	0.1–0.9
batch_size	73, 146, 219, 500, 1000

Thus, the bandwidth, power, and data rate of the UE in the 5G network are used to train this LSTM network. 3628800 pieces of data were utilised to train the LSTM, and they were from simulations in which the 5G network was run without LSTM. As a result, the LSTM is used to allocate sufficient power and bandwidth to the UEs with greater QoS levels. As a result, the 5G network's bit rate is raised while communication is taking place.

5. SYSTEM IMPLEMENTATION

Implementing the LSTM based RRM to control fluctuating traffic rates, the MATLAB software and SIMULINK model were created and utilised for the simulated study of resource management in virtual private networks. The monitoring method will identify virtual private network congestion by using a dynamic host model system. An interactive environment for developing algorithms, visualising data, analysing data, and doing numerical calculations, MATLAB is a high-level technical computer language. It has several power simulation libraries. MATLAB is an acronym for matrix laboratory. MATLAB is a software program for high-performance numerical computing and visualisation that was created by

MathWorks Inc. With hundreds of accurate and dependable built-in mathematical functions, MATLAB offers an interactive environment. Matrix algebra, complex arithmetic, linear systems, differential equations, signal processing, optimisation, nonlinear systems, and several other kinds of scientific calculations are among the many mathematical issues that these functions may solve.

The input box in the simulation creates data packets. The packet size is represented by the properties of each data set. After then, the data packets are sent via the data network. The MATLAB/Simulink Model for Communication Network Resource Management is shown in Figure 5. Its primary components were the following: resource assignment, network sink, logic module (if not), ingress committed rate, traffic source modules, node access control modules, parameter input box, display box, and scope.

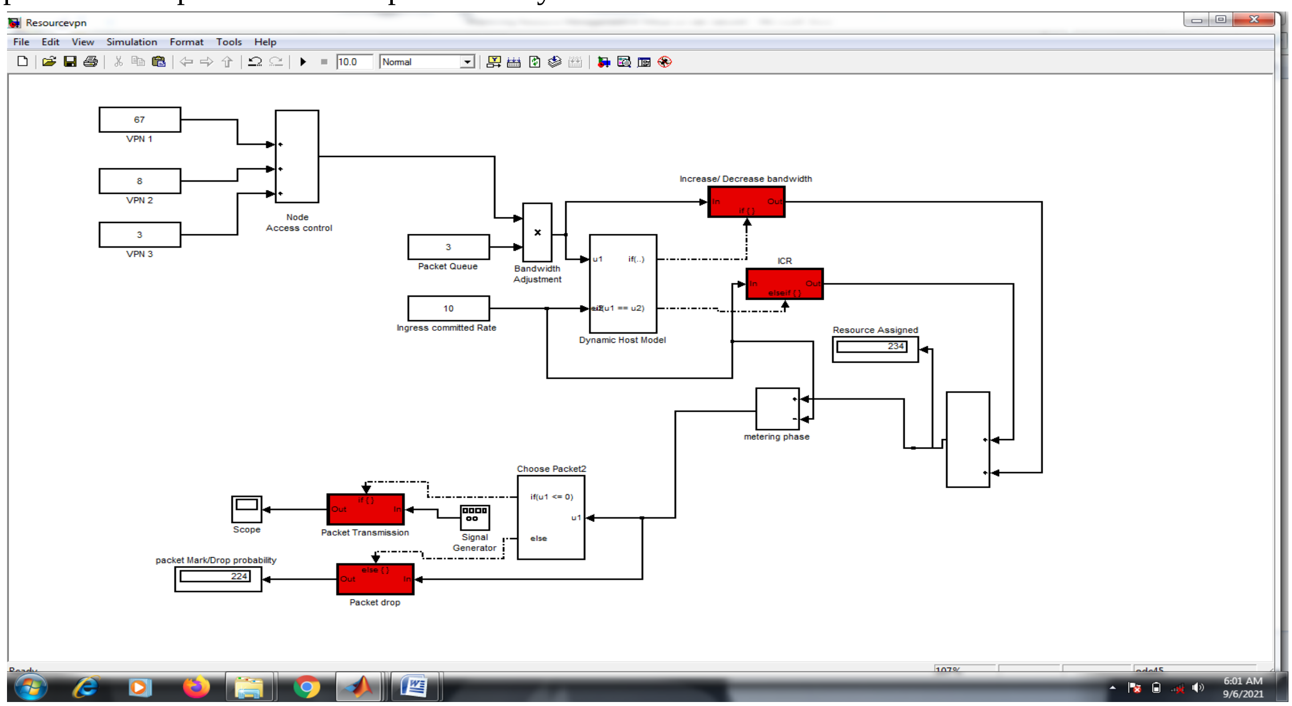

Figure 5: MATLAB Model of LSTM-RRM System on a Network

Three VPNS are used in this work's model to fill it with traffic; the system is scalable and can support many VPNS. Three traffic sources provide audio, video, and best-effort packets for every VPN.

6. RESULTS AND DISCUSSION

This section provides a comprehensive description of the LSTM-RRM method's findings and discussion. Network Simulator-3, which operates on a Windows 8 operating system with an Intel core i3 CPU and 4GB RAM, was used to develop and simulate the LSTM-RRM technique. This LSTM-RRM technique uses guard interval insertion and frequency interleaving to reduce losses in the 5G context. The LSTM-based RRM is then completed in order to allot sufficient resources for the targeted UEs. The system bandwidth is 100 MHz, and the BS height taken into account for this LSTM-RRM technique is 10 m.

Here, throughput, outage, Jain's index, and dual connectivity are used to assess the LSTM-RRM method's performance. These results are contrasted with DRRM(Montero et al., 2018) to show the effectiveness of the LSTM-RRM method. The DRRM was also implemented and simulated in MATLAB to evaluate the LSTM-RRM method.

The UE throughput comparison between DRRM and LSTM-RRM is displayed in Figure 6 and Table 2. Here, the number of UEs is changed from 5 to 30 in order to make the comparison. The investigation indicates that the LSTM-RRM outperforms the DRRM in terms of UE throughput. As an illustration, the LSTM-RRM's UE throughput ranges from 15 Mbps to 63 Mbps, whereas the DRRM's UE throughput ranges from 10 Mbps to 61 Mbps. In particular, compared to the DRRM, the LSTM-RRM's UE throughput for 30 UE is increased by up to 50%. By employing frequency interleaving to reduce burst errors and guard level insertion to minimise Inter-Symbol Interference (ISI), the LSTM-RRM is able to achieve greater UE throughput.

Table 2: Analysis of UE throughput for LSTM-RRM and DRRM

Number of UEs	UE Throughput (Mbps)	
	DRRM	LSTM-RRM
5	60	62
10	37	43
15	29	34
20	21	27
25	17	23
30	9	14

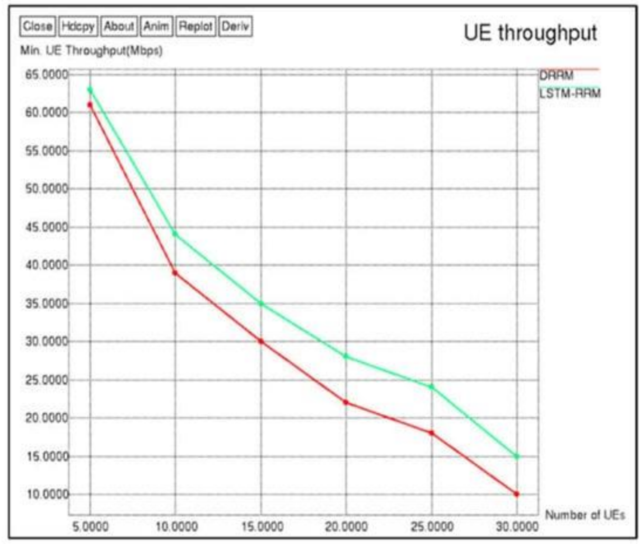

Figure 6: Comparative result of minimum UE throughput

The dual connectivity comparison between the LSTM-RRM approach and DRRM is displayed in Figure 7 and Table 3. The ability to link several base stations (BSs) using the same radio access technology is known as dual connectivity (DC). The proportion of connected UEs in dual connectivity in relation to the total number of UEs in the system is specifically depicted in Figure 9 and Table 7. Because of its efficient RRM between the UEs, the LSTM-RRM approach provides greater dual connectivity than the DRRM. Compared to the DRRM, the LSTM-RRM's dual connection for 30 UE is enhanced by up to 12%. The 5G system's connection is enhanced by the usage of LSTM, which allocates power and bandwidth optimally.

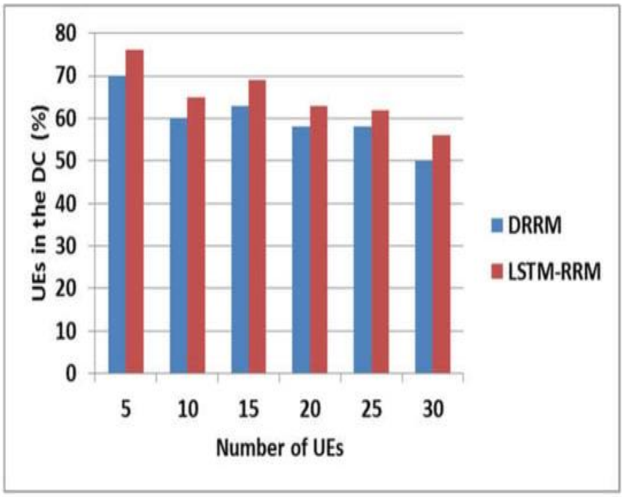

Figure 7: Comparative result of dual connectivity

Table 3: Analysis of dual connectivity for LSTM-RRM and DRRM

Number of UEs	UE Throughput (Mbps)	
	DRRM	LSTM-RRM
5	69	75
10	59	64
15	62	68
20	57	62
25	57	61
30	49	55

7. CONCLUSION

The study effectively illustrated how Radio Resource Management (RRM) based on Long Short-Term Memory (LSTM) could improve network performance and resource management in a 5G LTE-A setting. The system effectively distributed bandwidth and power to User Equipments (UEs) by utilising LSTM's capabilities, giving priority to those with greater data transmission requirements. As a consequence, network traffic congestion decreased and Quality of Service (QoS) levels increased.Furthermore, the LSTM model's performance was improved by integrating hyperparameter tweaking using Grid Search Optimization (GSO), which optimised variables such batch size, learning rate, and neurone count. Frequency interleaving and guard interval insertion were added to improve system dependability by reducing Inter-Symbol Interference (ISI) and burst errors.

According to simulation findings, the LSTM-RRM technique fared better than the DRRM approach on several important metrics, such as dual connectivity, Jain's fairness index, downtime, and UE throughput. For example, as compared to DRRM, the LSTM-RRM improved UE throughput for 30 UEs by up to 50%. Additionally, a 12% improvement in dual connectivity performance demonstrated the method's capacity to sustain reliable connections across several Base Stations (BS). The LSTM-based RRM was confirmed by the study to be a scalable and successful approach to the problems associated with resource management in 5G networks. Future studies could look into including other machine learning algorithms and enlarging the system to manage more complex network scenarios and a variety of traffic patterns.

8. REFERENCES

Ali, K. B., Zarai, F., Khdhir, R., Obaidat, M. S., & Kamoun, L. (2018). QoS-aware predictive radio resource management approach based on MIH protocol. *IEEE Systems Journal*, *12*(2), 1862–1873. https://doi.org/10.1109/JSYST.2017.2741453

Balmuri K.R., Konda S., Lai W.-C., Divakarachari P.B., Gowda K.M., & Kivudujogappa H., (2022) A Long Short-Term Memory Network-Based Radio Resource Management for 5G

Network. Future Internet 2022, 14, 184. https://doi.org/10.3390/fi14060184

Belleschi, M., Fodor, G., Della Penda, D., Pradini, A., Johansson, M., & Abrardo, A. (2015). Benchmarking practical RRM algorithms for D2D communications in LTE advanced. *Wireless Personal Communications*, *82*(2), 883–910. https://doi.org/10.1007/s11277-015-2658-1

Benzaid, C., & Taleb, T. (2020). AI-driven zero touch network and service management in 5G and beyond: Challenges and research directions. *IEEE Network*, *34*(2), 186–194. https://doi.org/10.1109/MNET.001.1900333

Bui, N., and Widmer J., (2018). Data-driven evaluation of anticipatory networking in LTE networks. *IEEE Transactions on Mobile Computing*, *17*(10), 2252–2265. https://doi.org/10.1109/TMC.2018.2812845

Cai, T., van de Beek, J., Nasreddine, J., Petrova, M., & Mähönen, P. (2011). A TD-LTE prototype system with modules for general-purpose cognitive resource management and radio-environmental mapping. *International Journal of Wireless Information Networks*, *18*(3), 131–145. https://doi.org/10.1007/s10776-011-0155-6

Condoluci, M., Araniti, G., Molinaro, A., & Iera, A. (2015). Multicast resource allocation enhanced by channel state feedbacks for multiple scalable video coding streams in LTE networks. *IEEE Transactions on Vehicular Technology*, *65*(6), 2907–2921. https://doi.org/10.1109/TVT.2015.2468475

De La Fuente, A., Escudero-Garzás, J. J., & García-Armada, A. (2017). Radio resource allocation for multicast services based on multiple video layers. *IEEE Transactions on Broadcasting*, *64*(3), 695–708. https://doi.org/10.1109/TBC.2017.2702298

Elgendy, O. A., Ismail, M. H., & Elsayed, K. M. (2018). Radio resource management for LTE-A relay-enhanced cells with spatial reuse and max–min fairness. *Telecommunication Systems*, *68*(4), 643–655. https://doi.org/10.1007/s11235-018-0431-8

Haddad, M., Elayoubi, S. E., Altman, E., & Altman, Z. (2011). A hybrid approach for radio resource management in heterogeneous cognitive networks. *IEEE Journal on Selected Areas in Communications*, *29*(4), 831–842. https://doi.org/10.1109/JSAC.2011.110406

Jo, S., Jong, C., Pak, C., & Ri, H. (2021). Multi-agent deep reinforcement learning-based energy-efficient power allocation in downlink MIMO-NOMA systems. *IET Communications*, *15*(12), 1642–1654. https://doi.org/10.1049/cmu2.12128

Kaddour, F. Z., Vivier, E., Mroueh, L., Pischella, M., & Martins, P. (2014). Green opportunistic and efficient resource block allocation algorithm for LTE uplink networks. *IEEE Transactions on Vehicular Technology*, *64*(9), 4537–4550.

https://doi.org/10.1109/TVT.2014.2371238

Li, Q., Hu, R. Q., Qian, Y., & Wu, G. (2012). Intracell cooperation and resource allocation in a heterogeneous network with relays. *IEEE Transactions on Vehicular Technology, 62*(5), 1770–1784. https://doi.org/10.1109/TVT.2012.2225634

Monteiro, V. F., Sousa, D. A., Maciel, T. F., Cavalcanti, F. R. P., Silva, C. F., & Rodrigues, E. B. (2018). Distributed RRM for 5G multi-RAT multiconnectivity networks. *IEEE Systems Journal, 13*(2), 192–203. https://doi.org/10.1109/JSYST.2018.2803064

Naqvi, S. A. R., Pervaiz, H., Hassan, S. A., Musavian, L., Ni, Q., Imran, M. A., Ge, X., & Tafazolli, R. (2018). Energy-aware radio resource management in D2D-enabled multi-tier HetNets. *IEEE Access, 6*, 16610–16622. https://doi.org/10.1109/ACCESS.2018.2817901

Pramudito, W., & Alsusa, E. (2013). A hybrid resource management technique for energy and QoS optimization in fractional frequency reuse-based cellular networks. *IEEE Transactions on Communications, 61*(12), 4948–4960. https://doi.org/10.1109/TCOMM.2013.112213.130

Pramudito, W., & Alsusa, E. (2014). Confederation-based RRM with proportional fairness for soft frequency reuse LTE networks. *IEEE Transactions on Wireless Communications, 13*(4), 1703–1715. https://doi.org/10.1109/TWC.2014.012314.130

Prasad, G., & Rukmini, M. S. S. (2020). Radio resource management strategy for mobile networks based on QoS sensible confederation. *Test Engineering and Management, 83*, 1761–1769.

Rostami, S., Arshad, K., & Rapajic, P. (2017). Optimum radio resource management in carrier aggregation-based LTE-advanced systems. *IEEE Transactions on Vehicular Technology, 67*(1), 580–589. https://doi.org/10.1109/TVT.2017.2759959

Saddoud, A., Doghri, W., Charfi, E., & Fourati, L. C. (2020). 5G radio resource management approach for multi-traffic IoT communications. *Computer Networks, 166*, 106936. https://doi.org/10.1016/j.comnet.2019.106936

Saleh, H., Alharbi, A., & Alsamhi, S. H. (2021). OPCNN-FAKE: Optimized convolutional neural network for fake news detection. *IEEE Access, 9*, 129471–129489. https://doi.org/10.1109/ACCESS.2021.3113067

Sande, M. M., Hlophe, M. C., & Maharaj, B. T. (2021). Access and radio resource management for IAB networks using deep reinforcement learning. *IEEE Access, 9*, 114218–114234. https://doi.org/10.1109/ACCESS.2021.3103222

Soret, B., & Pedersen, K. I. (2014). Centralized and distributed solutions for fast muting adaptation in LTE-advanced HetNets. *IEEE Transactions on Vehicular Technology, 64*(1), 147–158.

https://doi.org/10.1109/TVT.2014.2337891

Tiwana, M. I., & Tiwana, M. I. (2014). A novel framework of automated RRM for LTE SON using data mining: Application to LTE mobility. *Journal of Network and Systems Management*, *22*(2), 235–258. https://doi.org/10.1007/s10922-013-9278-4

Tseliou, G., Adelantado, F., & Verikoukis, C. (2015). Scalable RAN virtualization in multitenant LTE-A heterogeneous networks. *IEEE Transactions on Vehicular Technology*, *65*(11), 6651–6664. https://doi.org/10.1109/TVT.2015.2470700

Wang, H., Rosa, C., & Pedersen, K. I. (2015). Radio resource management for uplink carrier aggregation in LTE-Advanced. *EURASIP Journal on Wireless Communications and Networking*, *2015*(1), 121. https://doi.org/10.1186/s13638-015-0372-7

Wang, H., Rosa, C., & Pedersen, K. I. (2016). Dual connectivity for LTE-advanced heterogeneous networks. *Wireless Networks*, *22*(5), 1315–1328. https://doi.org/10.1007/s11276-015-1010-y

Zhang, Z., Xiao Y., Ma Z., Xiao M., Ding Z., & Lei X., (2019). 6G wireless networks: Vision, requirements, architecture, and key technologies. *IEEE Vehicular Technology Magazine*, *14*(3), 28–41. https://doi.org/10.1109/MVT.2019.2921208