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Enhancing Spectrum Sharing with Real-Time Traffic Pattern Recognition using Gated Recurrent Unit

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Abstract: As a result of an expanding number of connected devices and a greater demand for bandwidth, efficient radio spectrum management is more vital than ever. Spectrum sharing, especially in cognitive networks, offers a flexible technique that allows numerous users to use the same frequency bands at the same time, resulting in improved network performance. This paper looks at how real-time traffic pattern detection utilizing Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks can enhance spectrum sharing in wireless communication systems. In this research, we look at the problems of integrating machine learning models for spectrum management, with a specific emphasis on improving LSTM and GRU networks for resource-constrained contexts. By examining traffic patterns, it is demonstrated that these models can minimize packet loss and enhance resource allocation. The findings show that, while both LSTM and GRU successfully reduce error rates, the GRU model outperforms the former because of its quicker learning speed and lower error values, making it particularly helpful in dynamic network environments. These findings underscore the rising importance of machine learning in spectrum management, paving the way for more flexible and efficient communication systems, particularly in high-density locations where dependable connection is critical.

Keywords: Spectrum sharing; Cognitive networks; Real-time traffic pattern recognition; Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Machine learning; Resource optimization; Internet of Things (IoT); 5G wireless communication; Network performance

1. Introduction

Given the exponential development of connected devices and wireless services, effective radio spectrum management has become a critical issue. With the increase in bandwidth demand, spectrum sharing, particularly inside cognitive networks, appears to be an interesting option for optimizing radio resource utilization[1]. This dynamic technique lets numerous users utilize the same frequency bands at the same time, hence increasing network efficiency. However, present spectrum management approaches are frequently rigid and inactive, restricting their capacity to react to changing user requirements and quick technical advancements. It is therefore critical to investigate improved strategies that can better handle these difficulties[2].

Spectrum sharing in neural networks is based on improved real-time traffic pattern detection tools. This not only improves the utilization of resources but also allows allocation choices to be matched to evolving user demands[3]. However, integrating machine learning models, such as long short-term memory (LSTM) networks or gated recurrent units (GRU), poses difficulties in terms of model size and computational complexity [4]. Although more research has apparently established that these models may considerably increase system performance and precision, their implementation on resource-constrained devices remains challenging. Optimizing these models is thus critical to ensuring their usefulness in real-time scenarios[5].

The spectrum offering becomes essential in the context of the Internet of Things (IoT) and fifth generation (5G) wireless communication systems to provide stable and efficient connection [6]. However, difficulties such as packet loss, packet delay, and interference demand creative solutions that use machine learning capabilities to evaluate and anticipate traffic patterns in real time [7]. Adapted techniques, such as the usage of machine learning models, can help maximize current assets and improve user experience in dynamic contexts. Integrating modern methodologies into bandwidth operations is thus important to solving those challenges.

Previous research has shown that understanding traffic patterns is critical to optimizing spectrum management [8]. According to studies, new machine learning approaches not only recognize traffic trends, but they also dynamically change spectrum allocation in response to these trends. However, no approach currently fits all these requirements. This emphasizes the necessity of looking into creative methods that mix accuracy and velocity to efficiently minimize packet loss rate, an essential indicator for transmission productivity [9].

The present paper discusses the use of LSTM and GRU models to improve spectrum sharing via real-time traffic pattern recognition. Previous research has shown that machine learning can accurately predict traffic trends and dynamically change spectrum allocations depending on this information [10]. Despite advancements, an optimized spectrum management system remains ultimate, highlighting the need for innovative technologies that balance accuracy and speed to minimize packet loss rates. This paper examines existing approaches, offers the results, and discusses the future implications for improved spectrum management in wireless networks. The integration of deep learning with traffic pattern analysis aims to enhance resource allocation and ensure reliable connectivity in dynamic environments, thereby contributing to the development of efficient spectrum management systems that address the increasing demands of modern wireless communications, especially in high-density user networks [6].

2. Related work

Research on spectrum sharing in cognitive networks has been active and produced several important findings. The authors of [11] examined methods for boosting cognitive radio networks' capacity, focusing on how resource usage might be maximized through spectrum sharing. Together, the examined works point out important implementation hurdles for this technology, such as regulatory concerns and interference management, and they also suggest creative ways to get beyond these barriers [12].

In [13], an enhanced Gated Recurrent Unit (GRU) model forecasts traffic at mobile communication base stations. With the growing data volume, accurate traffic prediction is vital for effective network management. The GRU model outperforms Convolutional Neural Network (CNN) and traditional models like Autoregressive (AR) and Autoregressive Integrated Moving Average (ARIMA) in capturing data patterns. Experimental results indicate that the GRU reduces the MAE (Mean Absolute Error) by 27.04% compared to AR, 37.89% compared to ARIMA, and 9.12% compared to CNN. This study demonstrates the advantages of the GRU model for traffic prediction, improving user experience and optimizing network resources.

Other important studies in [14] and [15] have proposed advanced approaches for optimizing spectrum sharing. The work in [14] demonstrates that employing spectrum sharing techniques significantly enhances IoT connectivity in 5G networks, increasing capacity and reducing latency. Additionally, the research in [15] provides an in-depth analysis of spectrum occupancy using machine learning algorithms, revealing that their novel spectrum sharing scheme utilizing dynamic long short-term memory effectively optimizes resource allocation and minimizes interference.

Recent studies have significantly advanced our understanding of spectrum sharing through innovative methodologies. In [16], the authors introduced a spectrum sharing method leveraging dynamic long-term memory models, which demonstrated enhanced network performance. Additionally, the work in [17] proposed a comprehensive framework that integrates intelligent techniques to optimize spectrum allocation. Furthermore, the survey in [18] examined various machine learning strategies aimed at enhancing the efficiency of spectrum sharing, shedding light on the potential of AI-driven approaches in this domain.

The authors in [19] presented an optimizing communication networks for traffic prediction, which is a crucial aspect of spectrum sharing in intelligent transport systems. Additionally, the study in [20] explored improvements in long short-term memory (LSTM) models to enhance their effectiveness in traffic forecasting. Another significant contribution examined various machine learning strategies aimed at boosting the efficiency of spectrum sharing within the context of 5G [16], highlighting their potential for advancing network performance.

This research work in [21] investigated various approaches to improve the prediction of signal-to-interference-plus-noise ratio (SINR), a critical factor in effective spectrum management.

Two studies in [22] and [23] highlighted the importance of cutting-edge technologies in optimizing spectrum utilization in modern networks. Respectively, one study presented a deep learning-based network for spectrum sharing, while the other integrated geospatial data for improved specifications in 3D spectrum utilization. Together, these studies demonstrate the potential of advanced technologies to enhance spectrum management.

This research in [14] presented a comprehensive overview of various spectrum management techniques and technological advancements pertinent to 5G networks. Furthermore, studies such [24] and [25] are part of a broader research initiative focused on identifying best practices for optimizing spectrum usage in developing technologies. These efforts are crucial for enhancing the efficiency and performance of future wireless communication systems.

The authors in [26] offered novel spectrum utilization techniques based on yield charts for hybrid sensors. This effort shows continuous technological developments in spectrum sharing. In line with earlier research on sharing technologies, this study adds to a larger framework targeted at increasing spectrum use, emphasizing the relevance of such advances in optimizing resource management and boosting overall system performance.

3. Methodology and materials

The methodology which was used in this research work is illustrated in figure 1. The numerous steps in the research process are shown in detail in this image, which also carefully highlights important elements and how they relate to one another. Every step is intended to build on the one before it, guaranteeing a logical progression that improves the research's overall coherence.

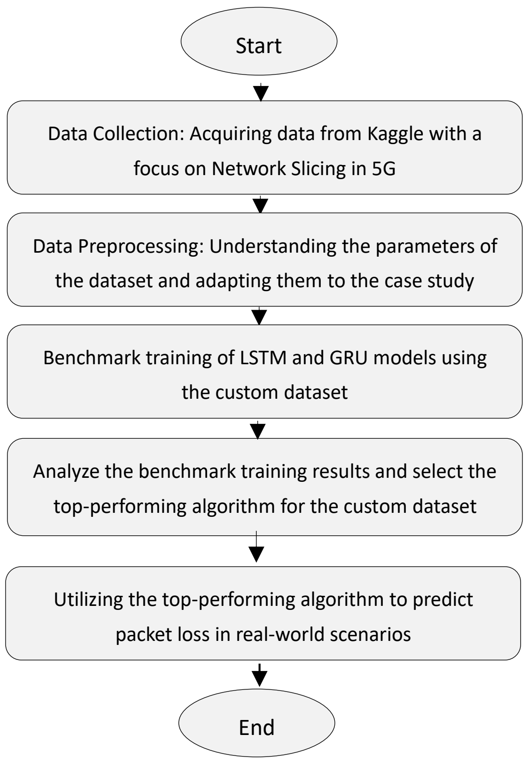

Figure 1.: Description of the methodology for the proposed research work

3.1. Dataset collection

The dataset that was used in this work was obtained from [27], comprises 31,583 rows (excluding the header) and 15 columns, including key features such as LTE/5G Category, Packet Delay, and Packet Loss Rate, which are essential for analysing network performance. This data was utilized to enhance spectrum sharing by recognizing traffic patterns in real time, allowing for more efficient management of network resources and improved quality of service for users.

Table 1: Display of the First 10 Rows of the Dataset

LTE/5g Category	Time	Packet Loss Rate	Packet delay	IoT	LTE/5G	GBR	Non-GBR	AR/VR/Gaming	Healthcare	Industry 4.0	IoT Devices	Public Safety	Smart City & Home	Smart Transportation	Smartphone	slice Type
14	0	1.00E-06	10	1	0	0	1	0	0	0	0	1	0	0	0	3
18	20	0.001	100	0	1	1	0	1	0	0	0	0	0	0	0	1
17	14	1.00E-06	300	0	1	0	1	0	0	0	0	0	0	0	1	1
3	17	0.01	100	0	1	0	1	0	0	0	0	0	0	0	1	1
9	4	0.01	50	1	0	0	1	0	0	0	0	0	1	0	0	2
19	2	1.00E-06	10	1	0	0	1	0	0	1	0	0	0	0	0	3
15	2	0.01	300	1	0	1	0	0	0	0	1	0	0	0	0	2
19	3	0.001	50	0	1	0	1	1	0	0	0	0	0	0	0	1
8	20	0.001	150	0	1	0	1	0	0	0	0	0	0	0	1	1
13	10	0.001	150	0	1	0	1	0	0	0	0	0	0	0	1	1

An overview of the main variables and their starting values is provided by table 1, which shows the dataset's first ten rows. As the study progresses, researchers can spot trends and insights thanks to this overview, which is crucial for comprehending the data's structure and acts as a basis for more analysis.

Table 2: The dataset content

Variable	**Explanation**
LTE/5G Category	Category of LTE/5G services
Time	Time, likely in milliseconds
Packet Loss Rate	Rate of packet loss, expressed as a percentage or in exponential notation
Packet Delay	Delay in packet transmission, expressed in milliseconds
IoT	Indicator for IoT devices
LTE/5G	Indicator for LTE/5G services
GBR	Indicator for Guaranteed Bit Rate services
Non-GBR	Indicator for Non-Guaranteed Bit Rate services
AR/VR/Gaming	Indicator for augmented reality, virtual reality, and gaming applications
Healthcare	Indicator for healthcare applications
Industry 4.0	Indicator for advanced industrial applications
IoT Devices	Number or indicator of IoT devices
Public Safety	Indicator for public safety services
Smart City & Home	Indicator for public safety services
Smart Transportation	Indicator for smart transportation applications
Smartphone	Indicator for smartphone usage
Slice Type	**Type of slicing, indicating different network configurations**

Advanced spectrum sharing optimization techniques are required for the development of LTE/5G networks, particularly given the variety and constantly shifting traffic demands. As seen in Table 2, these techniques must adapt to different usage scenarios to effectively manage and allocate resources.

- Category: LTE/5G Deploying GRU models requires an understanding of the unique context of LTE or 5G services. These models enable optimal spectrum allocation by analyzing and forecasting traffic patterns specific to each category.

- Time and Packet Delay: Improving network performance requires the ability to process and anticipate time-sensitive data. By proactively managing network resources to minimize delays and enhance overall service quality, GRUs can efficiently identify patterns in latency and packet delay.

- Packet Loss Rate: By predicting congestion and redistributing spectrum resources appropriately, real-time traffic pattern recognition via GRUs can reduce packet loss and increase data transmission reliability.

- Industry 4.0 and the Internet of Things: As networks accommodate more IoT devices, LSTM can examine their traffic patterns, guaranteeing effective spectrum use in settings with a high density of connected devices. For Industry 4.0 applications that need seamless connectivity, this analysis is essential.

- Augmented Reality (AR)/Virtual Reality (VR)/Gaming and Healthcare: Applications that need guaranteed performance, like telemedicine or gaming, can have their bandwidth prioritized by real-time traffic monitoring. In latency-sensitive applications, LSTMs can improve user experience by adaptively managing spectrum resources through continuous learning from historical traffic data.

- Guaranteed Bit Rate (GBR) and Non-GBR: Network operators can use GRU networks to distinguish between different service types and dynamically modify the spectrum to accommodate both GBR and non- GBR services, guaranteeing the best possible quality of service based on traffic patterns in real time.

- Smart City & Transportation: More efficient spectrum sharing plans may result from applications in smart cities and transportation that identify traffic patterns. By anticipating traffic spikes and allocating resources to maintain vital communication, GRU models can improve urban connectivity.

- Public Safety: By using GRUs for real-time traffic recognition, public safety communications can be prioritized more successfully. This guarantees that in times of crisis, emergency services will always have the bandwidth they require.

- Slice Type: GRU's capacity to recognize unique traffic patterns is a key advantage of network slicing since it makes it possible to create customized slices that correspond to service needs and usage trends, thus optimizing spectrum efficiency.

Use of IoT Devices and Smartphones: GRUs can spot trends in how IoT devices and smartphones are used, offering insights that help manage available spectrum resources more effectively. With the increasing number of connected devices, this is particularly crucial.

3.2. Data Preprocessing

The data was acquired through downloading, cleaning, and preparation, focusing on key variables like Packet Loss Rate, which impacts service quality. The research project used machine learning tools and cloud computing to train models, taking use of Google Colab's [23]capabilities. Initially, Python was used, with TensorFlow and Keras [28] helping to create neural networks for detecting real-time traffic patterns.

Throughout model training, a thorough preprocessing phase was carried out. This includes cleaning the data to eliminate outliers and missing values, normalizing continuous variables to guarantee consistent scaling, and creating relevant variables to improve model performance. Relevant methods, such as basic component analysis, were used to minimize dimensionality while increasing computing efficiency and model correctness.

The first examination in figure 2 indicates intriguing tendencies, such as spikes in Packet Loss Rate across specific categories, which indicate possible areas for network improvement. The new approach focuses on combining these preprocessing stages with advanced neural network architectures to provide reliable model performance in dynamic traffic scenarios.

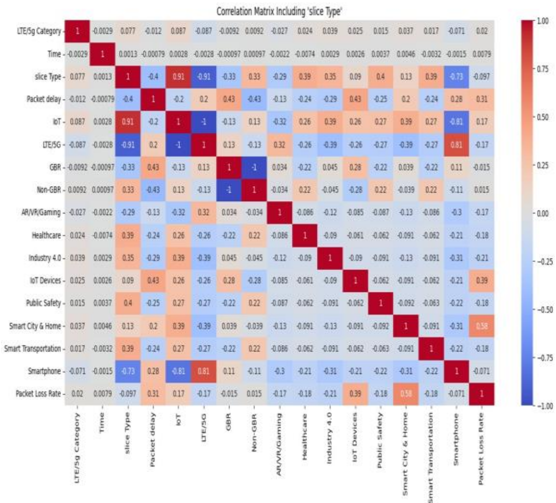

Figure 2: Correlation matrix of Packet Loss Rate with other variables

This correlation graph highlights the relationships between packet loss rate and other variables in this dataset, such as packet delay, service type (such as healthcare and smart transportation), and LTE category. These significant interactions highlight how these factors influence the packet loss rate considered as the target, thus highlighting their importance in evaluating network performance.

3.3. Considered Algorithms

A three-layer architecture that aims to improve spectrum sharing through real-time traffic pattern recognition is proposed in this paper. The first layer involves generating data through various wireless communication devices, integrating technologies such as the Internet of Things (IoT) to capture dynamic traffic patterns. The second layer focuses on data integration, where the collected data is centralized for further analysis. The third layer is dedicated to data processing, which uses machine learning techniques to evaluate traffic patterns and improve spectrum distribution. Given that the dataset contains constant variables, regression techniques appropriate for supervised machine learning are chosen. Based on past studies, we have a varied set of algorithms. Finally, we firmly choose Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), as these approaches successfully handle the gradient difficulties inherent in standard Recurrent Neural Networks (RNN) [29]. The evaluated studies demonstrate that these networks can process data with minimal latency, often in milliseconds, allowing for quick analysis and optimization.

3.3.1. LSTM (Long Short-Term Memory)

Each cell in the Long Short-Term Memory (LSTM) [18] algorithm contains three gates: an input gate, a forget gate, and an output gate (figure. 3).

Gates manage data flow within LSTM cells, enabling retention, forgetting, and generation of new information [18].

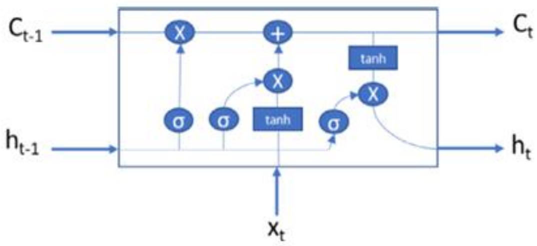

Figure 3: An LSTM Cell

- The forget gate (σ) controls data removal from the cell state. Using the current input and previous hidden state, it generates an activation vector (0-1) for each cell state component. Values near 0 indicate forgetting, while values near 1 indicate retention.

- The input gate (σ) controls how much new data is added to the LSTM cell state. Using the current input and previous hidden state, it generates an activation vector (0-1) for each cell state component. Values near 0 indicate forgetting, while values near 1 indicate retention of significant data.

- The output gate (tanh) controls the amount of information output from the LSTM. Based on the current input and previous hidden state, it generates an activation vector (0-1) for each cell state component. This vector is then multiplied by the cell's activation function output to obtain the final output.

Table 3: LSTM model parameters

Optimal Parameters	Values
Input size	1
Hidden layers	2
Hidden units	50
Batch size	8
Output size	1
Model architecture	• LSTM layer (100 units, tanh activation, return sequences=True) • Dropout layer (0.2) • LSTM layer (100 units, ReLU activation, return sequences=False) • Dropout layer (0.2) • Dense layer (1-unit, sigmoid activation)
Epochs	50
Optimizer	Adam
Learning rate	0.001
Dropout	0.2 (used in both Dropout layers)
Loss function	Mean Absolute Error (mean_absolute_error)
Activation functions	• LSTM layer 1: tanh • LSTM layer 2: ReLU • Dense layer: sigmoid

This algorithmic setup in table 3 looks appropriate for a regression issue as it avoids overfitting with dropout layers while still providing efficient learning with the Adam optimizer [30] and an appropriate learning rate. The architecture is intended to handle sequential data, making it suitable for time series analysis and other comparable applications.

3.3.2. GRU (Gated Recurrent Unit)

To identify temporal relationships in data sequences, GRU neural networks are built. Their internal structure is more straightforward, with just two gates to regulate the information flow within the cells, but it is comparable to that of LSTMs [19].

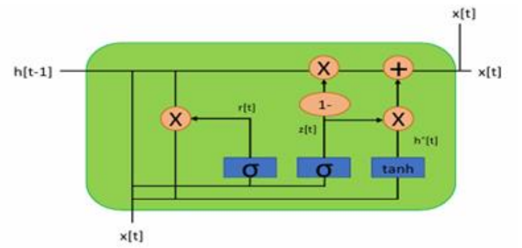

Figure 4: Diagram of a one unit Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) is a simplified variant of LSTM that employs gating mechanisms to control information flow. Each GRU cell features two main gates: the update gate and the reset gate, as shown in its architecture (figure 4) in [20]. These gates allow the GRU to manage memory effectively, enabling it to retain, reset, or generate new information.

- The Update Gate (z[t]) controls how much of the previous hidden state is carried to the current state. It uses the current input and the previous hidden state to generate an activation vector ranging from 0 to 1 for each component. Values near zero indicate that previous information should be discarded, while values close to one suggest retention. This gate effectively manages the GRU's memory.
- The Reset Gate (r[t]) determines how much past information to forget when updating the hidden state. It uses the current input and the previous hidden state to create an activation vector. Values near zero suggest forgetting past information, while values close to one indicate retention. This selective memory reset is beneficial when new information significantly differs from previous data.
- The Hidden State (tanh) of the GRU is obtained from the update and reset gates. When the reset gate is applied to the previous hidden state, it determines how much of that state to forget. The updated hidden state combines the retained information, and any new information derived from the current input.

Table 4: GRU model parameters

Optimal Parameters	Values
Input size	1
Hidden layers	2
Hidden units	50
Batch size	8
Output size	1
Model architecture	• GRU layer (100 units, tanh activation, return sequences=True) • Dropout layer (0.2) • Dense layer (100 units, ReLU activation) • Dropout layer (0.2) • Dense output layer (1-unit, sigmoid activation)
Epochs	50
Optimizer	Adam
Learning rate	0.001
Dropout	0.2 (used in both Dropout layers)
Loss function	Mean Absolute Error (MAE)

This setup is intended for a regression task that utilizes GRU networks, prioritizing regularization through dropout layers and efficient learning through Adam optimization. The architecture is designed to handle sequential data, making it ideal for tasks like time series analysis and similar applications. The use of loss-based MAE indicates the need to reduce absolute errors in predictions, which is frequently beneficial in many real-world scenarios.

4. Results and discussion

The analysis of the Mean Squared Error (MSE) as a function of the number of epochs executed by the LSTM and GRU algorithms reveals a consistent downward trend in the loss curves throughout both the training and testing phases as illustrated in figure 5. This gradual reduction in error indicates that both models effectively minimize loss over successive epochs, ultimately stabilizing at a low value by the conclusion of the training iterations. The graph indicates the loss of training (blue curve) and validation (orange curve) of the LSTM model, which both show a substantial decline and stabilize around 0,0025 after around 12 epochs.

This quick convergence indicates effective learning and strong generalization abilities. The proximity of the two curves suggests that the LSTM model adapts adequately to training data without requiring additional learning. In general, these low loss values reflect the model's robustness on unknown data, highlighting its effectiveness.

The illustration in figure 6 shows the model's training loss and validation loss of the GRU model, both of which exhibit a dramatic reduction until stabilizing around 0.000193 after about 8 epochs. This quick convergence suggests effective learning and good generalization ability. The tight alignment of the two curves indicates that the model responds well to the training data without overfitting. Overall, the minimal loss numbers demonstrate the model's durability on previously encountered data, indicating its efficacy.

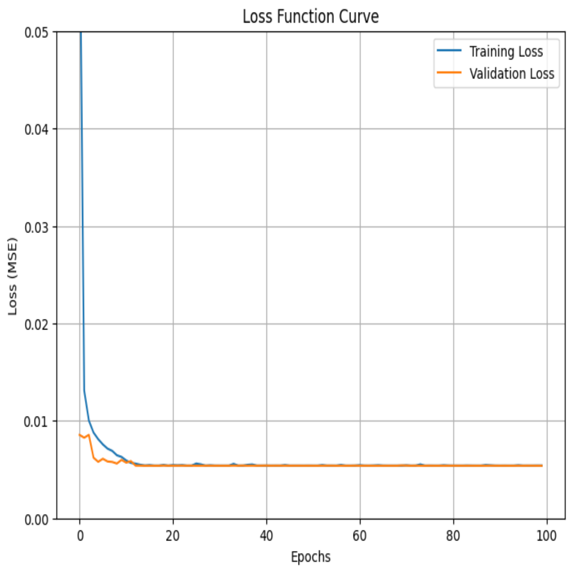

Figure 5: Obtained loss functions of LSTM algorithm

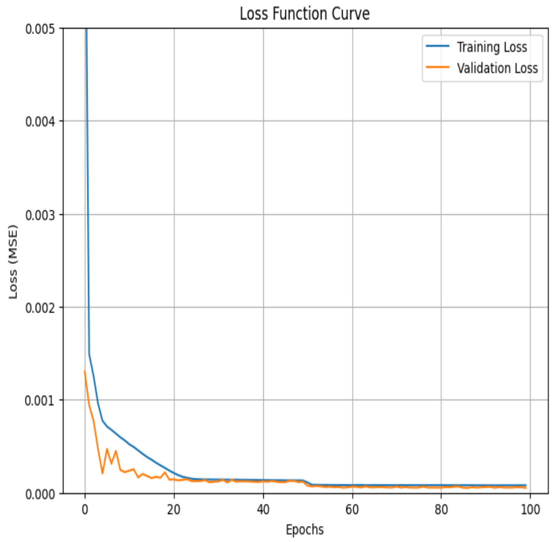

Figure 6: Obtained loss functions of GRU algorithm

Regardless of the training or testing phase (Figures 5 and 6), the loss curves for both models show a consistent downward trend, rapidly decreasing until stabilization at a minimum by the end of the epoch. For the LSTM model, the loss curve stabilizes around 0.0025 after approximately 12 epochs, indicating effective learning and strong generalization abilities. The reduced noise in the test phase further supports the model's ability to adapt to new data.

In contrast, the GRU algorithm converges significantly more quickly, stabilizing around 0.000193 after about 8 epochs, despite starting with a higher initial error. This rapid convergence highlights the GRU's effective learning and strong adaptation capabilities. While the GRU stabilizes with a slightly higher error than LSTM, both models demonstrate robust performance.

Modeling with our dataset's two techniques is effective if there are no overfitting or underfitting issues found by loss curve analysis.

4.1. Results in terms of loss functions

Loss functions give information about learning capacity (underfitting/overfitting) and convergence speed (processing time). To monitor the model's progress and identify potential issues with overfitting or underfitting, loss curves were generated after each algorithm deployment, using the mean square error (MSE) as a function of the number of epochs performed by the LSTM and GRU algorithms.

To thoroughly assess our machine learning model, various evaluation metrics can be employed to gauge its effectiveness. The selection of these metrics is contingent upon the specific nature of the problem at hand. Evaluation metrics offer a quantitative measure of a model's performance. It is advisable to utilize multiple metrics for a more comprehensive understanding of performance and to align the metrics with the problem type.

The Gated Recurrent Unit (GRU) model significantly outperforms previous studies, achieving over a 37% reduction in prediction error with a Mean Absolute Error (MAE) of 0.0000584556 and a Mean Squared Error (MSE) of 0.0000000545. In comparison, the LSTM stabilizes at a MAE of 0.0000539443 and an MSE of 0.0000000539 in [16]. The GRU converges faster, stabilizing at 0.000193 after 8 epochs, while the LSTM reaches 0.0025 after 12 epochs, demonstrating the GRU's superior effectiveness in spectrum management in high-density environments.

Table 5: Performance metrics obtained

	LSTM		**GRU**	
	Training	Testing	Training	Testing
R2	0.9971486521	0.9971291123	0.9971138532	0.9973132827
MAE	0.000053949	0.0000539443	0.0000584556	0.0000545467
MSE	0.000000053	0.0000000539	0.0000000545	0.0000000507
RMSE	0.0002321157	0.0002321065	0.0002333606	0.0002251964

Given that we are dealing with a regression problem, the following metrics are most appropriate for evaluating model performance:

- Coefficient of Determination (R-squared): This metric (equation 1) indicates the proportion of variance in the target variable explained by the model, helping to determine how well the model fits the data [31].
- Mean Absolute Error (MAE): This metric (equation 2) represents the average of the absolute differences between the actual and predicted values [31].
- Mean Squared Error (MSE): This metric (equation 3) calculates the average of the squared differences between the actual values and the predicted values.
- Root Mean Squared Error (RMSE): This metric (equation 4) is used to evaluate the accuracy of a prediction model. It calculates the square root of the

average of the squared differences between predicted values and actual values [31].

The mathematical representations of these metrics are defined as follows [20]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (1)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}| \quad (2)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y})^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y})^2} \quad (4)$$

The usage of two methods in the data set's case study was practical since they both consider identifying long-term reliance in sequential data.

Upon examining the outcomes shown in Table 5, the GRU network performs better than the LSTM network in terms of R^2, MAE, MSE, and RMSE for both the training and testing stages. In particular, the GRU model exhibits decreased error values and increased predicted accuracy, which is consistent with the findings from the algorithms' implementation.

As proof of all this, it is important to point out that during the testing phase, the GRU model stabilizes at around the 8th epoch with less noise in the loss curve, demonstrating efficient learning and strong generalization to recent data. This is important because lower error rates indicate that the GRU is more robust in different situations, making it a better option for tasks requiring flexibility.

Compared to the GRU, the LSTM model stabilizes at a greater error rate even while it exhibits promising learning efficiency, with error convergence by the 20th epoch. This disparity is reflected in the performance metrics in Table 5, which support the finding that although each model has advantages, applications requiring reliable performance on new datasets are better suited for the GRU design.

In the final analysis, Table 5's performance measurements support the conclusions mentioned, showing that the GRU model is more effective in generalizing solutions to unexpected data in addition to having superior performance metrics. This supports the idea that the GRU is the better option for improving spectrum sharing by identifying traffic patterns in real time.

5. Conclusion

This study underscores the critical role of real-time traffic pattern recognition in enhancing spectrum sharing through the application of Gated Recurrent Unit (GRU) networks. The findings demonstrate that GRU networks not only significantly reduce error rates but also offer faster convergence, making them particularly advantageous for adapting to the dynamic nature of wireless communication environments. As the demand for efficient and reliable communication continues to escalate, integrating machine learning techniques like GRU into spectrum management becomes imperative for optimizing resource allocation and alleviating network congestion.

By leveraging advanced deep learning methodologies, this research paves the way for more adaptive and intelligent spectrum management systems. The capability to accurately predict traffic patterns in real time empowers make informed, data-driven decisions, dynamically adjusting spectrum allocation to meet evolving demands. This is especially crucial in the context of modern wireless networks, where the surge of connected devices and high-bandwidth applications intensifies the pressure on available spectrum resources.

Furthermore, this study lays a foundation for future research aimed at refining machine learning models for spectrum management, considering additional factors such as interference mitigation, energy efficiency, and multi-agent decision-making. Addressing these challenges will enhance cognitive radio networks, ensuring more efficient spectrum utilization and improved connectivity, even in spectrum-constrained environments. Ultimately, the integration of GRU networks into spectrum management strategies represents a significant advancement toward developing robust, adaptive, and intelligent communication systems capable of meeting the ever-growing demands of wireless technologies.

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