Implementation of LSTM Neural Networks for Predicting Competition in Telecommunications Markets

Diego Armando Giral-Ramirez
Universidad Distrital Francisco José de Caldas
Technological Faculty
Bogotá, Colombia
e-mail: dagiralr@udistrital.edu.co

Luis Fernando Pedraza-Martínez
Universidad Distrital Francisco José de Caldas
Technological Faculty
Bogotá, Colombia
e-mail: lfpedrazam@udistrital.edu.co

Cesar Augusto Hernández-Suarez
Universidad Distrital Francisco José de Caldas
Technological Faculty
Bogotá, Colombia
e-mail: cahernandezs@udistrital.edu.co

***Abstract*—The telecommunications services market faces significant challenges in an increasingly flexible and customer-adaptable environment. Research has highlighted that the monopolization of spectrum by an operator reduces competition and negatively impacts users and the overall dynamics of the sector. This article addresses the importance of competition analysis and its prediction in telecommunications markets. A Long-Short Term Memory (LSTM) network is implemented to forecast the number of users, the amount of revenue, and the amount of traffic for fifteen network operators. The ability of LSTMs to handle temporal sequences, long-term dependencies, adaptability to changes, and management of complex data makes them an excellent strategy for predicting and forecasting the telecommunications market. As identified in the literature review, diverse works involve LSTM and telecommunications. However, many questions remain in the area of prediction. Various strategies can be proposed, and permanent work must focus on providing cognitive engines to address more challenges. MATLAB is used for the design and subsequent implementation, with a root mean square error index of 0.0776; the results demonstrate the accuracy of the implemented strategy**.

Keywords-deep learning; LSTM; market operations; neural networks; competition prediction; styling.

I. INTRODUCTION

The synergy of information and communication technologies over the last decade has impacted all aspects of society, particularly in government, education, and health services [1][2].

The telecommunications services market operates in increasingly flexible and adaptable environments to meet customer needs, leading to a rise in data sales volume and becoming a robust source of revenue for service providers [3]. This growth has fostered competition among providers to retain and attract new customers. In order to ensure fair competition in the provider market, governments have implemented regulatory policies [4].

Regulatory policies take different approaches, such as data security and protection, interconnection, and billing [5]. Regulatory areas, such as spectrum, data protection framework, and billing rules, have experienced exponential growth driven by the increasing demand and technological evolution in the telecommunications sector [6].

Research has shown that the monopolization of spectrum by an operator not only reduces competition in the market but also has a direct negative impact on users and the overall dynamics of the sector. Therefore, spectrum management strategies should aim to prevent unnecessary spectrum accumulation, seeking to balance the market power of telecommunications services [7]. Competition analysis in telecommunications markets and its corresponding prediction are crucial in spectrum management. These elements are essential for improving competitiveness, reducing the digital divide, facilitating regional development, and identifying potential investments [8].

Competition analysis and prediction are challenging to model due to their scale, multidimensional nature, and complexity. Uncertainties arising from the evolution of demand, prices, and user needs make it necessary to establish robust methodologies to address these challenges [9][10]. As shown in Figure 1, different strategies have been implemented to predict market movements. The most prominent ones can be classified into four categories: statistical methods, machine learning, pattern recognition, and hybrid approaches [11].

Machine Learning (ML) provides systems with the ability to learn. It focuses on developing algorithms capable of accessing data and using it to learn autonomously. Deep Learning (DL) is a branch of machine learning that employs artificial neural networks to model and solve problems. There are two main types of DL: Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Figure 2 depicts the subset of techniques based on ML and DL.

 ISBN: 978-1-68558-145-9

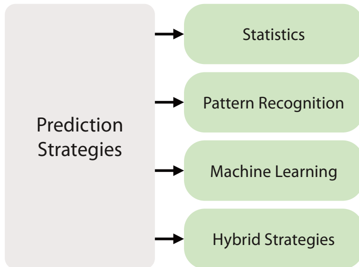

Figure 1. Techniques for predicting the financial market.

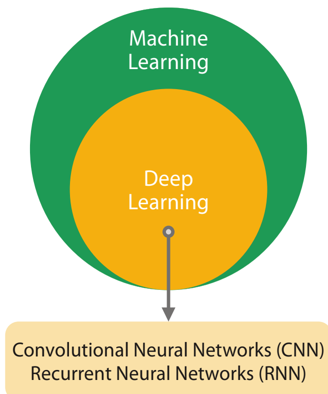

Figure 2. Subset of ML and DL [12].

An RNN model allows processing and transforming a sequential data input into a specific sequential output. An LSTM processes input data by forming a loop with time steps and updates the state of the RNN. Essentially, an RNN extends its memory to learn from essential experiences that occurred long ago. The ability of LSTMs to handle temporal sequences, long-term dependencies, adaptability to changes, and management of complex data makes them an excellent strategy for predicting and forecasting the telecommunications market.

Regarding previous works, no study was identified that specifically related the keywords LSTM and Competition Prediction. Consequently, the works described below correspond to the identified applications associated with data prediction using LSTM for telecommunications systems.

In [13], the authors propose a multitask learning algorithm based on deep learning called Multitask Learning Fusion. The algorithm's goal is to improve the prediction of network traffic types.

In [14], a domain order-based shallow fusion deep learning model is designed and applied to a decision support system to evaluate the risk of customer churn in telecommunication systems. The strategy involves a Fully Connected Layer Convolutional Neural Network - Long Short-Term Memory (FCLCNN-LSTM).

In [15], the author addresses the challenge of predicting cellular traffic behavior. The author proposes providing network operators with a tool to model mobile network traffic and optimize connected resources. A hybrid scheme with Vector Autoregressive (VAR) and deep learning is proposed for this prediction.

Many questions in the prediction area need to be resolved, and diverse research projects exist. Continued work should focus on providing cognitive engines to address more challenges for different applications. Based on the previously described information, this article presents an artificial intelligence proposal to predict the number of users, traffic level, and operators' income in the telecommunications market. The objective is to use this prediction proposal to analyze competition in telecommunications markets.

The rest of this paper is organized as follows: Section II describes the methodology, Section III describes the results, and the conclusions and acknowledgment close the article.

II. Methodology

Figure 3 presents the flowchart for the competition analysis in telecommunications markets, using the number of users, the amount of revenue, and the amount of traffic prediction. The methodology is divided into five stages. The first, second, and third stages correspond to the preprocessing and processing of the database for training and validating the LSTM network. The fourth stage involves implementing the architecture of the LSTM network, and finally, the fifth stage corresponds to the obtained metrics. Each one of the stages is described below.

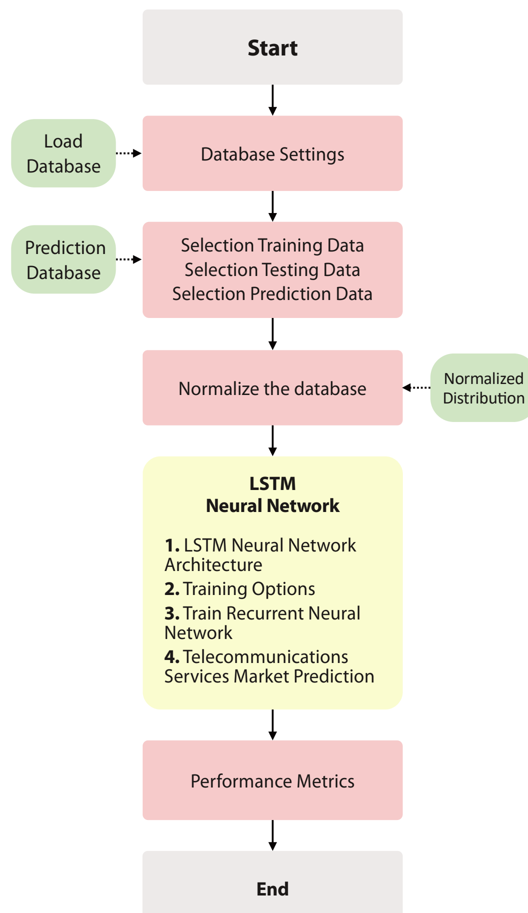

Figure 3. Flowchart of the implemented methodology.

A. Database Settings

The database corresponds to the number of users, the amount of revenue, and the amount of traffic for fifteen network operators. The data is taken from the Commission of Regulation of Communications of the Republic of Colombia from 2012 to 2022. Table 1 presents the characteristics of the database.

TABLE I. CHARACTERISTICS OF THE DATABASE

Total Operators	15
Period	2012-2022
Number of rows	6594
Number of users	Prepaid
	Postpaid
	Total
Ingress	Prepaid
	Postpaid
	Total
Traffic	Prepaid
	Postpaid
	Total

B. Selection Data

The Test-Validation technique is employed for the training, validation, and testing process, distributing the data in proportions of 70%, 20%, and 10%, respectively. The data used comes from real information from the Colombian telecommunications market. The prediction is carried out for the year 2022.

It is crucial to highlight that training, validation, and testing were conducted simultaneously with the information from all fifteen companies. Although one available methodology involves training a separate network for each company, the decision was made to leverage a characteristic of deep learning: the ability to handle large volumes of information. Therefore, a single network was trained for all fifteen companies.

C. Normalized Database

In order to ensure that the training process does not diverge and, consequently, that the predictors do not fail, the database is normalized. The criterion is based on the normal distribution, with a mean of zero and unit variance (Equation (1)).

$$X_{Normalized} = \frac{X_{Database} - \mu}{\sigma} \tag{1}$$

D. LSTM Neural Network

Given that LSTM networks incorporate memory units that allow them to learn when to forget previous hidden states explicitly and when to update hidden states with new information, the LSTM architecture is illustrated in Figure 4. Figure 4 illustrates the data in the input gate, forget gate, output gate, memory cell internal state, and hidden state. The state updates satisfy the operations described in Equation (2), where $X_t \in R^{n\times d}$ and the hidden state of the previous time step is $H_{t-1} \in R^{n\times h}$. Correspondingly, the gates at time step t are defined as follows: the input gate is $I_t \in R^{n\times h}$, the forget gate is $F_t \in R^{n\times h}$, and the output gate is $O_t \in R^{n\times h}$. W_{xi}, W_{xf}, $W_{xo} \in R^{d\times h}$, W_{hi}, W_{hf}, $W_{ho} \in R^{h\times h}$, $W_{xc} \in R^{d\times h}$, and $W_{hc} \in R^{h\times h}$ are weight parameters, and b_i, b_f, b_o, $b_c \in R^{1\times h}$ are bias parameters.

$$\begin{aligned}
F_t &= \sigma\left(W_{xf}X_t + W_{hf}H_{t-1} + b_f\right)\\
I_t &= \sigma\left(W_{xi}X_t + W_{hi}H_{t-1} + b_i\right)\\
\tilde{C}_t &= \tanh\left(W_{xc}X_t + W_{hc}H_{t-1} + b_c\right)\\
O_t &= \sigma\left(W_{xo}X_t + W_{ho}H_{t-1} + b_o\right)\\
C_t &= F_t \odot C_{t-1} + I_t \odot \tilde{C}_t\\
H_t &= \tanh\left(O_t \odot C_t\right)
\end{aligned} \tag{2}$$

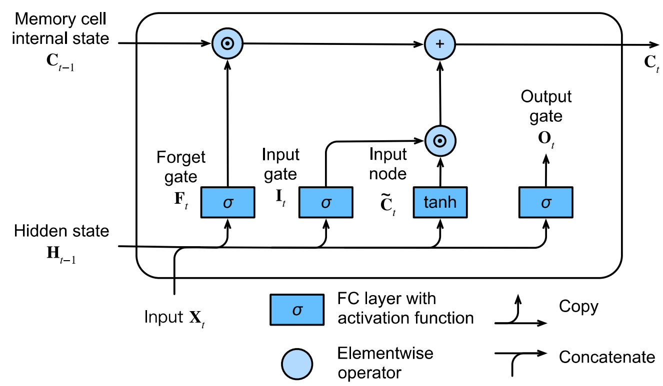

Figure 4. Architecture LSTM [16].

E. Performance Metrics

The Root Mean Square Error (RMSE) is a performance metric. The prediction uses data corresponding to 2022, meaning the network anticipates the data for this period. Since this data is known, the actual and predicted values are compared.

III. RESULTS

This section presents the results obtained according to the implemented methodology and is classified into three parts. The first part addresses the database; despite the public information, data preprocessing was necessary. The second part focuses on the implemented LSTM network architecture. Finally, the third part addresses the prediction of the data.

The implementation was carried out on an Intel(R) Core(TM) i7-7700HQ 2.8GHz processor with 24 GB of RAM running the Microsoft Windows 10 64-bit operating system using MATLAB version R2023b.

A. Database

Figure 5 and Figure 6 show the information corresponding to two of the five companies used to predict telecommunications markets.

Each figure comprises information regarding the number of users, the total revenue, and the amount of traffic corresponding to each company. As detailed in Table 1, this information is available for prepaid and postpaid services.

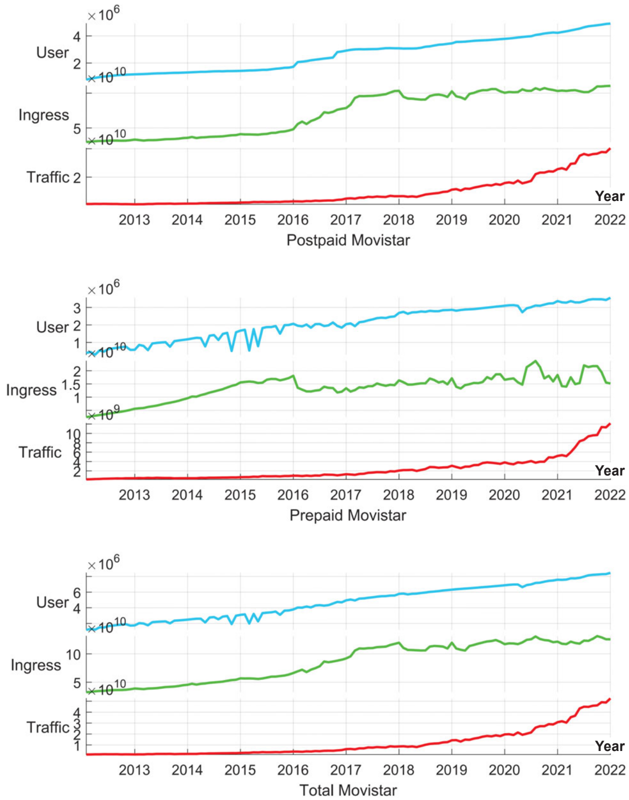

Figure 5. Database of the telecommunications company Movistar.

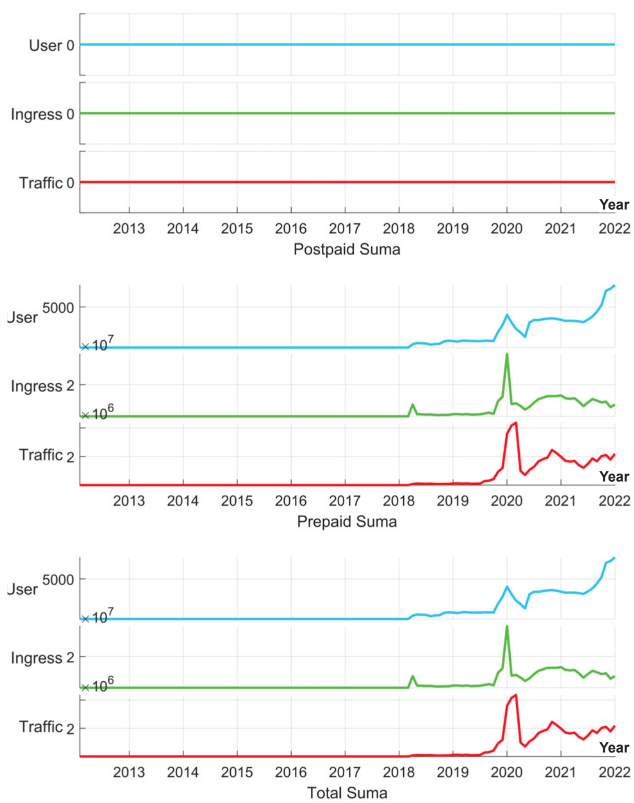

Figure 6. Database of the telecommunications company Suma.

B. *LSTM Neural Network*

The programming of an LSTM network varies depending on the simulation tool being used. Even if the model is the same, some simulators may require a greater number of parameters for implementation. MATLAB, for instance, has a toolbox that facilitates the straightforward implementation of an LSTM network. Algorithm 1 describes the implementation of an LSTM architecture using MATLAB.

Algorithm 1. LSTM Architecture Implementation.

```
numChannels = size(DataBase)
layers = [
   sequenceInputLayer(numChannels)
   lstmLayer(128)
   fullyConnectedLayer(numChannels)
   regressionLayer]

options = trainingOptions("adam", ...
   MaxEpochs = 400, ...
   SequencePaddingDirection="left", ...
   Shuffle = "every-epoch", ...
   Plots = "training-progress", ...
   Verbose = 0)
```

C. *Market Prediction*

An open-loop methodology was employed for the prediction. The open-loop forecast allows for predicting the next time unit in a sequence using only input data. This methodology was chosen because it allows forecasts to be made when the actual values of the RNN are provided before making the next prediction.

Figure 7, Figure 8, and Figure 9 show the forecast behavior obtained for three of the fifteen analyzed companies. RMSE was used for each test sequence to assess accuracy, comparing predictions with actual values. The average RMSE obtained was 0.0776.

The results of these three companies are presented according to their market behavior. Claro is characterized by having a more significant number of users than Movistar, while Movistar has a more significant number of users than Avantel. Additionally, it is essential to highlight that the RMS obtained in the prediction process for each company was at most 0.09.

The solid line represents the actual market values, while the dashed line corresponds to the predicted information for the year 2022. To analyze the forecasted data, three companies were selected: one with a high level of competition in the market (Figure 7), another with an intermediate level of competition (Figure 8), and one with a low level of competition (Figure 9). All data presented in the figures is normalized.

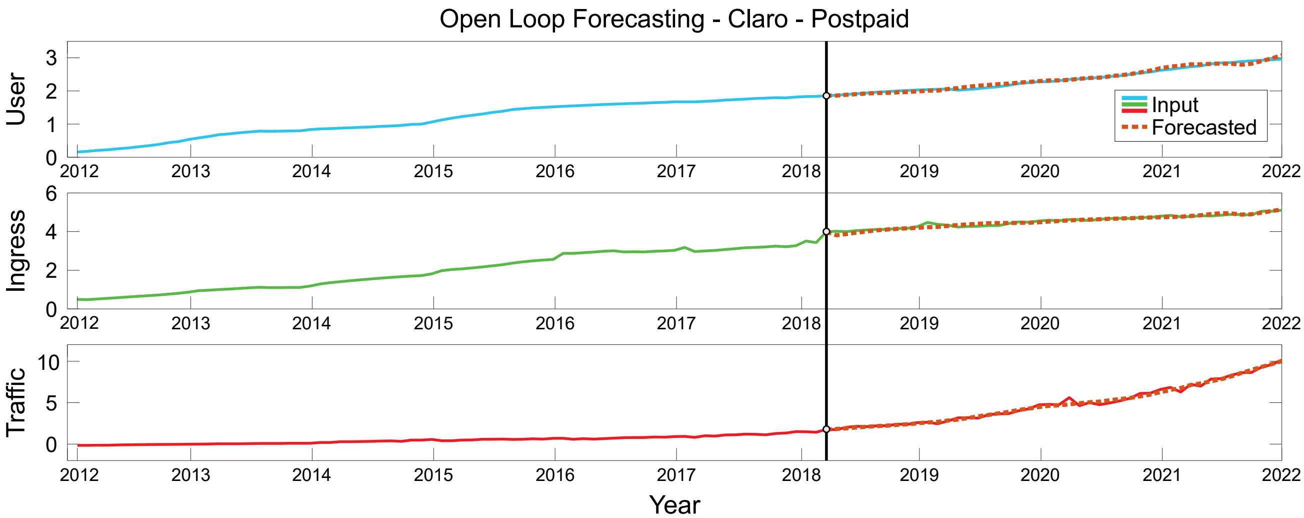

Figure 7. Prediction for a company with a high level of competition in the market.

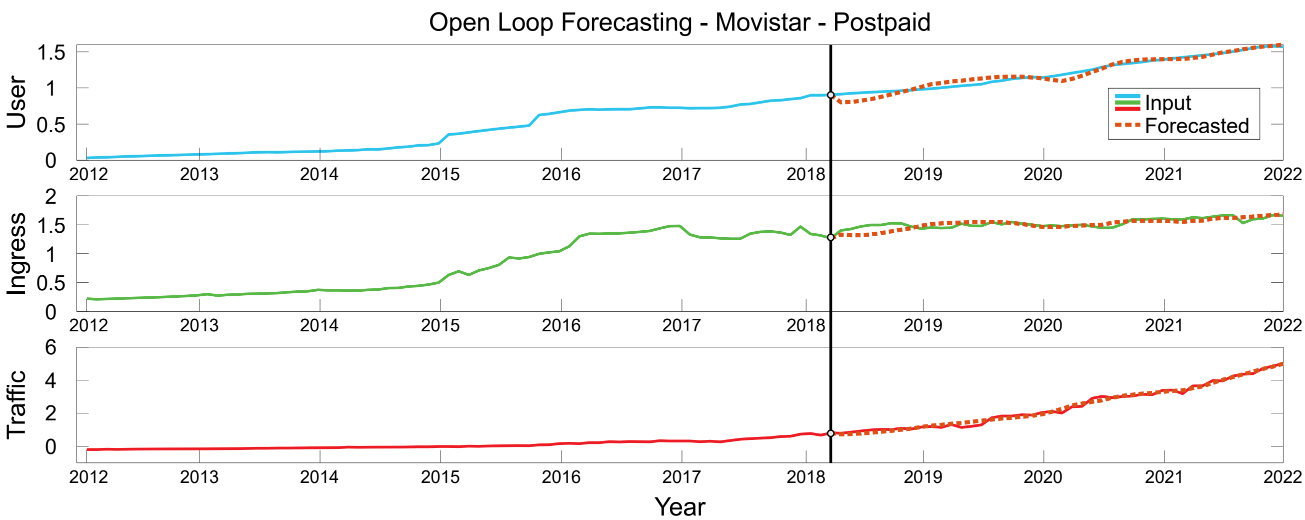

Figure 8. Prediction for a company with an intermediate level of competition in the market.

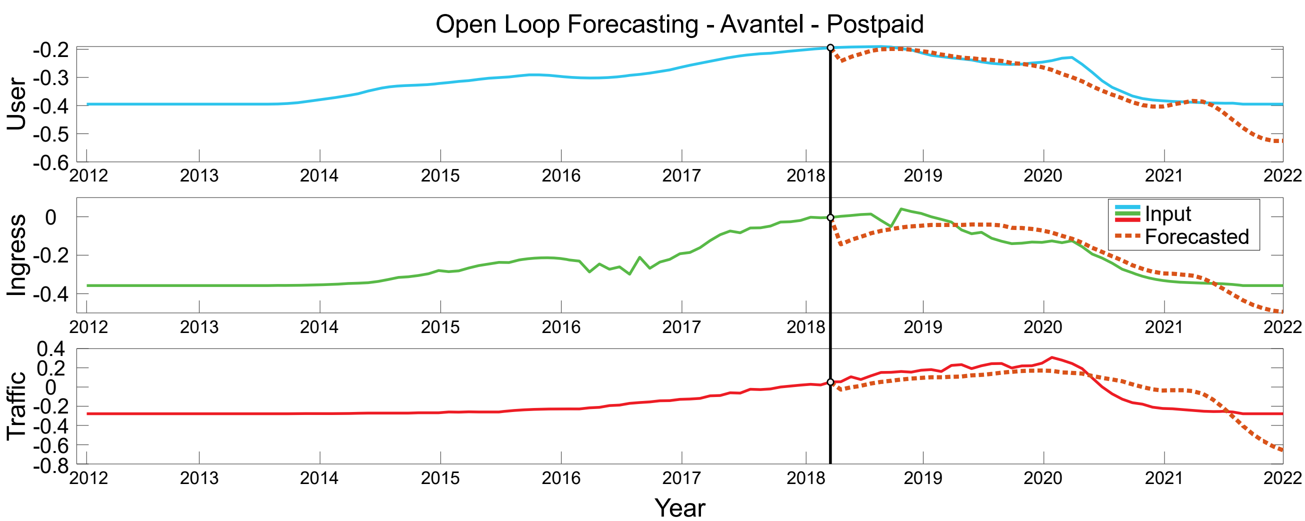

Figure 9. Prediction for a company with a low level of competition in the market.

 ISBN: 978-1-68558-145-9

IV. CONCLUSIONS

This research implemented an LSTM network to predict the communications market. The results, with an RMSE index of 0.0776, demonstrate the accuracy of the implemented strategy. Using an LSTM network, with its ability to store temporal behaviors, proved to be an effective strategy for predicting market behavior.

Applying deep learning-based strategies, such as the LSTM network, emerges as a valuable tool to anticipate and adapt to the changing dynamics of the communications market, thus offering a promising perspective for future research and practical applications.

Although advances in prediction are promising, many questions remain to be resolved. Future work should utilize advances in artificial intelligence and metaheuristic optimization to obtain even more accurate and reliable results. In addition, it is necessary to handle other error criteria for prediction. This involves developing scalable strategies that can handle heavier computational loads and efficiently address problems of greater complexity.

ACKNOWLEDGMENT

The authors thank the Investigations Office of the Universidad Distrital Francisco Jose de Caldas and Minciencias for supporting this investigative project.

REFERENCES

[1] A. J. Adetunji and B. O. Moses, “The role of network technologies in the enhancement of the health, education, and energy sectors,” *Netw. Commun. Technol.*, vol. 7, no. 1, p. 39, 2022.

[2] M. Ilchenko, L. Uryvsky, and S. Osypchuk, “World trends of modern information and telecommunication technologies development,” in *2019 International Conference on Information and Telecommunication Technologies and Radio Electronics (UkrMiCo)*, 2019, pp. 1–7.

[3] Z. Wang, L. Gao, J. Huang, and B. Shou, “Toward flexible wireless data services,” *IEEE Commun. Mag.*, vol. 57, no. 12, pp. 25–30, 2019.

[4] A. Mehrotra and S. Menon, “Telecommunication & Networking Changing Customer Profile & Preferences,” in *2021 2nd International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, 2021, pp. 221–226.

[5] D. Giral, C. Hernández, and C. Salgado, “Spectral decision for cognitive radio networks in a multi-user environment,” *Heliyon*, vol. 7, no. 5, 2021, doi: 10.1016/j.heliyon.2021.e07132.

[6] C. A. Hernández Suárez, D. A. Giral Ramírez, S. Franco, and L. Camila, *Multi-user spectral allocation model for decentralized cognitive radio networks*. Editorial Universidad Distrital Francisco José de Caldas, 2021.

[7] O. S. de Miera Berglind, “Spectrum concentration and market competition. Implications for the use of caps in Mexico,” in *2015 Conference of Telecommunication, Media and Internet Techno-Economics (CTTE)*, 2015, pp. 1–8.

[8] O. Franchuk, M. Petrova, and G. Tolkachova, “Elements of control of competitiveness of telecommunication companies,” *Economics Ecology Socium*, vol. 4, no. 2, pp. 22–30, 2018, doi: 10.31520/2616-7107/2018.2.4-3.

[9] V. Glass and T. Tardiff, “Analyzing Competition in the Online Economy,” *Antitrust Bull.*, vol. 68, no. 2, pp. 167–190, 2023.

[10] M. Fisher, S. Gallino, and J. Li, “Competition-based dynamic pricing in online retailing: A methodology validated with field experiments,” *Manage. Sci.*, vol. 64, no. 6, pp. 2496–2514, 2018.

[11] Z. Berradi, M. Lazaar, O. Mahboub, and H. Omara, “A comprehensive review of artificial intelligence Techniques in Financial Market,” in *2020 6th IEEE Congress on Information Science and Technology (CiSt)*, 2021, pp. 367–371.

[12] D. Giral, C. Hernández, and C. Salgado, “Spectral decision in cognitive radio networks based on deep learning,” *Expert Syst. Appl.*, vol. 180, p. 115080, Oct. 2021, doi: 10.1016/j.eswa.2021.115080.

[13] L. Liu, Y. Yu, Y. Wu, Z. Hui, J. Lin, and J. Hu, “Method for multi-task learning fusion network traffic classification to address small sample labels,” *Sci. Rep.*, vol. 14, no. 1, p. 2518, 2024, doi: 10.1038/s41598-024-51933-8.

[14] C. Wang, C. Rao, F. Hu, X. Xiao, and M. Goh, “Risk assessment of customer churn in telco using FCLCNN-LSTM model,” *Expert Syst. Appl.*, vol. 248, p. 123352, 2024, doi: https://doi.org/10.1016/j.eswa.2024.123352.

[15] M. Di Mauro, G. Galatro, F. Postiglione, W. Song, and A. Liotta, “Hybrid learning strategies for multivariate time series forecasting of network quality metrics,” *Comput. Networks*, vol. 243, p. 110286, 2024, doi: https://doi.org/10.1016/j.comnet.2024.110286.

[16] J. Quinn, J. McEachen, M. Fullan, M. Gardner, and M. Drummy, *Dive into deep learning: Tools for engagement*. Corwin Press, 2019.