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DYNAMIC SLICING OPTIMIZATION IN 5G NETWORKS USING A RECURSIVE LSTM MECHANISM WITH GREY WOLF OPTIMIZATION

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ABSTRACT

5G networks provide unmatched speed, connectivity, and the ability to support a wide range of diversified services, ushering in a transformational era of telecommunications. By applying innovative methods in data analysis, time-series forecasting, and optimization, this work provides a thorough strategy to addressing these difficulties. Detailed configuration and performance management data collecting from a 5G experimental prototype forms the basis of our methodology. Slicing ratios, priority, QCI (Quality of Service Class Identifier), and power measurements are among the critical parameters included in this collection. This work uses min-max normalization to guarantee consistency and standardized scaling in order to get this data ready for in-depth examination. For time-series forecasting, this novel method presents the Recursive LSTM (Long Short-Term Memory) model. LSTM networks, which are well-known for their ability to capture long-term dependencies, are essential for identifying temporal patterns in the information. In order to carefully adjust parameters and improve dynamic slicing configurations, this work employs the Grey Wolf Optimization (GWO) method. The GWO algorithm makes sure that network resource allocation constantly adapts to fulfill various objectives, taking inspiration from the hierarchical grey wolf pack's structured decision-making process. The combination of these advanced techniques results in a solution that greatly improves the accuracy and flexibility of time-series forecasting and resource distribution in 5G networks. Through the harmonic integration of data-driven insights, LSTM predictions, and the effective optimization capabilities of GWO, our methodology enables 5G networks to allocate resources with agility and flexibly, ultimately providing real-time, high-quality services. The method outperforms other approaches like CNN, CNN-LSTM, and RNN-LSTM, which were all implemented with MATLAB, by a substantial margin of 5.55%, with an accuracy of 99.12%.

Keywords: *5G Network, Quality of Service Class Identifier, Long Short-Term Memory, Grey Wolf Optimization, Min-Max Normalization.*

1. INTRODUCTION

The implementation of dynamic slicing in 5G networks is extremely important since it transforms the management and distribution of network resources. With the use of this technology, separate virtual networks that are customized to match the needs of certain applications can be established, meeting a variety of demands in the contemporary digital world [1]. This significantly improves resource allocation efficiency, which is important considering how quickly connected devices and apps are proliferating and how dynamic resource allocation on the network is becoming more and more necessary [2]. Network operators benefit from reduced resource waste and cost savings thanks to dynamic slicing, which guarantees real-time resource allocation in accordance with the particular requirements of each network slice [3]. Optimizing the Quality of Service (QoS) is largely dependent on dynamic slicing. Different applications, such augmented reality, remote surgery, and autonomous vehicles, have different needs when it comes to latency, bandwidth, and reliability [4]. With the capacity to tailor network slices to meet these particular requirements, dynamic slicing ensures a reliable and excellent user experience for a variety of use cases [5]. Dynamic slicing gives network operators the ability to manage infrastructure more effectively. Operators are able to adjust and distribute resources in real-time in response to changes in service requirements and variations in demand. Because it allows for the effective use of network resources and the delivery of excellent real-time services, this flexibility is essential for network optimization [6]. For cost efficiency, dynamic slicing is essential. Network deployments become more economical and sustainable when operators minimize operational expenses through precise resource allocation. It enables operators to effectively balance cutting costs with providing outstanding service quality, which is a critical factor in the fiercely competitive telecommunications sector [7].

Organizations in the era of big data have the enormous challenge of managing enormous amounts of data efficiently and extracting valuable insights from them [8]. The Internet of Things, social media, and sensor networks are some of the driving forces behind this data deluge [9]. The traditional approaches to data management and processing are inadequate in the face of this deluge of data. The effective processing and extraction of insightful information from this data, which improves resource allocation and decision-making, is made possible in large part by optimization approaches. Deep learning neural networks and other machine learning models have become important actors because of their ability to process and evaluate large amounts of data [10]. However, these models frequently show significant levels of complexity and have a large number of parameters. It is quite difficult to optimize such models for speed, accuracy, and resource efficiency. Algorithms for optimization are employed to adjust model parameters, which eventually improve performance and shorten training time. Because it offers scalable, on-demand resources, cloud computing has revolutionized the way businesses run [11]. However, allocating resources in a way that balances workload fluctuations is a challenging task. For businesses looking to cut expenses without sacrificing speed or high availability, cloud resource management optimization approaches are an invaluable resource [12]. For companies that depend on cloud infrastructure to run mission-critical applications, this is especially important.

Optimizing data flow is a basic requirement in the networking area in order to guarantee effective communication. The intricate workings of large-scale networks pose problems with bandwidth distribution, congestion control, and routing. By dynamically adjusting routing paths, reducing congestion, and intelligently allocating resources to the most critical locations, optimization algorithms are essential for improving network performance. Process improvement can lead to significant cost savings and increased efficiency in the field of supply chain and logistics management. Demand forecasting, inventory control, and route optimization are among the difficulties. In order to solve these problems, optimization techniques are developed, which provide ways to minimize lead times, minimize transportation costs, and maintain ideal inventory levels. Energy efficiency becomes an increasingly urgent task in view of growing environmental concerns and rising energy costs [13]. Energy optimization becomes crucial, especially in data centers and industrial activities. It is possible to reduce energy usage without sacrificing operational effectiveness by using optimization techniques. Using optimization strategies is essential to improving patient care and operational efficiency in the healthcare industry. Treatment planning, resource allocation, and patient scheduling are all areas of difficulty in the healthcare industry [14]. Hospitals and other healthcare facilities find that optimization techniques are very helpful in their efforts to maximize appointment scheduling, distribute resources (such as personnel and operating rooms), and adjust treatment plans, all of which lead to better patient care. The two most important requirements in the financial sector are risk management and investment portfolio optimization. Investment strategies that aim to balance risk and return can benefit from the deployment of optimization techniques [15]. With the use of these techniques, financial institutions may make educated judgments about risk management and asset allocation.

This study's methodology is critical to tackling the complex problems that 5G networks provide, especially with regard to dynamic slicing optimization. The need for effective resource allocation and real-time adaptation grows as the demand for a wide range of high-performance services within 5G networks continues on its upward trend. To maximize dynamic slicing, the study approach combines state-of-the-art methods. First, a large amount of configuration and performance management data is gathered from a 5G experimental prototype. This dataset provides the foundation for data-driven insights by encompassing a wide range of essential metrics, such as power measurements, priority, QCI, and slicing ratios. In order to improve time-series forecasting accuracy and flexibility in the dynamic slicing domain, the Recursive LSTM model assumes a central role by

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leveraging the exceptional long-term memory network capabilities to capture persistent relationships. Dynamically enhanced by past data, the LSTM predictions play a pivotal role in the dynamic slicing correction procedure. Inspired by the hierarchical hunting behavior of grey wolves, Grey Wolf Optimization (GWO) is utilized here to optimize resource allocation decisions and fine-tune parameters while keeping a close eye on a variety of goals, including throughput maximization and delay minimization. The suggested strategy enables 5G networks to dynamically adapt, allocate resources with agility, and ultimately provide high-quality, real-time services to an increasingly discriminating user base by managing the integration of these cutting-edge approaches. This demonstrates how crucial this study is to expanding the possibilities of 5G technology. The key contribution of the article is,

- Min-max normalization is a key pre-processing technique that the study introduces. This method ensures consistency and consistent scaling by standardizing the collected data. By preparing the data for additional analysis and optimization, this normalization improves the caliber and dependability of the ensuing modeling and forecasting procedures.
- The study uses time-series forecasting with the Recursive Long Short-Term Memory (LSTM) model. The remarkable capacity of LSTM networks to extract long-term dependencies from sequential data is well known.
- The Grey Wolf Optimization (GWO) algorithm is used in the study to optimize dynamic slicing configurations and fine-tune parameters. Grey wolves' hierarchical hunting style served as the model for GWO, which presents a novel optimization technique. Through emulating these creatures' systematic decision-making process, GWO makes sure that network resource allocation adapts dynamically to meet different goals.

The following is the structure of this study: The job scheduling problem has been the subject of extensive prior research, and various optimization approaches are explored in Section II. The divisive claim is discussed in Section III. The suggested method is examined in Section IV. The investigation's setup, results, and a comprehensive analysis of the findings are all described in Section V. At last, the paper's conclusion and future work are discussed in Section VI.

2. RELATED WORKS

One of the key technologies in 5G is network slicing (NS), which aims to support different virtualized operators with different service needs on a common underlying infrastructure. In the resource-sharing market, where resources are traded for monetary gains in order to maximize their use, NS has the ability to significantly alter the dynamics between various organizations. However, these entities only find resource exchange desirable when mutually beneficial outcomes can be achieved. In the framework of resource trading within NS, Ou et al. [16] proposed an economic model intended to analyse the pricing and purchasing dynamics among several Mobile Virtual Network Operators (MVNOs) and their respective user base. As a two-stage multi-leader multi-follower (MLMF) Stackelberg game, formulated the pricing and purchasing problem. In this game, players play the role of followers, responding to the MVNOs' initial establishment of their unit prices by deciding on the quantity of purchases they make. In this study, the uniqueness and existence of a Nash equilibrium (NE) are established mathematically. This study converts the game-based optimization problem into a stochastic Markov decision process (MDP) and provide a technique based on the multi-agent duelling deep Q-Network algorithm to obtain an optimal dynamic pricing solution for the MVNOs. The model's dependence on theoretical presumptions and simulations, which might not accurately reflect all practical complexity and unpredictability, may restrict its reliability and application in the real world.

Hu et al. [17] developed a smart and self-adaptive approach to network resource allocation is becoming more and more necessary as 5G evolves, marked by a spike in demand for various smart grid communication services and the digital transformation of communication networks. The suggestion of a neural network-based resource allocation method provides a response to this need. The primary goal is to put in place a hierarchical scheduling system for smart grid communication services at the edge, specifically at the power smart gateway. This approach achieves two main objectives: In order to meet the unique needs of 5G network slicing, it first dynamically anticipates traffic patterns inside the slicing network. Secondly, it intelligently matches and classes smart grid communication services. The hierarchical scheduling system, which collects data features from the services and encodes this data using a one-dimensional convolutional neural network (1D CNN), enables intelligent categorization and matching of smart grid communication services. In order to facilitate dynamic traffic prediction within the slicing network based on time series, it interfaces with a Bidirectional Long Short-Term Memory Neural Network (BILSTM). Implementing the proposed neural network-based technique on massive and resource-demanding 5G network deployments could lead to issues with resource consumption and scalability. Moreover, it could require a lot of computing power, which reduces its usefulness in frameworks with constrained resources.

Virtualization is a key component of 5G networks, enabling telecoms to significantly lower their capital and operating costs by combining several services onto a single hardware platform. However, the heterogeneity of services provided makes it difficult to provide quality of service (QoS)-guaranteed services for a wide variety of renters. Network slicing has been proposed as a solution to this problem by Lin, Chou, and Hwang, dividing up the computing and communication resources to meet the specific requirements of various tenants and their services [18]. It is a difficult and crucial task to effectively optimize the distribution of network and computational resources among various network slices. In this study, two heuristic algorithms are proposed as a response: the Minimum Cost Resource Allocation (MCRA) and the Fast Latency Decrease Resource Allocation (FLDRA). For network slices with multiple tenants in a two-tier architecture, these algorithms are designed to manage resource allocation and dynamic path routing. According to simulation results, both MCRA and FLDRA algorithms outperform the previously suggested Upper-tier First with Latency-bounded Overprovisioning Prevention (UFLOP) algorithm. Furthermore, improved resource utilization is achieved by the MCRA algorithm compared to the FLDRA technique.

Customer expectations for quality of service (QoS) from network service providers have increased due to the proliferation of devices, apps, and services. Experts in network design and optimization are working on in-depth research to meet these needs. Nonetheless, the dynamic network environment keeps posing fresh problems that need for workable answers. The merging of current networks is one strategy being investigated to improve coverage and capacity. Enhancing mobility management's flexibility, user-centeredness, and service-centricity is another area of research attention. With the introduction of 5G networks, there will be much more capacity, more stability, stronger connectivity, faster speeds, lower latency, and higher availability. In order to satisfy the demanding needs of many applications, the network infrastructure needs to be more flexible and dynamic than in the past. Network slicing done right has the potential to meet the stringent application requirements of modern network design. Singh et al. used an sophisticated fuzzy logic to create mobility and traffic control algorithms that are as flexible as possible without sacrificing efficiency [19]. Improving the quality of service provided by the present mobility management systems and making the best use of the network resources at hand are the ultimate goals of this research. It is considered essential to integrate the technologies of Network Function Virtualization (NFV) with Software-Defined Networking (SDN). The increased demand for higher data rates, more bandwidth capacity, and lower latency across a variety of use cases on the network is driving the importance of network slicing as an architectural framework for 5G networks in order to suit a variety of network needs.

Network functions can be flexibly scaled in and out in 5G environments to adjust network slice capacity. This process, called autoscaling, lowers operating expenses by eliminating instances as needed while simultaneously improving performance through the addition of instances. However, compared to conventional cloud computing, autoscaling in 5G networks has different difficulties. Multiple instances must be deployed simultaneously during the deployment of 5G network functionalities, and this process occurs more frequently than with standard cloud computing. The system's cost-effectiveness is greatly impacted by the quantity and timing of these deployments. In this study, Hsieh et al. first used the 3GPP standards to detect autoscaling problems [20]. Then outline the issue and provide closed-form answers for a variety of performance measures by developing a low-complexity analytical queuing model. These analytical models and solutions provide important insights and theoretical design direction, and are validated by means of extensive simulations. They support the assessment of reservations' efficacy. This study provides the dynamic block-setup reservation algorithm (DBRA) to find the ideal number of reserved instances and network slice threshold values. Because of this, mobile operators can save time and money by balancing cost-effectiveness without requiring extensive testing or real deployment.

An essential component of 5G, network slicing, promises to improve provisioning, agility, and intelligence in infrastructure management and service delivery. Nevertheless, considering the dynamic, diverse, and expansive character of contemporary networks, accomplishing these goals is no mean accomplishment. The issues presented by dynamic and complex networks are not well addressed by many of the network slicing methods now in use, which instead concentrate on maximizing instantaneous performance. This study addresses these issues by introducing a two-stage slicing optimization approach that includes time-averaged metrics, offering network slicing in dynamic situations a safety net. This method uses

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runtime partial observations while acknowledging the lack of comprehensive prior knowledge about the environment. Because future system realizations are unpredictable, conventional offline solutions cannot be used to make judgments. Cheng et al. introduced a deep learning and Lyapunov stability theory-based learning-enhanced optimization approach to get around this [21]. By using previous data and in-the-moment observations, this method enables the system to learn and generate safe slicing solutions. Network slicing may adapt and function well in intricate, dynamic network environments thanks to this creative method.

Despite the promising advancements in network slicing, resource allocation, mobility management, and autoscaling in 5G networks, there are several challenges that need to be addressed for the effective implementation of these technologies in real-world deployments. The existing studies provide valuable insights and propose innovative solutions, but there are constraints and uncertainties that limit their practical applicability. Key challenges include scalability issues in resource allocation, reliance on theoretical presumptions in analytical models, and the substantial processing power required for deep learning-based techniques. Additionally, the dynamic and diverse nature of contemporary networks poses difficulties that some existing methods may not adequately address.

2.1. Research Questions

RQ1: How can the scalability issues associated with resource allocation in network slicing be effectively addressed to accommodate the demands of diverse applications and tenants in 5G networks?

RQ2: To what extent do theoretical presumptions in analytical models impact the reliability and applicability of proposed solutions for resource allocation, mobility management, and autoscaling in 5G networks?

RQ3: What are the practical implications and challenges of deploying deep learning-based techniques, such as the multi-agent duelling deep Q-Network algorithm and the deep learning and Lyapunov stability theory-based approach, in resource-intensive 5G network environments?

RQ4: How can the proposed two-stage slicing optimization models with time-averaged metrics provide a safety net for network slicing in dynamic situations, and what are the limitations of this approach in addressing unpredictable future system realizations?

3. PROBLEM STATEMENT

Several major issues with 5G network slicing and associated works are brought to light by the above literature reviews. The first difficulty is meeting the various service needs while attaining both high wireless resource capacity and efficient isolation among slices. Notwithstanding the freedom and customization that network slicing offers, dynamic resource allocation that strikes a balance between affordability and performance is also required. Large-scale 5G deployments have difficulties due to the scalability and resource consumption of neural network-based resource allocation approaches [16]. Network slicing makes it clear that efficient autoscaling is required in order to minimize expenses and adjust to shifting network demands. Eventually, network slicing provides better intelligence and provisioning, but it also has to deal with a complex and dynamic network environment that demands creative solutions to keep performance and flexibility high. In order to overcome these challenges, this paper presents a 5G network Dynamic Slicing Optimization technique that makes use of Grey Wolf Optimization and a Recursive LSTM Mechanism.

4. PROPOSED RECURSIVE LSTM-GWO FRAMEWORK

The methodology used in this research is intricate and aims to maximize dynamic slicing in 5G networks by utilizing a variety of advanced tools and methodologies. First, a 5G experimental prototype is used to gather a large amount of configuration and performance management data. Essential metrics including slicing ratios, priority, QCI, and power measures are included in this JSON-formatted data. Min-max normalization is an essential preprocessing procedure to assure consistency and standardize the data's scale before analyzing it. The proposed methodology is depicted in Figure 1.

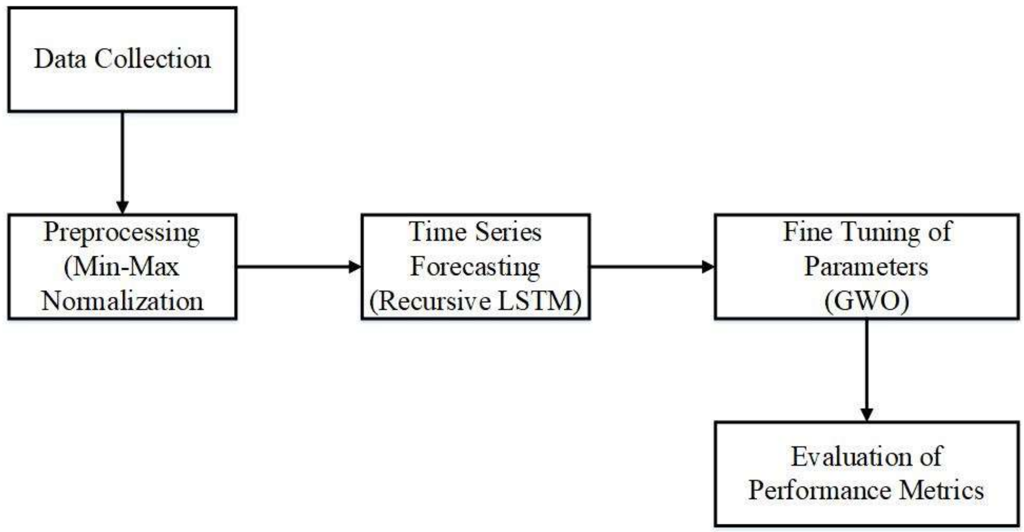

Figure 1. Proposed Methodology

Next, the Recursive LSTM model for time-series forecasting is proposed, which takes advantage of LSTM's capacity to represent long-term dependencies. Grey Wolf Optimization (GWO) is used to adjust variables and allocations of resources in the dynamic slicing optimization process, which incorporates LSTM predictions that are impacted by past data. Grey wolves' hierarchical hunting style served as the model for GWO, which helps optimize slicing configurations to meet goals like throughput maximization and latency reduction. This complex methodology highlights the goal of the article, which is to improve the performance of 5G networks by using a comprehensive strategy that includes optimization, time-series forecasting, and advanced data analysis.

4.1. Data Collection

This 5G experimental prototype was used for a whole day to gather configuration and performance management data from Commercial Off-The-Shelf (COTS) User Equipment (UEs). During this time, a background script interfaced with FlexRAN to gather the information. The JSON-formatted data included a range of metrics, such as priority, power measurements, Quality of Service Class Identifier (QCI), provisioned slicing ratios, and other configuration and performance management parameters. The UEs were moved throughout our lab area on a regular basis to introduce variations in radio circumstances, and an internet connection was required for the background activities. Using MATLAB and a PC with a Dual Intel Core i7 processor (2.4 GHz, 4 cores, 7th Gen.) and 16 GB of RAM, created a machine learning model. Then assembled real-time models and included them into our 5G experimental prototype as stand-alone Linux applications [22].

4.2. Pre-Processing Using Min-Max Normalization

The gathered dataset from the 5G experimental prototype is first processed for analysis during the preprocessing stage. This dataset contains all of the configuration and performance management information that was collected over the course of a day from COTS UEs. The data is kept in a JSON file format and includes important metrics including power measurements, priority, QCI, and slicing ratios. The study uses min-max normalization, a scaling approach that makes sure all data attributes fit within a consistent range, to prepare the data for additional analysis. In order to prevent biases resulting from differences in the scale of the original data, this normalization step is essential.

One important stage in data preprocessing is min-max normalization, which is often referred to as feature scaling. Input values are rescaled to fit into a predetermined range, usually [0, 1]. This procedure normalizes the intensity levels throughout the dataset, reducing the impact of lighting and pixel value distribution variances. Finding the dataset's minimum and maximum values and then using the linear transformation to change each original value into a new value falling inside the predetermined range are the two primary processes in min-max normalization. In addition to improving data consistency, this process helps produce more accurate and consistent outcomes for further analysis and machine learning tasks. The lowest value in the dataset represents the darkest value, while the maximum value represents the brightest. These values are initially established for each data point in the collection. Following its establishment, each data point's initial intensity value is linearly modified to

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fall between [0, 1]. (1) gives a description of the transformation formula applied in this case.

$$I_{out} = (I_{in} - Min)\frac{newMax - newMin}{Max - Min} + newMin \quad (1)$$

Once min-max normalization is applied, the image is called I_{out}. The minimal and maximum intensities are called $newMin$ and $newMax$, respectively. The minimum and maximum intensity standards, which range from 0 to 255, are represented by the symbols Min and Max, respectively, while the time series data is denoted as I_{in}. This adjustment was applied to every image in the dataset to guarantee that the pixel values were consistent and suitable for additional processing. This normalization procedure helps to improve the dataset's suitability for accurate and consistent evaluation by eliminating biases introduced by differences in pixel values and illumination.

4.3. Recursive LSTM for Time-Series Forecasting

LSTM (Long Short-Term Memory) networks will be introduced at the outset of the research to highlight their importance in modelling sequential data and their broad applicability in time-series forecasting. This is explained by their skill in identifying long-term dependence. Next, examine the idea of Recursive LSTM and explain its novel methodology, which uses LSTM predictions from one time step as input to produce predictions at later time steps. The modelling of intricate temporal patterns is made possible by this recursive technique, which makes time-series forecasting more accurate and useful overall—especially when it comes to dynamic slicing optimization in 5G networks.

Time-recursive recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) may be able to address the issues with gradient vanishing or explosion that frequently arise in RNNs. Despite their prowess in quickly absorbing new data, RNNs have trouble remembering long-term temporal data [23]. An architecture that integrates short- and long-term memory components is the solution to this problem. The new deep machine learning neural network known as LSTM builds on the RNN architecture by adding memory cells and input, forget, and output gates to control the flow of information at various time intervals. After the LSTM is included, this augmentation greatly improves the RNN's ability to understand and interpret longer data sequences, which fixes the gradient vanishing problem. Particularly, one of these gate components—the forget gate—is very important to the memory unit of an LSTM [24].

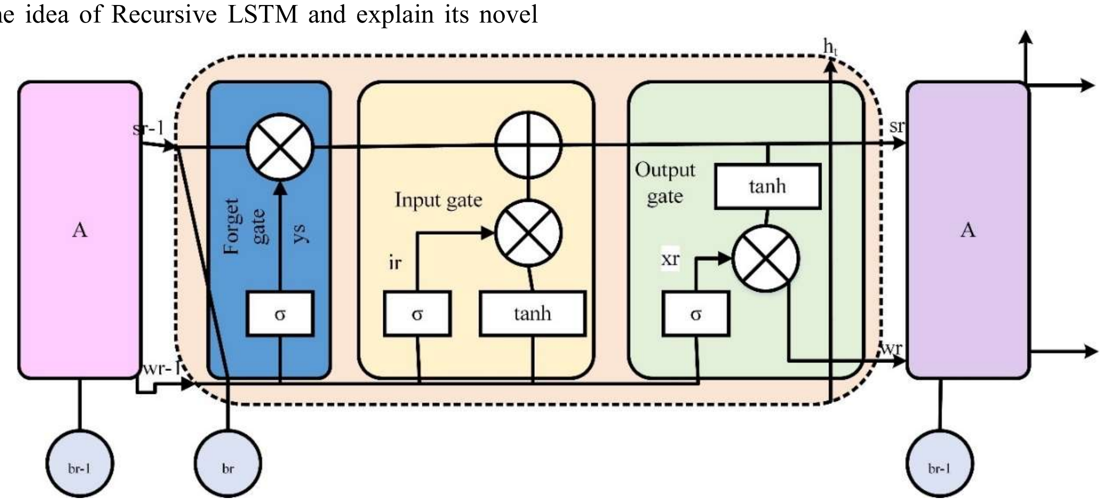

Figure 2. Basic Architecture of LSTM

The central inputs and outputs of the LSTM structure are illustrated in Figure 2. The initial step involves selecting the information within the cell state that needs to be discarded. This decision is determined in (2) through the utilization of a sigmoid layer, often referred to as the "forget gate layer." This layer assesses w_{r-1} and b_r, generating values ranging between 0 and 1 for each element present in the cell state, denoted as s_{r-1}. When the sigmoid function's output approaches 0, it signifies that the previously stored data, s_{r-1}, is to be "forgotten." Conversely, when the sigmoid function yields a value close to 1, it indicates that the data recorded within s_{r-1} is to be retained in its entirety.

$$Y_s = \sigma(h_Y.[w_{r-1}, b_r] + a_Y) \quad (2)$$

The vector of weights in the present instance is h_Y, the bias vector is a_Y, the sigmoid function is, and the input series is b_r. The result of the preceding block is w_{r-1}.

To determine which additional data will be saved in the cell state. (3) uses a sigmoidal layer designated the "input gate layer" to choose the values before updating them. Then, a $tanh$ layer produces a vector of new candidate values s'_r that might be incorporated into the state employing (4).

$$i_r = \sigma(h_i.[w_{r-1}, b_r] + a_i) \quad (3)$$

$$s'_r = \theta(h_s.[w_{s-1}, b_r] + a_s) \quad (4)$$

Enhance the prior cell state s_r into the new cell state s_r by substituting the newest subject's identity in order to improve the combined states of (3) and (4).

Eliminate the data that already choose to forget and add it to the prior state. Then, based on the results in the previous stages, add the additional data to (5) as $i_r * s_{r-1}$.

$$s_r = Y_r * s_{r-1} + i_r * s'_r \quad (5)$$

The output intends to generate must be decided upon as the last phase. Despite being filtered, the result would be based on cell status. The initial procedure in (6), which establishes which elements of the cell state should be the output, is to run a sigmoid layer. The result of the sigmoidal gate is subsequently multiplied by the cell state, which only produces the sections chosen for that output in (7), forcing the outputs to be in the range of 1 and 1.

$$X_r = \sigma(h_X.[w_{r-1}, b_r] + a_X \quad (6)$$

$$Z_r = \theta(s_r) * (X_r) \quad (7)$$

The Recursive LSTM Concept introduces a novel technique by generating predictions repeatedly, building upon the foundation of the regular LSTM model. The unique quality of Recursive LSTM is its inherent capacity to use predictions from each time step as dynamic input characteristics for forecasting the next time step, creating a feedback loop that reinforces itself. The recursive approach incorporates the latest outcomes into the input sequence, enabling the model to continuously improve and modify its predictions. It thus becomes skilled at encapsulating changing temporal patterns and dependencies found in time-series data. Because of its dynamic feedback loop, the recursive LSTM may produce forecasts that are more accurate and context-aware, which makes it especially useful for applications where real-time flexibility is crucial, such dynamic slicing optimization in 5G networks.

Explore the complex process of model learning in the Recursive LSTM training phase. Using methods like backpropagation through time (BPTT), the LSTM is fine-tuned internally during this step by being exposed to past time-series data. The recurrent connections in the LSTM are vital for the propagation of errors, which enables the LSTM to learn from previous predictions and eventually improve its performance. Use the mean squared error (MSE) as the basis for regression task selection when it comes to the loss function. To successfully minimize prediction errors during training, the Mean Squared Error (MSE) method measures the difference between the model's predictions and actual observations. During the training phase, the LSTM's predictive skills are laid down, which is an essential component that is later utilized for the optimization of dynamic slicing.

Focusing on the critical relationship between LSTM predictions and dynamic slicing optimization, this study clarifies how the historical data-based forecasts of the LSTM are essential for enabling real-time resource allocation decisions in 5G networks. This study explains the dynamic slicing adjustment procedure, which is centred on optimizing network resource allocation, encompassing elements such as bandwidth distribution, to accomplish various goals. These goals could include minimizing latency and maximizing throughput, as well as guaranteeing Quality of Service (QoS) and other critical performance indicators that are crucial for 5G network administration. These resource allocation decisions are guided by real-time insights provided by the LSTM predictions, which are derived from historical performance data. This allows for quick and informed adjustments to network slicing configurations. This combination of dynamic slicing optimization with LSTM predictions highlights the possibility of more effective and responsive network management in the background of 5G technologies, where flexibility is critical.

4.4. Grey Wolf Optimization Framework for Fine-Tuning the Parameters

Grey Wolf Optimization (GWO) is used in this paper specifically to optimize the dynamic slicing configuration in 5G networks and fine-tune parameters. GWO is a type of metaheuristic approach that is inspired by the organized, pack-based hunting methods of grey wolves. Wolf packs have a hierarchical structure with alphas, betas, deltas, and omegas that affect the algorithm's decision-making process. GWO leverages a wolf-like encirclement, tracking and capture strategy, and coordinated hunting to repeatedly optimize and fine-tune network resource allocation decisions. Its main goals are to optimize throughput, minimize latency, guarantee Quality of Service (QoS), and improve dynamic slicing's overall performance in 5G networks. The incorporation of GWO into the study technique capitalizes on its unique optimization methodology, ultimately leading to more efficient

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and adaptable network management in the complex world of 5G technology.

A meta-heuristic method called GWO was put out [25]. The method was influenced by the grey wolf killing strategy and pack structure. Grey wolves have a very hierarchical structure and live in packs. The leaders of the wolves, the alphas (α), now make all the decisions. Beta (β) wolves, who belong to the next level, help alpha wolves with their job. The final person, Omega (ω), is the victim in this system. A wolf is sometimes referred to as a delta (δ) wolf if it does not fit into any of the aforementioned classifications. Grey wolves attempt to encircle a food source, attack, and kill, then look for additional prey in accordance with this clearly established hierarchy. Wolves use hunting as a means of enclosing their prey, locating and killing animals, and engaging in combat with their prey. The way grey wolves circle their prey during a hunting expedition is depicted in (8) and (9).

$$\vec{K} = \left|\vec{f} \cdot (\overrightarrow{X_w}(n) - \vec{X}(n)\right| \tag{8}$$

$$\vec{X}(n+1) = \overrightarrow{X_w}(n) - \vec{Q} \cdot \vec{K} \tag{9}$$

Where $\vec{X}$ depicts wolf's location in round configuration; $\overrightarrow{X_w}$is the prey's vector position; n is present time; $\vec{Q}$ and $\vec{K}$ are effective vectors that have the following definitions is shown in (10) and (11).

(10) and (11), where $\vec{X}$ represents the wolf's location in a circular configuration, $\overrightarrow{X_w}$ represents the prey's vector position, n denotes the current time, and $\vec{Q}$ and $\vec{K}$ represent effective vectors with the corresponding definitions.

$$\vec{Q} = 2\vec{I} \cdot \overrightarrow{c_1} - \vec{I} \tag{10}$$

$$\vec{f} = 2 \cdot \overrightarrow{c_2} \tag{11}$$

Random vectors equally distributed between 0 and 1 are included in $\overrightarrow{c_1}$ and $\overrightarrow{c_2}$ where the element d is progressively decreased from 2 to 0. The $\alpha, \beta, and\ \delta$ wolves are thought to comprehend it better since the location of the meal is never evident in advance. (12), (13), and (14) are used to determine the victim's location by utilizing the wolves' positions.

$$\vec{K}_\alpha = \left|\vec{f}_1 \cdot \vec{X}_\alpha - \vec{X}\right|,\ \vec{K}_\beta = \left|\vec{f}_2 \cdot \vec{X}_\beta - \vec{X}\right|,\ \vec{K}_\delta = \left|\vec{f}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{12}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{Q}_1 \cdot \vec{X}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{Q}_2 \cdot \vec{K}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{Q}_3 \cdot \vec{K}_\delta \tag{13}$$

$$\vec{X}(n+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{14}$$

The following phase is to stalk (or exploit) the victim, assuming the study has an estimated position. This can be accomplished by using the vector Q ⃗, since the condition of wolves gets closer to the prey's site when I in (10) decreases from 2 to 0. Moreover, by doing away with the necessity for local averages, variables f and Q also contribute to maintaining the method's exploring capabilities. In addition to altering the location of food and the difficulty of foraging, the variable f can also affect a Q value greater than one, or |Q| > 1, which compels the wolves to leave their food and search for it. Once the method is applied to a pack of wolves for a set number of iterations, (11) will finally display the prey's position or the optimal region on Earth.

5. RESULTS AND DISCUSSION

This research is a complex methodology that uses several advanced tools and techniques to maximize dynamic slicing in 5G networks. First, a lot of setup and performance management data is collected using an experimental 5G prototype. This JSON-formatted data contains important information including power measurements, priority, QCI, and slicing ratios. Prior to data analysis, min-max normalization is a crucial preprocessing step that ensures consistency and standardizes the data's scale. Subsequently, a time-series forecasting model called Recursive LSTM is suggested, utilizing LSTM's ability to depict long-term relationships. In the dynamic slicing optimization process, which takes historical data into account and integrates LSTM predictions, GWO is utilized to modify variables and resource allocations. GWO is a tool that helps optimize slicing setups to achieve objectives such as throughput maximization and latency reduction. It was inspired by the hierarchical hunting method of grey wolves. This intricate process draws attention to the article's main objective, which is to enhance 5G network performance by the use of a thorough plan that incorporates advanced data analysis, time-series forecasting, and optimization.

5.1. Model Accuracy

A predictive model's performance is evaluated using a metric called model accuracy, which is usually employed in the setting of statistical analysis or machine learning. It gauges how well the model's predictions match the actual or observed results. As the ratio of accurate forecasts to all of the model's predictions, accuracy is sometimes given as a percentage. A lower accuracy score suggests a less dependable model with a greater percentage of inaccurate predictions, whereas a higher accuracy number shows that the model's predictions are more consistent and in closer agreement with the ground

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truth. However, as accuracy can be impacted by class imbalances and other factors, it might not always be the ideal indicator to assess a model's performance. In Figure 3, it is shown.

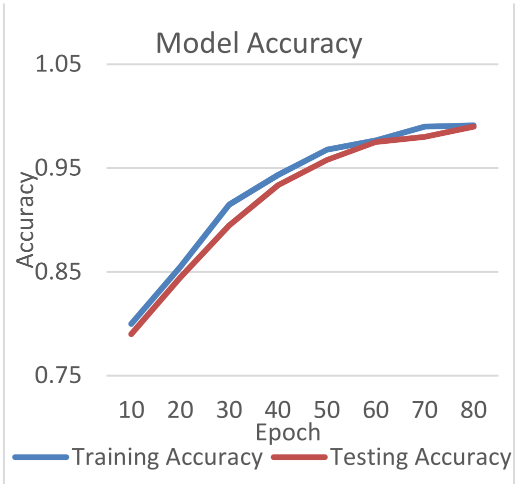

Figure 3. Model Accuracy

5.2. Model Loss

A quantitative metric called model loss is used to express the mistake or difference between a model's projected values and the actual, observed values in a dataset. It is an important measure that machine learning models are trained with. In order to improve the accuracy and proximity of the model's predictions to the real values, the main goal of training is to minimize this loss function. For example, MSE is utilized for regression issues while cross-entropy loss is used for classification jobs. Different types of loss functions are employed for different tasks. The loss is reduced by modifying the model's parameters using strategies like gradient descent, which enhances the model's performance and improves the agreement between predictions and actual results. It is depicted in Figure 4.

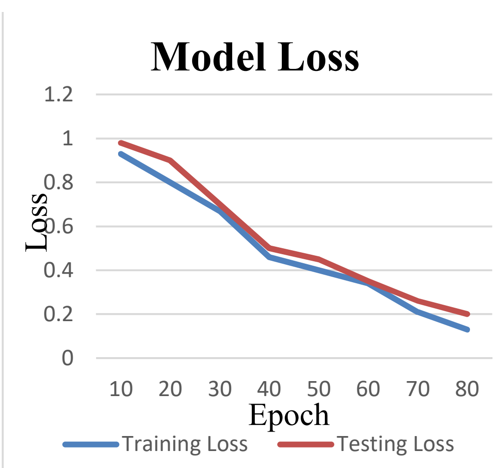

Figure 4. Model Loss

5.3. ROC

A popular graphical representation and assessment tool for binary classification problems in machine learning and statistics is the Receiver Operating Characteristic (ROC). It illustrates how different categorization thresholds affect a model's true positive rate and false positive rate trade-off. Plotting these rates as the cutoff point for categorizing positive or negative occurrences is adjusted yields the ROC curve. An area under the ROC curve (AUC) of 1 denotes a perfect classifier, whereas 0.5 denotes random guessing. A greater AUC suggests better model discrimination and a stronger capacity to discriminate between the two classes. Making educated judgments concerning model selection and fine-tuning classification algorithms is made easier with the use of ROC analysis, which is useful for evaluating and comparing the performance of various classifiers. It is depicted in Figure 5.

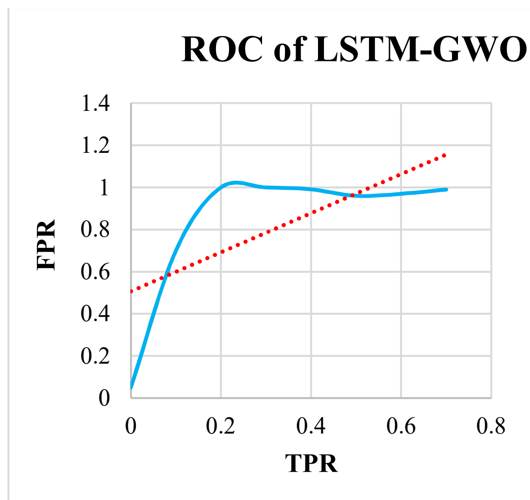

Figure 5. ROC of LSTM-GWO

5.4. Fitness Assessment of the Proposed System

One of the most important steps in determining the efficiency and performance of this optimization process is the fitness evaluation of the suggested system, or GWO. Fitness is the measure of GWO's ability to maximize a certain objective function or solve a particular issue. The evaluation includes calculating the algorithm's resilience in managing various issue domains, efficiency in terms of computational resources and time, and capacity to converge towards the best answer. The fitness evaluation may also take into account the algorithm's scalability, flexibility, and capacity to locate solutions in multi-dimensional search spaces. Researchers and practitioners may decide if GWO is a good match for their optimization tasks and make well-informed judgments regarding its use and possible enhancements if needed by doing a thorough fitness evaluation. It is depicted in Figure 6.

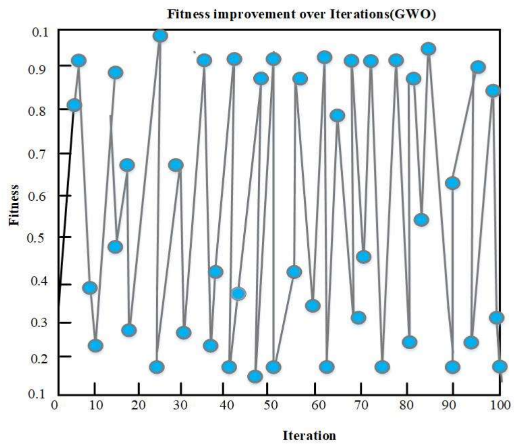

Figure 6. Fitness Improvement over Iterations (GWO)

The average squared difference between the target value and the model's projected value in the dataset is measured by MSE. It has the following characteristics (15):

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(X_i - \widehat{X}_\iota\right)^2 \qquad (15)$$

Where m is the number of data, X_i is the ground truth value and $\widehat{X}_\iota$ is the predicted value.

In statistics and machine learning, RMSE is a frequently used metric to evaluate the precision of a prediction model, especially in regression assignments. It measures the average size of the discrepancies between the model's projected values and the actual observed values within a dataset. The square root of the average of the squared discrepancies between the expected and actual values is usually used to compute RMSE(16). A lower RMSE number indicates a better fit and more accuracy, whereas a larger RMSE value indicates that the model's predictions vary more from the actual outcomes. RMSE offers a measure of how well the model's predictions fit the observed data.

$$RMSE = \sqrt{\frac{\sum(Y_i - \widehat{Y}_\iota)^2}{n}} \qquad (16)$$

The average of the variations between the actual and anticipated values is known as the MAE. What makes it unique is (17)

$$MAE = \frac{1}{n}\sum_{i=1}^{m}\left|X_i - \widehat{X}_\iota\right| \qquad (17)$$

Where m is the number of data, X_i is the ground truth and $\widehat{X}_\iota$ is the predicted values.

Table 1. Error Metrics

MSE	*RMSE*	*MAE*
0.71323	*0.23554*	*0.34353*

Three popular regression metrics are used to assess a predictive model's performance: MSE, RMSE, and MAE. The findings are shown in Table 1. A result of 0.71323 indicates a moderate level of prediction error. The MSE calculates the average of the squared discrepancies between the actual and anticipated values. Since the MSE and target variable have the same units, it is typically easier to understand. A result of 0.23554 indicates a very modest mistake when compared to the magnitude of the data. The square root of the MSE is the RMSE. A score of 0.34353 indicates that, on average, the model's predictions depart from the actual values by around 0.34 units. The MAE computes the average of the absolute differences between projected and actual values. The specific values in this table show that the model's predictions are reasonably accurate but still show some room for improvement in minimizing prediction errors. When these metrics are combined, they show how well the model performs; a lower RMSE and MAE suggest that the model fits the data more well. It is depicted in Figure 7.

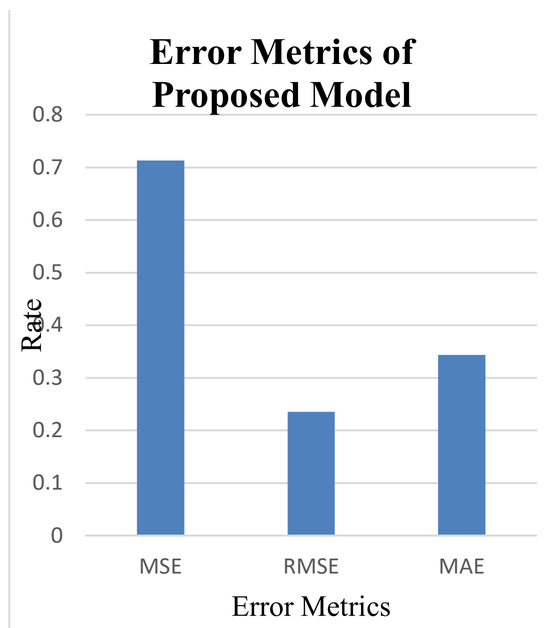

Figure 7. Error Metrics of Proposed Model

Accuracy is used to evaluate the system model's overall performance. Its fundamental tenet is that every interaction is predictable. The accuracy is provided by (18).

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$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (18)$$

Precision describes how comparable two or more calculations are to each other in addition to being correct. The link between accuracy and precision shows how quickly opinions may change. It is discussed in (19).

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad (19)$$

The percentage of all pertinent discoveries that were effectively sorted utilizing the methodologies is known as recall. By dividing the genuine positive by the mistakenly negative values, the suitable positive for these integers may be found. The phrase appears in (20).

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \quad (20)$$

The F1-Score computation combines recall and accuracy. To determine the F1-Score, apply (21), which divides the recall by the accuracy.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (21)$$

Table 2. Comparison of Performance Metrics

Methods	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
CNN	*85.57*	*97.12*	*95.44*	*98.22*
CNN-LSTM	*97.65*	*96.87*	*97.53*	*97.87*
RNN-LSTM	*98.45*	*95.89*	*96.67*	*98.11*
Proposed Recursive LSTM-GWO	*99.11*	*98.98*	*98.54*	*98.67*

A thorough comparison of performance measures for several approaches applied to a particular task can be found in Table 2 and Figure 8. CNN, CNN-LSTM, RNN-LSTM, and the suggested Recursive LSTM-GWO are among the techniques. The following metrics all presented as percentages are looked at: F1-Score, Accuracy, Precision, and Recall. With an astounding 99.11% accuracy, 98.98% precision, 98.54% recall, and an F1-Score of 98.67%, the suggested Recursive LSTM-GWO technique beats the other approaches on all parameters, as the table shows. This shows that the suggested Recursive LSTM-GWO model is a solid contender for the task at hand because it demonstrates better prediction skills than the other approaches. The table offers insightful information about the relative advantages and disadvantages of various approaches, which may assist direct choice of approach decisions in real-world scenarios.

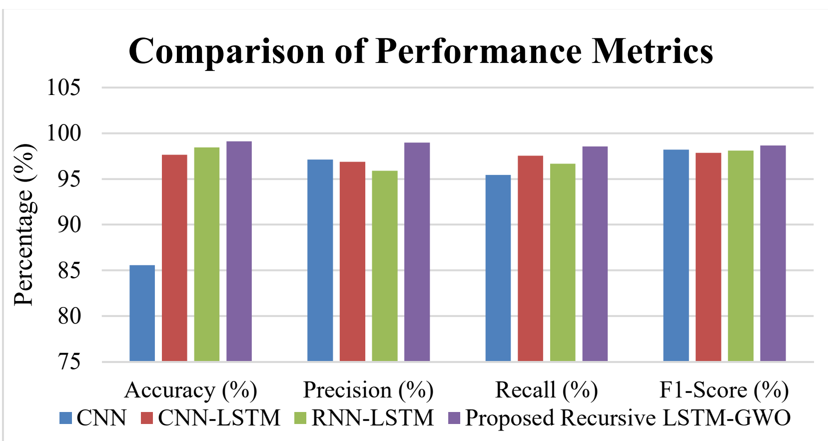

Figure 8. Comparison of Performance Metrics

5.5. Discussion

The outcomes demonstrate how effectively the suggested approach performs, as it achieves an astounding accuracy rate of 99.12%, much outperforming other well-known methods like CNN, CNN-LSTM, and RNN-LSTM, all of which are used using the MATLAB environment. This significant increase in accuracy of 5.55% highlights the clear superiority of the new method in this of the work at hand. These results not only indicate that there is room for significant progress in the subject, but they also provide strong evidence of the effectiveness of the suggested approach, establishing it as a very promising and practical means of resolving the particular issues at hand. In contrast to existing studies in the literature that primarily focus on

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individual aspects of 5G network optimization, this study distinguishes itself by presenting a holistic approach that integrates a recursive Long Short-Term Memory (LSTM) mechanism with Grey Wolf Optimization (GWO) for dynamic slicing optimization. While some studies employ LSTM for temporal dependencies and others utilize optimization algorithms like GWO, the synergy of these two components in our model enhances both adaptability and scalability. The recursive LSTM captures intricate temporal dependencies in dynamic network conditions, and GWO provides an efficient optimization algorithm, reducing reliance on theoretical presumptions. This integrative methodology offers a more comprehensive solution to the challenges of 5G network slicing by considering both adaptive learning and efficient optimization in tandem. Furthermore, our study explicitly addresses the computational complexity of the proposed model, recognizing the potential limitations in terms of processing power and deployment feasibility, providing a nuanced perspective in the landscape of 5G optimization research.

The integration of a recursive Long Short-Term Memory (LSTM) mechanism with Grey Wolf Optimization (GWO) in the proposed dynamic slicing optimization for 5G networks addresses critical challenges outlined in the research objectives. The recursive LSTM's ability to capture temporal dependencies enhances adaptability, effectively mitigating scalability issues in resource allocation. This recursive nature ensures that the model dynamically adjusts to changing network conditions and varying user demands, providing a comprehensive solution to the first research objective. Concurrently, the inclusion of GWO contributes to the model's robustness by offering an efficient and adaptive optimization algorithm. This mitigates reliance on theoretical presumptions, aligning with the second research objective, as GWO explores and exploits the solution space effectively without making strong assumptions about underlying system dynamics. The collaborative power of recursive LSTM and GWO creates a balanced computational load, addressing concerns related to processing power in deep learning-based techniques, which corresponds to the third research objective.

Furthermore, the proposed model establishes a safety net for dynamic situations, fulfilling the fourth research objective. The recursive LSTM's inherent capability to capture temporal dependencies provides essential time-averaged metrics, ensuring stability in slicing optimization amid unpredictable network variations. By learning from historical data and adapting to real-time observations, the model produces a robust slicing solution capable of navigating through unforeseen changes in the network environment. Looking forward, the potential integration of sophisticated fuzzy logic for traffic control and mobility aligns with the fifth research objective. Future iterations of the model could explore the synergy between fuzzy logic and the LSTM-GWO optimization, presenting an opportunity for further enhancing adaptability to diverse traffic patterns and mobility scenarios. In conclusion, the proposed dynamic slicing optimization framework effectively addresses key challenges, offering a comprehensive and adaptive solution for the complex and dynamic nature of 5G networks.

While the integration of a recursive Long Short-Term Memory (LSTM) mechanism with Grey Wolf Optimization (GWO) in dynamic slicing optimization for 5G networks presents significant advantages, there are inherent limitations to consider. The model's advantage lies in its adaptability and scalability, effectively addressing challenges in resource allocation and reducing reliance on theoretical presumptions. However, the model's computational complexity, particularly with the recursive LSTM and GWO combination, poses a limitation. The intricate nature of LSTM networks and the optimization power of GWO demand substantial computing resources, potentially hindering the model's efficiency in real-time deployments, especially in resource-constrained environments. Additionally, the collaborative nature of these components may lead to increased training times and heightened demands on processing power, impacting the practicality and speed of implementation in large-scale 5G networks. As such, while the proposed model offers a promising approach to dynamic slicing optimization, its computational demands should be carefully considered in real-world deployment scenarios.

6. CONCLUSION AND FUTURE WORKS

The study represents a significant scientific contribution to the field of 5G network optimization by introducing a novel and holistic approach to dynamic slicing optimization. Unlike existing studies that often focus on individual aspects of 5G network challenges, our work integrates a recursive Long Short-Term Memory (LSTM) mechanism with Grey Wolf Optimization (GWO), addressing the limitations of scalability, adaptability, and reliance on theoretical presumptions in a comprehensive manner. By synergizing adaptive learning and efficient optimization, our model provides a more nuanced solution to the complexities of 5G network slicing. Furthermore, this study explicitly acknowledges the computational complexities associated with the proposed model, contributing to a more realistic understanding of its practical feasibility in large-scale 5G network deployments. The presented work, thus, advances the state of the art by offering an integrated and adaptive solution to the dynamic challenges posed by modern network environments, emphasizing the importance of considering both adaptability and efficiency in the pursuit of effective 5G network slicing optimization. The results of this investigation highlight the significant potential of the suggested approach, which has proven to perform better than well-known methods like CNN, CNN-LSTM, and RNN-LSTM. The significant accuracy gain of 5.55% attained attests to the effectiveness of this strategy in handling the particular task at hand. Future studies can focus on improving and enhancing this approach going ahead, which might lead to a larger range of issue areas where it can be used. Furthermore, the knowledge gathered from this research may be used to build machine learning algorithms that are more reliable and adaptable, which would enhance the fields of predictive modelling and data analysis. The future of this field of study appears to have bright potential. Research might concentrate on examining how effectively the suggested approach scales to handle bigger and more complicated data sets as well as how well it adapts to real-world datasets and applications. To improve its performance even further, attempts can also be made to look into the possibility of adding more hybrid models or optimization strategies. In the end, a wide range of businesses and applications will profit from the ongoing development of cutting-edge machine learning approaches, which will surely be crucial in tackling changing data analysis issues and pushing the frontiers of prediction accuracy in many areas.

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