AICT 2024

The Twentieth Advanced International Conference on Telecommunications

ISBN: 978-1-68558-145-9

April 14 - 18, 2024

Venice, Italy

AICT 2024 Editors

Eugen Borcoci, National University of Science and Technology POLITEHNICA Bucuresti (UNSTPB), Romania

AICT 2024

Forward

The Twentieth Advanced International Conference on Telecommunications (AICT 2024), held between April 14th and April 18th, 2024, continued a series of international events covering a variety of challenging telecommunication topics ranging from background fields like signals, traffic, coding, communication basics up to large communication systems and networks, fixed, mobile and integrated, etc. Applications, services, system, and network management issues also received significant attention.

The spectrum of 21st Century telecommunications is marked by the arrival of new business models, new platforms, new architectures, and new customer profiles. Next generation networks, IP multimedia systems, IPTV, and converging network and services are new telecommunications paradigms. Technology achievements in terms of co-existence of IPv4 and IPv6, multiple access technologies, IP-MPLS network design driven methods, multicast and high speed require innovative approaches to design and develop large scale telecommunications networks.

Mobile and wireless communications add profit to a large spectrum of technologies and services. We witness the evolution 2G, 2.5G, 3G and beyond, personal communications, cellular and ad hoc networks, as well as multimedia communications.

Web Services add a new dimension to telecommunications, where aspects of speed, security, trust, performance, resilience, and robustness are particularly salient. This requires new service delivery platforms, intelligent network theory, new telecommunications software tools, new communications protocols, and standards.

We are witnessing many technological paradigm shifts imposed by the complexity induced by the notions of fully shared resources, cooperative work, and resource availability. P2P, GRID, Clusters, Web Services, Delay Tolerant Networks, Service/Resource identification and localization illustrate aspects where some components and/or services expose features that are neither stable nor fully guaranteed. Examples of technologies exposing similar behavior are WiFi, WiMax, WideBand, UWB, ZigBee, MBWA and others.

Management aspects related to autonomic and adaptive management includes the entire arsenal of self-ilities. Autonomic Computing, On-Demand Networks and Utility Computing together with Adaptive Management and Self-Management Applications collocating with classical networks management represent other categories of behavior dealing with the paradigm of partial and intermittent resources.

We take here the opportunity to warmly thank all the members of the AICT 2024 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to AICT 2024. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the AICT 2024 organizing committee for their help in handling the logistics of this event.

We hope that AICT 2024 was a successful international forum for the exchange of ideas and results between academia and industry and for the promotion of progress in the field of telecommunications.

AICT 2024 Chairs

AICT 2024 Steering Committee
Dragana Krstic, University of Niš, Serbia
Kevin Daimi, University of Detroit Mercy, USA
Gautam Srivastava, Brandon University, Canada
Sergei Semenov, HiSilicon, Sweden

AICT 2024 Publicity Chairs
Sandra Viciano Tudela, Universitat Politecnica de Valencia, Spain
José Miguel Jiménez, Universitat Politecnica de Valencia, Spain

AICT 2024
Committee

AICT 2024 Steering Committee

Dragana Krstic, University of Niš, Serbia
Kevin Daimi, University of Detroit Mercy, USA
Gautam Srivastava, Brandon University, Canada
Sergei Semenov, HiSilicon, Sweden

AICT 2024 Publicity Chairs

Sandra Viciano Tudela, Universitat Politecnica de Valencia, Spain
José Miguel Jiménez, Universitat Politecnica de Valencia, Spain

AICT 2024 Technical Program Committee

Ghulam Abbas, GIK Institute, Pakistan
Iwan Adhicandra, Bakrie University, Indonesia
Abdullah Al-Alaj, Virginia Wesleyan University, USA
Abdulazaz Albalawi (Aziz), University of California, Santa Cruz, USA
Michele Albano, Aalborg University, Denmark
Nicolae Dumitru Alexandru, "Gheorghe Asachi" Technical University of Iasi, Romania
Arrate Alonso Gómez, Mondragon Unibertsitatea, Spain
Marco Aurélio Spohn, Federal University of Fronteira Sul, Brazil
Marios Avgeris, Carleton University, Ottawa, Canada
Ilija Basicevic, University of Novi Sad, Serbia
Oussama Bazzi, Lebanese University, Lebanon
Carlos Becker Westphall, Federal University of Santa Catarina, Brazil
Sara Behjatjamal, Altinbas University, Turkey
Stefano Berretti, University of Firenze, Italy
Robert Bestak, Czech Technical University in Prague, Czech Republic
Petros Bithas, National and Kapodistrian University of Athens, Greece
Razvan Bocu, Transilvania University of Brasov, Romania
Antonella Bogoni, Scuola Superiore Sant'Anna-TeCIP Institute, Italy
Eugen Borcoci, University "Politehnica"of Bucharest (UPB), Romania
Christos Bouras, University of Patras, Greece
An Braeken, Vrije Universiteit Brussel, Belgium
Lubomir Brancík, Brno University of Technology, Czech Republic
Peter Brida, University of Zilina, Slovakia
Ivana Bridova, University of Zilina, Slovakia
Nicola Calabretta, Eindhoven University of Technology, Netherlands
Vítor Carvalho, 2Ai-EST-IPCA / Algoritmi Research Center - Minho University, Portugal
Fernando Cerdan, Polytechnic University of Cartagena, Spain
Adil Chekati, University of Tunis El Manar, Tunisia
Bo-Rong Chen, University of Illinois Urbana-Champaign, USA
Chen Chen, Chongqing University, China

Table of Contents

Simulation Based Energy Efficiency Analysis of DUDe 5G Networks

Chrysostomos-Athanasios Katsigiannis
Computer Engineering and Informatics Department
University of Patras
Patras, Greece
email: up1072490@upnet.gr

Apostolos Gkamas
Department of Chemistry
University of Ioannina
Ioannina, Greece
email: gkamas@uoi.gr

Konstantinos Tsachrelias
Computer Engineering and Informatics Department
University of Patras
Patras, Greece
email: up1096511@upatras.gr

Christos Bouras
Computer Engineering and Informatics Department
University of Patras
Patras, Greece
email: bouras@upatras.gr

Vasileios Kokkinos
Computer Engineering and Informatics Department
University of Patras
Patras, Greece
email: kokkinos@upatras.gr

Philippos Pouyioutas
Computer Science Department
University of Nicosia
Nicosia, Cyprus
email: pouyioutas.p@unic.ac.cy

***Abstract*— To be able to respond to the explosively increased data traffic demand of 5G and beyond networks (Internet of Things (IoT), Voice/Video calls, Peer2Peer (P2P) software, etc.), one of the most promising technologies is composed of Heterogeneous Networks (HetNets). In HetNets, base stations are brought closer to users with the placement of small base stations, which results in better spectral and energy efficiency for cellular systems. However, the HetNet topology challenges traditional cellular systems. One of the most important challenges is user association. Aiming to avoid the drawback caused by Downlink/Uplink Coupling (DUCo) access in HetNets user association, a Downlink/Uplink Decoupling (DUDe) Access approach has emerged. By allowing access points in the uplink and downlink association to be different, DUDe greatly improves the uplink performance of HetNets. In this paper, we evaluate the energy efficiency and resource allocation of the DUDe approach.**

Keywords*— Downlink/Uplink Decoupling (DUDe), Downlink/Uplink Coupling (DUCo), Resource Allocation, Energy Efficiency, Heterogeneous Networks, Downlink (DL), Uplink (UL).

I. INTRODUCTION

Modern 5G Networks offer great benefits compared to the 4G Long-Term Evolution (LTE) technology, with some of them being high speed, low latency and increased bandwidth. However, the volume of mobile traffic and the number of connected devices is predicted to increase significantly in the 5G era, which will lead to inevitable implications regarding the resource allocation and the total throughput of the networks. The 4G technologies had already achieved extreme densification by utilizing small Base Stations (BSs) throughout the network, leading to the modern HetNets [1]-[4].

In 4G HetNets the User Equipment (UE) devices were associated with the same BS for both Downlink (DL) and Uplink (UL) signals, resulting in the method known as Downlink/Uplink Coupling (DUCo) (see Figure 1). This access scheme, though, has a major drawback. The existence of major inequalities between the transmit power among high powered Macro BS and low powered small BSs, results in suboptimal BS association and thus in performance degradation, mainly affecting the UL. A fine solution to this problem is the decoupling of DL and UL signals in the current HetNets, commonly referred to as Downlink/Uplink Decoupling (DUDe), where the UE is connected to the optimal Macro cell BS for the DL and the optimal small cell (Micro-Pico-Femto) for the UL. Basically, the UL and DL are treated as separate network entities and a UE can connect to different serving nodes in the UL and DL, resulting in improved user/cell association and improved resource allocation.

Cell association in cellular networks has traditionally been based only on the received signal strength, despite the fact that transmit power and interference levels vary significantly. This approach was adequate in homogeneous networks with Macro base stations that all have similar transmit power levels. However, with the development of HetNet, there is a significant difference between the transmission power of different types of base stations, as stated above, making this approach extremely inefficient.

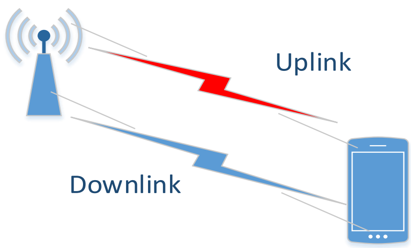


Figure 1. DUCo Example.

The motivation of this work is the improvement of energy efficiency in 5G networks. Energy efficiency is crucial for the success of 5G networks, as these networks will require a significant increase in energy consumption compared to their predecessors. With the proliferation of 5G-enabled UE and the explosion of data traffic, the demand for energy-intensive infrastructure components, such as base stations and data centers, will rise dramatically. By optimizing network architecture, using low-power components, and implementing intelligent power management strategies, operators can

 ISBN: 978-1-68558-145-9

significantly reduce energy usage without sacrificing performance.

DUDe has the potential to significantly improve the energy efficiency of 5G networks. By separating the uplink and downlink channels, operators can dynamically allocate network resources to match the requirements of different applications and services. This results in a more efficient use of resources and reduces the energy consumption of network components, such as base stations and routers. Additionally, decoupling can enable intelligent power management strategies, such as sleep mode for low-traffic devices, further reducing energy consumption.

The main objective of this paper is to validate the findings of previous research by investigating the performance of the system in terms of the number of users and considering different decibel (dB) values. The paper aims to fill the research gap by conducting a comprehensive analysis that incorporates various factors and parameters. By doing so, the paper intends to provide a deeper understanding of how the system performs in real-world conditions and assess its suitability for different deployment scenarios.

The rest of the paper is organized as follows. In Section II, we present a comprehensive review of the relevant technology, with an emphasis on its potential benefits for a 5G heterogeneous network in the realm of energy consumption. In Section III, we present a mathematical model that will be used throughout the paper to analyze the data. In Section IV, we describe and analyze the algorithms used in the simulation. In Section V, we present details of the simulation environment. In Section VI, we present and analyze how to use the DUDe technology to improve the distribution the simulation results, with diagrams and explanations to support the findings. Finally, we conclude our research work and outline potential areas for future research and development in Section VII.

II. DUDe Energy Efficiency Overview

DUDe has been researched by various studies. In one of these studies, researchers consider the resource allocation problem in LTE in unlicensed spectrum (LTE-U) networks using DUDe, formulating the problem as a game theoretic model incorporating user association, spectrum allocation and load balancing, for which they propose a decentralized expected Q-learning algorithm to solve [5]. Another paper proposes an UL and DL Supplementary UL (SUL) decoupling technology and an UL enhancement technology to coordinate New Radio Time Division Duplexing (NR TDD) and New Radio Frequency Division Duplexing (NR FDD) [6]. Lastly, several researchers study the concept of DUDe where DL cell association is based on received power DL, while UL is based on path loss.

However, another paper proposed a DUDe model where Macro-cell selection for DL is based on received power (as usual), but Micro, Pico and Femto-cells selection for UL is not based solely on path loss (link quality), but on a combination of parameters such as: link quality, cell load and cell backhaul capacity [7].

The authors of [8] focus on how to use DUDe technology to improve the distribution of network resources based on user distribution. The study found that,by considering the capacity limitations of each type of BS, the DUDe technology results in a more even distribution of users within the network.

DUDe is a complex technique that requires careful planning and coordination to be implemented effectively. It involves assigning different frequency bands and resources for the DL and UL channels, which requires careful coordination between network operators and device manufacturers. One of the key advantages of DUDe is its ability to reduce energy consumption. Wireless communication systems consume a significant amount of energy, which can have a negative impact on the environment and contribute to global warming. By decoupling the DL and UL channels, as shown in Figure 2, DUDe can reduce the amount of energy needed to operate the network, leading to energy savings over time. By eliminating interference through decoupling, DUDe can improve network performance and reliability, leading to a better user experience [9]- [12].

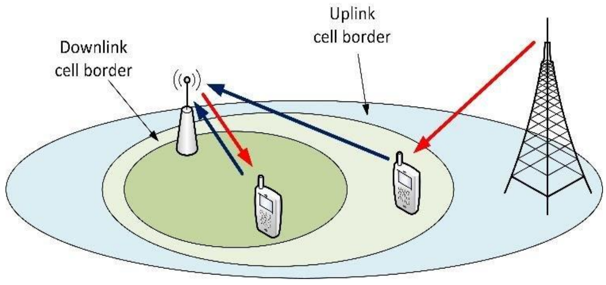


Figure 2. DUDe Example.

DUDe also has the potential to improve the efficiency of wireless communication systems by allowing for more flexible resource allocation. With separate frequency bands and resources for the DL and UL channels, network operators can allocate resources more efficiently and reduce the risk of congestion. This can help to ensure that users receive the quality of service they expect, even during periods of high network demand. In conclusion, DUDe is a promising radio resource management technique that can provide significant benefits for both network operators and end-users. By decoupling the DL and UL channels, DUDe can reduce energy consumption, improve network performance and reliability, and allow for more efficient resource allocation.

III. Mathematical Model Analysis

To determine the minimum distance between users and base station antennas, a mathematical model defined in TR 38.901 Section 7.4.1 is used [13]. The paper does not delve into a detailed analysis of this particular model, so we will not extensively scrutinize its equations from (1) to (3) as a result. The model calculates the Path Loss (PL) in different scenarios, such as Line-Of-Sight (LOS) and Non-Line-Of-Sight (NLOS) conditions.

$$PL_{\mathrm{RMa-LOS}} = \begin{cases} PL_1 & 10m \le d_{\mathrm{2D}} \le d_{\mathrm{BP}} \\ PL_2 & d_{\mathrm{BP}} \le d_{\mathrm{2D}} \le 10\mathrm{km} \end{cases} \quad (1)$$

$$PL_1 = 20\, log_{10}(\,40\pi d_{\mathrm{3D}} f_c/3) + min(\,0.03h^{1.72}, 10)\, log_{10}(\,d_{\mathrm{3D}}) - min(\,0.044h^{1.72}, 14.77) + 0.002\, log_{10}(\,h) d_{\mathrm{3D}} \quad (2)$$

$$PL_2 = PL_1(d_{\mathrm{BP}}) + 40\, log_{10}(\,d_{\mathrm{3D}} / d_{\mathrm{BP}}) \quad (3)$$

$$\mathrm{SNR} = \mathrm{Psignal/Pnoise} \quad (4)$$

The path loss is calculated using equations (1), (2), and (3). Equation (1) defines the path loss in LOS conditions and

NLOS conditions based on the distance between the user and the base station antennas. Equation (2) calculates the path loss based on the three-dimensional distance, carrier frequency, user height, and other parameters. Equation (3) modifies the path loss based on the breakpoint distance and the three-dimensional distance.

Once the minimum distance for each user from different types of antennas is determined, the next step is to compute the Signal-to-Noise Ratio (SNR) to find the antenna type that provides the best connection. Equation (4) represents the SNR as the ratio of the signal power to the noise power [14].

IV. ENERGY EFFICIENCY ALGORITHM

Our HetNet includes Macro BS (MB) small BS (Pico and Micro) and UEs. Consider a set of MBs (M = 1, 2, 3, 4.......|M|), a set of small cells (Pico => p = 1, 2, 3, 4.... |P|, Micro => m= 1, 2, 3, 4 |m|) and a set of UEs (U = 1, 2, 3, 4.......|U|). We assume that the MBs are placed at high levels to provide continuous uninterrupted coverage to large cells. In addition, we assume that the BSs with the least sensitivity are placed at lower levels within an area, and as a result, the coverage of the NLOS locations is as wide as possible in the entire area, even in the most remote/obstructed points to efficiently serve static users or users who are constantly in motion within the area.

Algorithm 1 Algorithm for 20dbm or 30dbm Transmit Power

```
//Initialize variables
Macro_cells
Micro_cells
Pico_cells
N = total number of UEs
occurrences_for_scenarios
SNR_matrix = zeros(N, occurrences_for_scenarios)
// calculate best SNR for each UE for occurrences_for_scenarios
for i in range(N):
    for j in range(occurrences_for_scenarios):
        // calculate SNR for current occurrences_for_scenarios
        SNR = calculate_SNR(UE_i, occurrences_for_scenarios _j)
        SNR_matrix[i][j] = SNR
    end
end
// calculate standard SNR value for each UE for each occurrences_for_scenarios
standard_SNR = zeros(N, occurrences_for_scenarios)
for i in range(N):
    for j in range(occurrences_for_scenarios):
        // calculate standard SNR for current snapshot
        standard_SNR[i][j]=sum(SNR_matrix[i][j])/occurrences_for_s
    cenarios
        // calculate transmit power for each UE for each
    occurrences_for_scenarios
transmit_power = zeros(N, snapshots)
    end
end
for i in range(N):
    for j in range(occurrences_for_scenarios):
        // calculate transmit power for current snapshot
        transmit_power[i][j] = calculate_transmit_power(UE_i,
    standard_SNR[i][j])
        // build coupled scenario and distribute UEs in the network
        coupled_power = zeros(N)
    end
end
for i in range(N):
    // if transmit power is less than 20 or 30 dbm, keep value
    if transmit_power[i][-1] < 20 if transmit_power[i][-1] <30:
    coupled_power[i] = transmit_power[i][-1]
    // if transmit power is above 20 dbm, change value to 20 dbm
    else:
    coupled_power[i] = 20 or 30
    // build decoupled scenario and distribute UEs in the network
        decoupled_power = zeros(N)
end
for i in range(N):
        // calculate transmit power using decoupling technology
        decoupled_power[i] = calculate_decoupled_transmit_power(UE_i,
standard_SNR)
        // compare energy efficiency between coupled and decoupled
scenarios
end
if sum(coupled_power) > sum(decoupled_power):
output("Decoupling technology is more energy efficient.")
else:
output("Coupling technology is more energy efficient.")
```

Figure 3. Algorithm 1

In our algorithm (Figure 3), we perform two different scenarios for distributing UE in a network: a DUCo scenario and a DUDe scenario. The algorithm starts by initializing some variables, including the number of Macro, Micro, and Pico cells, the number of UEs, and the number of snapshots used in the simulation. Then, for each UE and for each snapshot, the algorithm calculates the Signal-to-Noise Ratio (SNR) of each UE in the network. It stores these SNR values in a matrix.

Next, the algorithm calculates the standard SNR value for every UE in each snapshot by taking the average SNR value across all snapshots. It stores these values in a matrix called standard SNR. After calculating the standard SNR values, the algorithm calculates the transmit power for each UE in each snapshot. It stores these transmit power values in a matrix called transmit power. Next, the algorithm builds the DUCo and DUDe scenarios by distributing the UEs in the network.

For the DUCo scenario, the algorithm sets the transmit power of each UE to the last value in the transmit power matrix for that UE, unless that value is greater than a threshold (20 or 30 dBm in our simulations), in which case it sets the transmit power to the pre-selected threshold. For the DUCo scenario, the algorithm calculates the transmit power for each UE based on the typical SNR values and runs the scenarios for a number of snapshots (1000 in our simulations) in order to reduce the impact of random variations or uncertainties in the simulation outcomes.

V. SIMULATION ENVIRONMENT

Specifically, we consider a 5G DUDe network consisting of 2 Macro cells, 4 Micro cells, and 8 Pico cells, each equipped with specific transmit power in dBm. Furthermore, it should be noted that the capacity of the Macro cells is 2000 users, the capacity of the Micro cells is 200 users, and the capacity of the Pico cells is 46 users. This information is crucial in determining the optimal number of users that can be allocated to each type of cell. A total of N number of users are distributed within the network, each with their own transmit power in dBm. The gain from all antennas, including bandwidth and noise in the network, is also considered. For the implementation of our model and scenarios, we used MATLAB [15], due to the fact that the application provides appropriate libraries and, consequently, functions, which make it easy and reliable to create a demanding algorithm like the one above. In addition, Figure 4 depicts the layout of our network, where the two Macro cell antennas are located at the center, surrounded by small cells that are distributed around them.

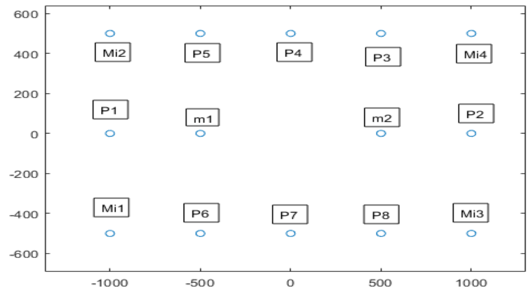


Figure 4. Topology of our network. (m) for Macro (mi) for Micro and (p) for Pico.

It is important to mention that users are randomly located between 1 and 2 meters apart from each other. The connection of the users is done in such a way that, for the DL processes the user will be connected to the Macro cell antennas. During UL processes, the user will connect to the small cell antennas, which can either be Micro or Pico cells. The selection of the appropriate small cell is based on the lowest path loss value, in addition to the transmission power.

Once the path loss has been calculated, we calculate the SNR using the variables mentioned in Table I. Utilizing the highest SNR, each user is connected to the best Base Station (BS) choice from the three categories, namely Macro cells, Micro cells, and Pico cells.

The direct result of this is that our model guarantees the non-interruption of the connection and less power consumption since the BS does not consume resources to serve users with great losses.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Amount of Base Stations	Macro cell = 2 Micro cell = 4 Pico cell = 8
Transmit power(dbm)	UE = 20, 30 Macro cell = 45 Micro cell = 33 Pico cell = 24
BS height (m)	Macro height = 30 Micro height = 10 Pico height = 5
Antenna gain (dbi)	Macro cell = 21 Micro cell = 10 Pico cell = 5
bandwidth (MHz)	20
Environmental parameters	UE1 = 100/UE2 = 500/UE3 = 1000 Position = random
Power Noise	Pnoise = -74+10log(Bandwidth(hz))

The purpose of the evaluation is to demonstrate the superior energy efficiency of the DUDe technique compared to the DUCo technique in a 5G network. This goal is achieved by calculating a common SNR value for each type of antenna (Macro, Micro, Pico) using the mathematical formula presented in Section III.

Next, the transmission power is calculated for different scenarios involving 500, 1000, and 2000 UEs for each antenna instance. The findings reveal that for the same SNR value, the power consumption of the DUCo technique is significantly higher than that of the DUDe technique.

VI. RESULTS EVALUATION AND ANALYSIS

Two scenarios, DUDe and DUCo, are implemented with transmit power of 20 dBm and 30 dBm. As the performed evaluation shows, the DUDe scenario requires less transmission power compared to the DUCo scenario, making a network that uses the DUDe technique in a more energy-efficient and environmentally friendly way. However, any transmission power values exceeding 20 dBm and 30 dBm are limited to 20 dBm and 30 dBm, respectively, in both scenarios, as algorithm 1 suggests.

The limit for UE transmission power (20dbm, 30dbm) in our scenarios and in general in mobile telecommunications is set by the Mobile Broadband Standard Partnership Project (3GPP) [16].

Also, in the context of the provided diagrams, we initially determine the average SNR values for each UE across 1000 snapshots. These average SNR values are our target for subsequent calculations. When calculating the required transmission power for each UE to achieve these target SNR values, we take into consideration a threshold: if the calculated power exceeds 20 dBm or 30 dBm, we set the transmission power to those respective limits, regardless of the calculation outcome.

In the set of Figures 5 to 10, in both scenarios, 'x' represents the average transmission power of the UEs Upon analyzing these figures, we can draw the following conlsusions: Increasing the transmission power of a UE results in a greater than 60% likelihood of establishing a DUDe association. Especially when the transmission power exceeds 10 dB, the likelihood of DUDe correlation notably increases to over 50%. Also, with a stronger signal, which means a higher SNR value, we observe a steady increase in the DUDe correlation probability. Based on the insights gained from Figures 5 to 10 and the data presented, we can assert that the DUDe scenario requires less transmission power to achieve similar outcomes compared to the coupled scenario. This observation has several benefits: it implies reduced antenna power consumption, more efficient user service, and a higher overall level of user satisfaction compared to the coupled scenario.

A. *Evaluation and analysis of 1st scenario*

In this evaluation scenario, we compare DUDe and DUCo in terms of energy efficiency by setting the UE transmission power at 20dbm. The results of the evaluations are displayed from Figure 5 to 7. In the diagrams presented in these figures, the x axis is the average transmission power of the UEs in dB and the F(x) axis is the possibility of successful DUDe or DUCo scenario. The implementation of the scenario was successful in meeting the goal of achieving the same result with less transmission power in the DUDe method. This means that our scenario was able to accomplish the desired outcome while using less transmission power, which is a significant achievement in the field of mobile telecommunications.

Based on Figures 5 to 7 provided, it is evident that the DUDe method has a higher likelihood of establishing successful connections compared to the DUCo (Downlink-Uplink Coordinated) method. For instance, considering a transmission with a UE transmit power of 10 dB, the DUDe method demonstrates a 50% chance of establishing a successful connection, while the DUCo method has a success rate of less than 40% across all three simulations involving 500, 1000, and 2000 users. Based on the information

 ISBN: 978-1-68558-145-9

provided in the previous discussion, it can be inferred that the DUDe technology has been found to provide at least 20% more successful connections compared to DUCo technology. This higher success rate implies that the DUDe technology offers better reliability and improved connectivity for users in the wireless communication system. Figures 5 to 7 would demonstrate the higher probability of successful connections with DUDe technology, further supporting the claim of its superior performance. It is important to note that with more successful connections, the DUDe technology can contribute to reducing energy consumption compared to DUCo technology. This can be attributed to the fact that successful connections require fewer retransmissions and less energy-intensive signaling processes, resulting in overall lower energy consumption. Therefore, the combination of higher success rates and lower energy consumption makes DUDe technology a more efficient and preferable choice compared to DUCo technology, as indicated by the probability diagrams and the research findings.

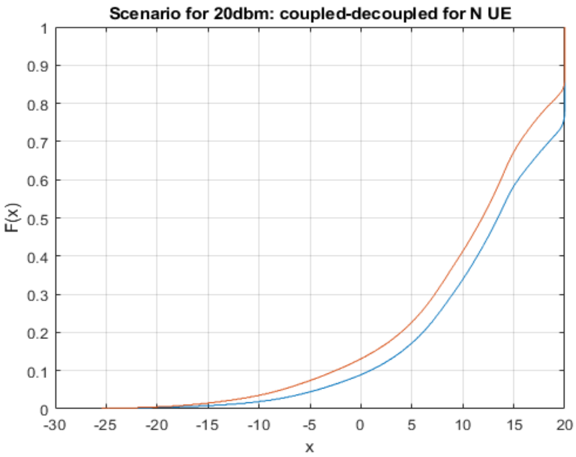


Figure 5. DUDe/DUCo comparison with 20dbm UE limit for N=500.

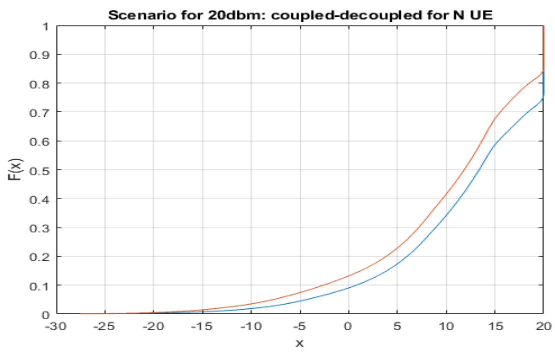


Figure 6. DUDe comparison with 20dbm UE limit for N=1000.

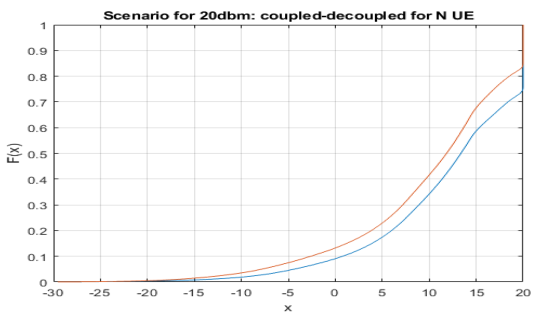


Figure 7. DUDe comparison with 20dbm UE limit for N=2000.

Similarly, when considering an SNR of 15 dB, Figures 5 to 7 illustrate that the probability of achieving low consumption with the DUDe method is 80%, whereas the primary DUCo technology only reaches 62%. The difference between the two technologies in this case is approximately 29%, further strengthening the initial hypothesis that the DUDe technology achieves lower power consumption for the same performance level.

These findings provide evidence supporting the notion that the DUDe method is more energy-efficient than the DUCo method. The research establishes a significant advantage of DUDe in terms of reduced power consumption, thereby reinforcing its potential for implementation in practical scenarios and aligning with the objective of developing sustainable and environmentally friendly 5G networks.

B. *Evaluation and analysis of 2nd scenario*

In this evaluation scenario, we compare DUDe and DUCo in terms of energy efficiency by setting the UE transmission power at 30dbm. The results of the evaluations are displayed on Figure 8 to 10. In the diagrams presented in these figures, x axis is the average transmission power of the UEs in dB and the F(x) axis is the possibility of successful DUDe or DUCo scenario. In this second scenario, it is worth noting that there is a limit of 30 decibels per milliwatt (30dbm) imposed by 3GPP, the Mobile Broadband Standard Partnership Project. This limit sets a cap on the maximum amount of transmit power that can be used to transmit signals in our scenario.

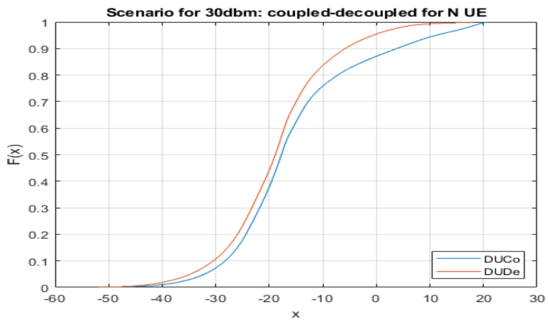


Figure 8. DUDe comparison with 30dbm UE limit for N=500.

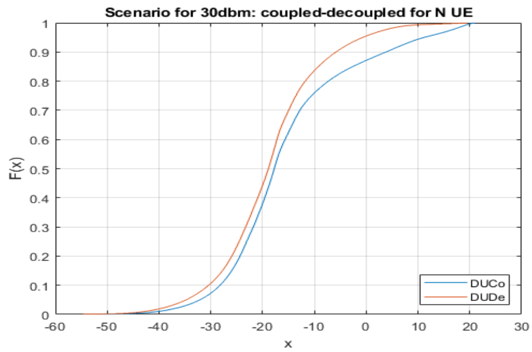


Figure 9. DUDe comparison with 30dbm UE limit for N=1000.

Despite this limit, our findings remain consistent with those of the first scenario. We have determined that the DUDe method for implementing a heterogeneous 5G network is more environmentally friendly than the DUCo method. This conclusion holds true even with the 30dbm limit in place. It is worth mentioning that the difference in energy consumption between the DUDe and DUCo methods is smaller in the second scenario than in the first. However, this does not change our overall conclusion that the DUDe method is more energy-efficient and will have a positive impact on the environment and society. To summarize, although the 30dbm limit is a factor to consider when implementing a 5G network, it does not change our conclusion that the DUDe method is the better choice for a more environmentally friendly network.

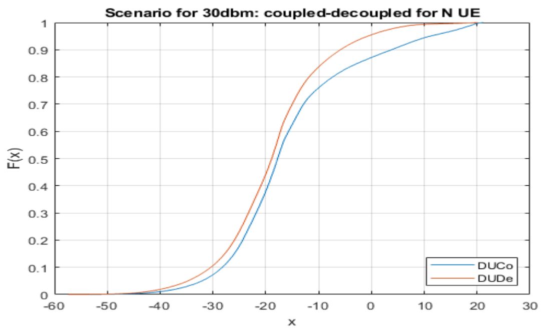


Figure 10. DUDe comparison with 30dbm UE limit for N=2000.

As diagrams in Figure 8 to 10 show and according to the data, it appears that increasing the transmission power of a UE results in a greater probability of DUDe association. When the transmission power is 2dbm or higher, there is a 70% and higher likelihood of a DUDe connection. These findings suggest that the algorithm designed for DUDe communication requires less transmission power to achieve similar results compared to the DUCo scenarios.

VII. Conclusions And Future Work

In this paper, we have compared the energy efficiency of DUCo and DUDe in a HetNet 5G network. Our analysis shows that DUDe is a more energy-efficient method for the same task, as it requires less energy consumption.

The results of our study suggest that DUDe can be a promising method to reduce energy consumption in 5G networks. By separating the DL and UL transmissions, we can optimize the use of resources and minimize energy consumption, while still providing high-quality network performance. This approach can have significant benefits for both mobile network operators and end-users, by reducing costs and improving overall user experience.

Furthermore, we believe that future work in this area could focus on optimizing bandwidth allocation using DUDe. By carefully allocating bandwidth to each cell, we can further improve energy efficiency, minimize interference, and maximize throughput. This approach could have significant benefits for large-scale 5G networks, where bandwidth allocation is critical to achieving optimal network performance. Also, the experiments yield consistent results, indicating that the findings remain unchanged regardless of the network's user population, whether it is extensive or limited in size. In other words, the number of users in the network has minimal impact on the conclusions drawn from our experiments.

Overall, our findings highlight the importance of adopting energy-efficient techniques in mobile networks to reduce the environmental impact of high-speed data transfer. We encourage further research in this area to explore new ways of optimizing network performance while minimizing energy consumption. By identifying new opportunities for sustainable innovation in mobile communications, we can create a more efficient and sustainable future for the industry.

Acknowledgment

This research has been co-financed by the Hellenic Foundation for Research & Innovation (H.F.R.I) through the H.F.R.I.'s Research Projects to Support Faculty Members & Researchers (project code: 02440).

References

[1] S. Ruiza et al., “5G and beyond networks” in ScienceDirect, Inclusive Radio Communications for 5G and Beyond, 2021, pp. 141-186.

[2] H. Elshaer, F. Boccardi, M. Dohler, and R. Irmer, “Downlink and Uplink Decoupling: A disruptive architectural design for 5G networks”, 2014 IEEE Global Communications Conference, Austin, TX, USA, 2014, pp. 1798-1803.

[3] H. Khan, M. Ali, I. Rashid, A. Ghafoor and M. Naeem, “Cell Association for Energy Efficient Resource Allocation in Decoupled 5G Heterogeneous Networks”, 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), Antwerp, Belgium, 2020, pp. 1-5.

[4] N. Garg, “Downlink and Uplink User Association in Dense Next-Generation Wireless Networks”, Ph.D dissertation, University of Texas at Austin 2015 [Online]. Availabe : http://hdl.handle.net/2152/30074.

[5] Y. Hu, R. MacKenzie and M. Hao, “Expected Q-learning for Self-Organizing Resource Allocation in LTE-U with DL-UL Decoupling”, European Wireless 2017; 23th European Wireless Conference, pp. 1-6, 2017.

[6] J. Guo, Y. Zhang, B. Guo, Z. Fan, and H. Song, “5G UL Coverage Enhancement Based on Coordinating NR TDD and NR FDD”, In: Sun, Signal and Information Processing, Networking and Computers. Lecture Notes in Electrical Engineering, vol. 917, 2023, Springer, Singapore. https://doi.org/10.1007/978-981-19-3387-5_168.

[7] H. Elshaer, F. Boccardi, M. Dohler and R. Irmer, “Load & backhaul aware DUDe DL/UL access in 5G systems,” 2015 IEEE International Conference on Communications (ICC), 2015, pp. 5380-5385, doi: 10.1109/ICC.2015.7249179.

[8] T. Konstantinos et al., “On the Optimization of User Allocation in Heterogeneous 5G Networks Using DUDe Techniques”, ICUFN 2023, in press.

[9] A. J. Muhammed, Z. Ma, Z. Zhang, P. Fan and E. G. Larsson, “Energy-Efficient Resource Allocation for NOMA Based Small Cell Networks With Wireless Backhauls”, in IEEE Transactions on Communications, vol. 68, no. 6, pp. 3766-3781, June 2020.

[10] Y. Shi, E. Alsusa, and M. W. Baidas, “A survey on downlink–uplink decoupled access: Advances, challenges, and open problems” In ScienceDirect, Computer Networks, vol. 213, 2022.

[11] H. Z. Khan et al., “Resource allocation and throughput maximization in decoupled 5G" 2020 IEEE wireless communications and networking conference (WCNC). IEEE, 2020.

[12] 3GPP, TR 38.901 Section 7.4.1 “Study on channel model for frequencies from 0.5 to 100 GHz”, release 17, March 2022.

[13] F. A. Niasar and A. Reza, “A novel approach to fairness-aware energy efficiency in green heterogeneous cellular networks,” Momen Wireless Networks, vol. 28, pp. 2651–2667, 2022.

[14] B. Błaszczyszyn and H. P. Keeler, “Studying the SINR Process of the Typical User in Poisson Networks Using Its Factorial Moment Measures”, in IEEE Transactions on Information Theory, vol. 61, no. 12, pp. 6774-6794, Dec. 2015.

[15] MathWorks, 2023. 5G Toolbox [Software]. Information retrieved 20/10/2024 from https://www.mathworks.com/products/5g.html.

[16] 3rd Generation Partnership Project (3GPP). (n.d.). 3GPP References Search. Information retrieved 20/10/2024 from 3GPP website: https://portal.3gpp.org/3gppreferences/SearchReferences.aspx.

Study of Income for Companies that Provide Mobile Internet Service in Colombia

Luis Fernando Pedraza, Cesar Augusto Hernandez, Ernesto Cadena Muñoz
Technological Faculty
Universidad Distrital Francisco José de Caldas
Bogotá, Colombia
e-mails: lfpedrazam@udistrital.edu.co, cahernandezs@udistrital.edu.co, ecadenam@udistrital.edu.co

***Abstract*— The telecommunications services market has been growing to satisfy customer needs. The above has prompted mobile phone operators to enhance their bandwidth and coverage for services like mobile Internet. This has had an impact on the operators' income. Therefore, this paper analyzes the income in the mobile Internet service of the three companies with the most significant penetration in the Colombian market from 2012 to 2022. For this, statistical measures are used. The results show that, in general, the companies' income has been increasing; however, the Claro operator's income is much higher than that of the rest of the operators during this period, despite the competitive dynamics in the market of this sector.**

Keywords-analysis of variance; coefficient of correlation; mobile Internet; statical measures; telecommunications market.

I. INTRODUCTION

The telecommunications services market is moving in increasingly flexible and adaptable environments to customers' needs. In addition, an increase in bandwidth is recognized due to the emergence of various services and applications on the Internet, which increases the volume of data sales, becoming a solid source of income for Internet Service Providers (ISP). Intense competition exists between these ISPs to maintain and attract new customers to their businesses, and they are forced to analyze the quality of the service and experience to improve interaction with their customers. Providers are interested in maintaining these clients and increasing the volume of consumption of their services [1][2].

Analyzing the relevant aspects of telecommunications inevitably involves using statistical or data analysis. We can better understand this by looking at the various aspects directly influenced by the sector, including users, infrastructure, technology, and services. Each factor plays a significant role and can be analyzed or measured on a large scale. This requires establishing trends, using metrics, and making comparisons. The various tools offered by statistical and data analysis facilitate these possibilities.

The importance of statistical analysis is verifiable if various studies carried out in the area are reviewed. For example, a variable of great interest within telecommunications is the clients (users) since the massification of services, bandwidth consumption, and the use of infrastructure will always be a function of these; therefore, for service providers, it is essential to understand the consumption trends and preferences that their customers have according to a given region, as done in [3][4]. Analyzing the industry's economic growth and the factors that influence its fluctuations is common. Researchers in a study cited in [5] analyzed the relationship between telecommunications technology and economic growth. Other studies also analyze the impact of Big Data analytics on telecommunications, specifically on governance, architecture, and other use cases, as shown in [6]. Studies looked at the telecommunications market in Latin American countries and found the need for improved spectrum management that follows established policies. Addressing competition in these markets is crucial to improve competitiveness, reduce the digital divide, and promote regional development. Potential investments are also identified through these studies. Countries that allocate more bandwidth and have competitive markets receive more social benefits [7].

Also, it is important to analyze that rapid expansions of market demands have gradually become saturated with the development of the telecommunications industry. Operators convert their attention from users to income. They try their best to increase telecom income via various measures, one of which being to set an amount of income as a goal. Many factors affect income, such as market demand, the policy of subsidies, the invention of new products, and so on. There are many issues to be determined if we analyze the income from the relationship between factors and the variation of income [8].

This paper aims to analyze the income for the three companies that obtained more than 90% of the total market revenue corresponding to mobile Internet service from 2012 to 2022 to determine how income is distributed in companies in this sector. The data is obtained from the Communications Regulation Commission of Colombia. For this, the following statistical measures are used: central tendency and variability, coefficient of correlation, and the analysis of variance (ANOVA). The results show growth in the income of the three operators; however, the Claro operator is the one that receives the most income from this service.

The structure of this paper is as follows: Section II explains the statistical variables used and the data from the telecommunications operators. Section III shows and describes the statistical results. Finally, Section IV presents the conclusions obtained.

II. STATISTICS FOR TELECOMMUNICATIONS

The telecommunications sector is one of the service-based sectors where both the team and the customer relationships are the backbone of the organization. The success of such an

 ISBN: 978-1-68558-145-9

organization will be based on the success of managing an excellent relationship with the clients. The above is possible with the use of statistics. “Statistics is a science that helps us make decisions and draw conclusions in the presence of variability” [9]. Different types of statistics could be applied depending on the case study.

Statistics allows us to understand customer behavior and define the significant variables essential in analyzing customer relationships. This is done through analytical and statistical tools and techniques such as Explanatory and Confirmatory Factor Analysis, Regression and ANOVA, Clustering Analysis, and Classification Analysis. In addition to collecting and reading data correctly, statistics supports its interpretation by making forecasts [10].

Our statistical analysis presents the basic quantitative measures offered by descriptive statistics (mean, standard deviation, and so on), the relationship between the variables analyzed using correlation, and the verification of a hypothesis through ANOVA for the characterization of income in the mobile Internet service of the three companies with the most significant penetration in the Colombian market. Below, we explain these statistical variables.

A. *Descriptive measures*

An average is a value typical or representative of a data set. Since such typical values tend to lie centrally within a set of data arranged according to magnitude, averages are also called measures of central tendency.

Several types of averages can be defined, the most common being the arithmetic mean, the median, the mode, the geometric mean, and the harmonic mean. Each has advantages and disadvantages, depending on the data and the intended purpose. In this study, we are interested in the arithmetic mean [11]:

1) *The arithmetic mean* is a measure of a continuous variable's location or central value. For a sample of observations *x1; x2; . . . ; xn* the measure is calculated as

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (1)$$

2) *Quartile deviation:* If a data set is arranged in order of magnitude, the median is the middle value (or arithmetic mean of the two middle values) that divides the set into two equal parts. By extending this idea, we can think of those values which divide the set into four equal parts. These values, denoted by Q_1, Q_2, and Q_3, are called the first, second, and third quartiles, respectively, the value Q_2 being equal to the median.

3) *Standard Deviation*: The standard deviation of a set of N numbers $X_1, X_2, \ldots, X_N$ is denoted by *std* and is defined by

$$std = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(x_j - \bar{x}\right)^2} \quad (2)$$

where x represents the deviations of each of the numbers X_j from the mean $\bar{x}$.

B. *Karl Pearson's Coefficient of Correlation*

A British biometrician developed a formula called the correlation coefficient to measure the intensity or degree of linear relationship between two variables.

The correlation coefficient between two random variables X and Y, usually denoted by $r(X, Y)$ or simply r_{xy}, is a numerical measure of the linear relationship between them and is defined as:

$$r(X,Y) = \frac{Cov\ (X,Y)}{\sigma_x \sigma_y} \quad (3)$$

where $Cov\ (X, Y)$ is the covariance between X and Y, which is a value that indicates the degree of joint variation of X and Y concerning their means. σ_x and σ_y are the deviations of X and Y, respectively, which is a measure used to quantify the dispersion of a set of numerical data [11].

C. *Analysis of Variance*

ANOVA is a statistical tool for analyzing how the mean value of a quantitative response (or dependent) variable is affected by one or more categorical variables, known as treatment variables or factors. While ANOVA allows us to compare the means of more than two populations, it can only tell us whether differences appear to exist, not specifically which population means are different. Consequently, the appropriate hypotheses for ANOVA are H_0: $\mu_1 = \mu_2 = \ldots = \mu_k$ (that the population mean responses are equal, where k is the number of populations) and H_a: at least one of the population mean responses, μ_i, is different [12].

The F-statistic is used to accept or reject the hypothesis. The F-statistic is simply a ratio of two variances. Variance is the square of the standard deviation. Therefore, the F-statistic can be summarized as follows:

A sample variance is calculated as SS/df, where SS is the sum of squared deviations from the mean, and df is the degree of freedom [13].

D. *Data*

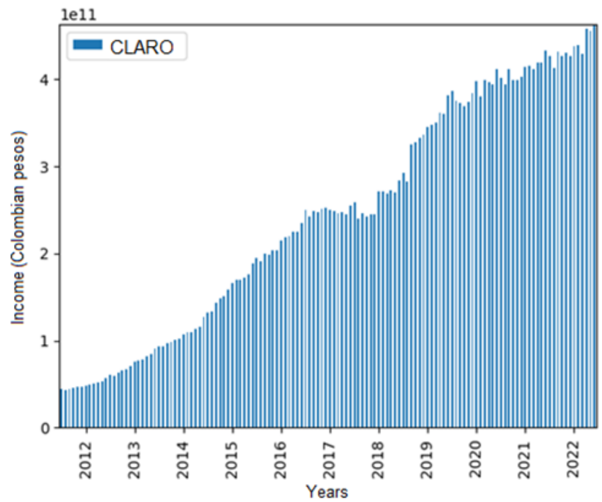
The data used for this study corresponds to the sum of postpaid (fixed charge) and prepaid data (on demand). The collection of data from mobile Internet operators in Colombia is carried out on the website of the Communications Regulation Commission (CRC) [14]; then, this data is organized, treated, and debugged to filter the information necessary for the subsequent statistical analysis. With this information, the income of the companies “Claro”, “Tigo” and “Movistar” are graphed, as shown in Figure 1.

III. RESULTS

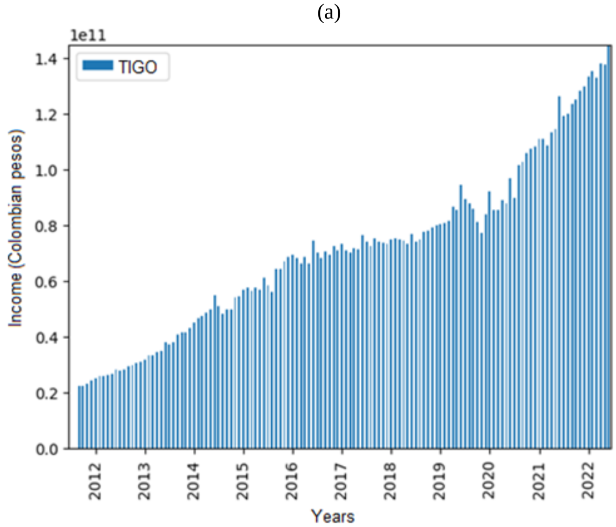
The statistical results of Figure 1 are presented below in Table I and Figure 2, which include data count, mean, standard deviation, minimum and maximum sample, and the distribution's first, second, and third quartiles. Table II shows whether there is an increasing trend in income for operators based on the data correlation. At an exploratory level,

 ISBN: 978-1-68558-145-9

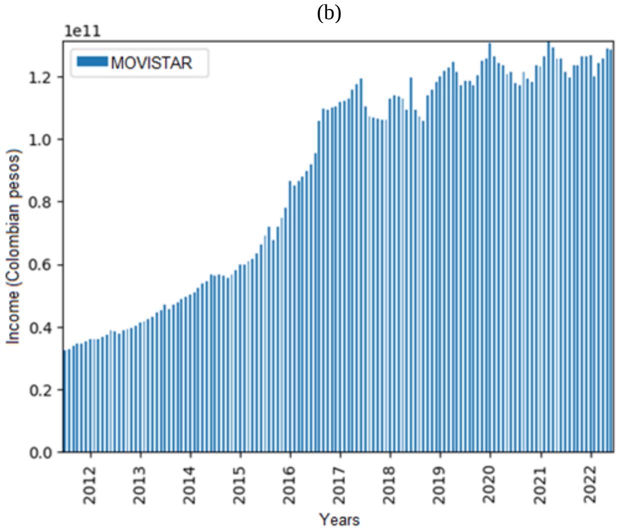
ANOVA is presented in Table III for the operators Tigo and Movistar, since their data have a degree of similarity.



(a)



(b)



(c)

Figure 1. Income in Colombian pesos for mobile Internet companies: (a) Claro, (b) Tigo, (c) Movistar.

TABLE I. STATISTICAL DATA OF MOBILE INTERNET INCOME FOR THE COMPANIES CLARO, TIGO AND MOVISTAR

Index	Claro	Tigo	Movistar
count	132	130	132
mean	242,972,245,121	71,155,903,596	88,576,078,279
std	132,142,308,577	30,241,219,067	34,615,171,364
min	42,717,665,502	22,412,389,160	32,386,111,291
Q_1(25%)	112,687,051,935	49,008,466,545	53,418,243,260
Q_2(50%)	245,620,245,469	71,566,749,718	106,526,211,467
Q_3(75%)	376,555,779,779	85,722,526,660	119,730,605,411
max	462,660,494,175	144,650,203,048	131,331,643,922

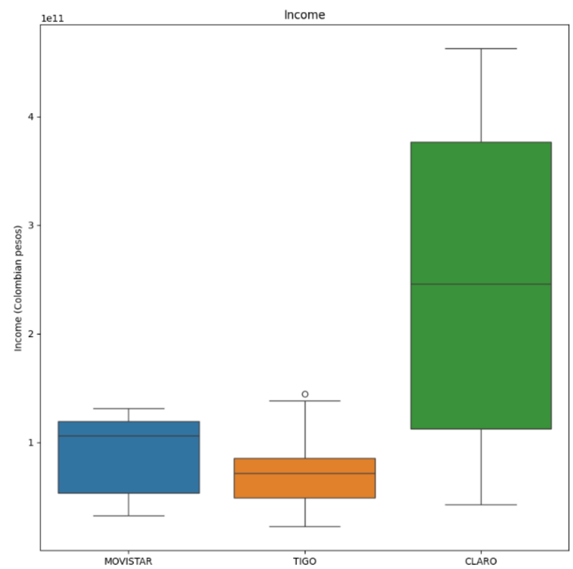


Figure 2. Boxplot for company income from mobile Internet.

TABLE II. COEFFICIENT OF CORRELATION IN MOBILE INTERNET INCOME FOR THE COMPANIES CLARO, TIGO AND MOVISTAR

	Claro income	**Tigo income**	**Movistar income**
Claro income	1	0.9586	0.9519
Tigo income	0.9586	1	0.8872
Movistar income	0.9519	0.8872	1

TABLE III. ANALYSIS OF VARIANCE IN MOBILE INTERNET INCOME FOR THE COMPANIES TIGO AND MOVISTAR

	Claro-Movistar income	**Tigo-Movistar income**
Mean squares	1.57E24	1.98E22
F	168.6319	18.795
Probability	4.197E-30	0.0000208
The critical value of F	3.87719	3.87747

 ISBN: 978-1-68558-145-9

The data exhibited in Figure 1, Table I, and Figure 2 indicate the following:

- Income growth for Claro and Tigo have a linear trend. For Movistar, growth is exponential until 2017, and then it grows oscillatory because of competition in the prices of other operators' plans [15].
- Claro recorded the highest mean income, $242.972.245.121, with a standard deviation of $132.142.308.577. Tigo presented the lowest mean income, $71.155.903.596, with a standard deviation of $30.241.219.067.

In the results of Table II, a high correlation coefficient is observed between the income of the companies evaluated.

With the values in Table III, the relationship of the variances can be compared using the F value to accept or reject the hypothesis. Here, it is observed that in all cases, the value of F is greater than the critical value for F and that the probability value is less than 0,05, which means that the hypothesis is rejected. Therefore, the compared mean values are statistically different.

IV. CONCLUSIONS

The free competition market for the telecommunications sector established in Colombia shows that, for mobile Internet, the operator Claro received, on average, more than twice the income of the operators Tigo and Movistar during the ten years covered by this study.

The high correlation between the incomes of the mobile Internet companies analyzed indicates that operators have increased their income from this service over time.

The ANOVA test between the companies' income confirms the information obtained in Table I regarding the significant difference in the mean income.

Although a high degree of income concentration is observed in the operator Claro, in Colombia, the dynamics of the mobile operator market are one of competition at a technological level and a decrease in rates.

This study shows the income gap between the largest operator and its closest competitors.

It is worth highlighting the work of telecommunications regulatory entities, such as the CRC, which require the frequent sending of information by operators to optimize the processes of collection, processing, and use of information as a tool for regulatory support.

This study does not analyze the consequences of changes in income, such as rates and number portability.

ACKNOWLEDGEMENT

The authors would like to thank the Universidad Distrital Francisco Jose de Caldas, Ministerio de Ciencia, Tecnología e Innovación and Comision de Regulacion de las Comunicaciones for supporting and funding this project.

REFERENCES

[1] M. Fiedler, K. De Moor, H. Ravuri, P. Tanneedi, and M. Chandiri, "Users on the move: On relationships between QoE ratings, data volumes and intentions to churn", in IEEE 42nd Conference on Local Computer Networks Workshops (LCN Workshops), 2017, pp. 97-102.

[2] C. Hernandez, E. Cadena, and L. Pedraza, "Measurement of Competitiveness in the Colombian Mobile Telecommunications Market based on the Linda Index," The Eighteenth International Conference on Systems and Networks Communications (ICSNC 2023) IARIA, Nov. 2023, pp. 10-15, ISSN: 2163-9027, ISBN: 978-1-68558-099-5.

[3] J. Calzada, B. García-Mariñoso and D. Suárez, "Do telecommunications prices depend on consumer engagement?" Information Economics and Policy, vol. 62, Mar. 2023, doi: 101018. 10.1016/j.infoecopol.2023.101018.

[4] A. Shahzad, R. M. S. Yaqub, A. Di Vaio, and R. Hassan, "Antecedents of customer loyalty and performance improvement: Evidence from Pakistan's telecommunications sector," Utilities Policy, vol. 70, Jun. 2021, doi: 10.1016/j.jup.2021.101208.

[5] K. Okeleke, H. F. Aquije and J. Joiner, *The Mobile Economy 2023*. [Online]. Available from: https://www.gsma.com/mobileeconomy/wp-content/uploads/2023/03/270223-The-Mobile-Economy-2023.pdf, [retrieved: 03, 2024].

[6] Comision de Regulacion de Comunicaciones, *Batería de indicadores para el análisis de la competencia en los mercados de comunicaciones.* [in English: Battery of indicators for the analysis of competition in communications markets], [Online]. Available from: https://postdata.gov.co/story/bateria-de-indicadores-para-el-analisis-de-competencia, [retrieved: 03, 2024].

[7] O. S. de Miera Berglind, "Spectrum concentration and market competition. Implications for the use of caps in Mexico," Conference of Telecommunication, Media and Internet Techno-Economics (CTTE), Dec. 2015, pp. 1-8, doi: 10.1109/CTTE.2015.7347228.

[8] M. Wang, Y. Wang, X. Wang and Z. Wei, "Forecast and Analyze the Telecom Income based on ARIMA Model," The Open Cybernetics & Systemics Journal, vol. 9, pp. 2559-2564, Oct. 2015, doi: 10.2174/1874110X01509012559.

[9] D. C. Montgomery and G. C. Runger, Applied statistics and probability for engineers, 7th ed., Singapore: Wiley & Sons, pp. 1, 2014.

[10] M. Abiad, "Increasing telecommunication service performance through statistical analysis", PhD Thesis, Doctoral School of Entrepreneurship, Engineering and Business, University Politehnica of Bucharest, pp. 11, 2021.

[11] M. Spiegel and L. Stephens, Schaum's Outline of Statistics, 6th ed., New York: Mc Graw Hill, 2018.

[12] B. Gunderson, *Statistics 250 Lab Workbook*, Department of Statistics, University of Michigan, 2015. [Online]. Available from: https://open.umich.edu/find/open-educational-resources/statistics/statistics-250-introduction-statistics-data-analysis#handouts, [retrieved: 03, 2024].

[13] H. J. Seltman, *Experimental Design and Analysis*, Carnegie Mellon University, 2018. [Online]. Available from: https://www.stat.cmu.edu/~hseltman/309/Book/Book.pdf

[14] Comisión de Regulación de Comunicaciones, *Postdata.* [Online]. Available from: https://postdata.gov.co/search/type/dataset, [retrieved: 03, 2024].

[15] Comisión de Regulación de Comunicaciones, "Revisión del mercado relevante servicios móviles" [in English: Review of relevant market mobile services], pp.74, 2023.

Competition Analysis in Cellular Networks: A Colombian Case

Ernesto Cadena Muñoz, Cesar Augusto Hernandez, Luis Fernando Pedraza
Technological Faculty
Universidad Distrital Francisco José de Caldas
Bogotá, Colombia
e-mail: ecadenam@udistrital.edu.co, cahernandezs@udistrital.edu.co, lfpedrazam@udistrital.edu.co

***Abstract*— Communications through cellular networks like the fifth cellular generation (5G) have become, together with the Internet, the central axis for information exchange. Government agencies seek to control competition, prices, and services provided to people. This is why it is necessary to establish a level of competition between cellular network service providers to regulate mobile services and protect users. In the literature, there is a lack of research in this field, and in Colombia, there is no documentation, only that generated by the regulatory authority, which makes it necessary to research different indexes of market competition to understand the dynamics of mobile services and formulate regulation strategies based on market behavior. This article includes a competition analysis carried out on cellular service providers in Colombia with data from the last 10 years, using the Herfindahl-Hirschman Index (HHI) and Stenbacka to calculate the market indices. The results show that the mobile service market in Colombia has a dominant service provider, a low competitive environment, and is highly concentrated, according to the index values calculated.**

Keywords- cellular networks, 5G, competition, mobile services, Stenbacka, HHI.

I. INTRODUCTION

The introduction of the cellular phone and cellular networks has transformed the way we live, offering essential mobile services that we need in the dynamic market of Industry 4.0. Along with technological advances and software development, there is a growing need in the world to regulate the mobile services market. Many technologies are available, but if the country does not have regulations, the service and installation of technology cannot be provided [1].

Regulation is also needed in cellular networks to provide an environment to promote competition in this market. Regulators in each country should adapt regulations to make the market competitive and improve quality, prices, and other metrics for the final user [1].

In this paper, we explore the case for Colombia's market focus in the competition of cellular service providers, to measure the variables that are very important for the country's regulatory entity to make regulatory changes if there exists a monopoly of one service provider, for example [1].

The rest of the paper is structured as follows: In Section II, we present the background. Section III describes the data used and the model to analyze it, along with the indexes used to measure the competition in mobile services in Colombia. The results are presented in Section IV, and finally, we conclude our work in Section V.

II. BACKGROUND

Cellular networks have been developed in the last three decades, and, thanks to the growth of electronics and the Internet, mobile services are part of our lives for work, study, or entertainment. But, as with any service, it must be regulated by the government authorities in each country, generating a market where the service providers and regulators must update their policies and laws to control traffic, prices, and services. It is a challenge to understand market behavior under certain laws or with the entrance of a new service or competitor, even with new virtual service providers [1].

Depending on the type of regulation (no regulation, partial regulation, or full regulation), service providers can assign the service prices and conditions to the users. In any case, a monopoly of some services can be created, where a single operator can manage the market and change it according to its purposes. Competition in this type of market is very hard to achieve. In a market without a monopoly, service providers compete with prices, quality, or other variables, which leads to better service conditions and prices for end users [1].

Telecommunications companies need to offer a large variety of innovative services. The focus of these companies is to keep existing customer loyalty with innovation, prices, and Quality of Service (QoS), and to increase the number of users in a very competitive market, which is the scenario of mobile services. It is recognized that a law generated by the government can encourage competition or limit it. It is important for the regulators to measure the impact of these variables in the mobile service environment in order to make informed adjustments to the regulations [2].

Nowadays, the telecommunication services industry is very dynamic, and, with each new generation or technology, there are new possibilities. At the same time, there is also a need for regulation to control this competition; the service providers strive to provide good quality service while also sustaining their business and their profits. Then, a way to

 ISBN: 978-1-68558-145-9

measure market competition is necessary to establish strategies to control prices, QoS, or to detect a monopoly [3].

The assessment of competition has sparked considerable debate in the economic literature. Traditionally, competition has been gauged through various indicators, including the count of market players, metrics of market concentration like market shares and the HHI, rates of entry and exit, and profitability, among others. Each one of these metrics offers a unique perspective on competition, yet capturing the entirety of this intricate and multi-faceted concept remains challenging [4].

To address the above challenges, some concentration ratios, such as the four-firm concentration ratio (CR4) or the HHI, measure the market share of the largest firms on the market. Higher values indicate lower competition. The H-statistic measures the difference between the observed HHI and the HHI that would result from perfect competition. Higher values suggest lower competition [5].

To measure the competition or dominance in the market, some works directly estimate the concentration ratio in mobile phone markets with the countries' competitiveness indicators or indexes showing the concentration level of a country's mobile telecommunications market and its competitiveness [6][7].

The Global Competitive Index (GCI) is used with the HHI to estimate the competitiveness of mobile telecommunications services in some developed or developing countries, showing the efficiency of the indexes [7]. In [8], Kostić and Živković show the mobile telecommunication networks and services market in the Republic of Serbia and analyze the competition with the HHI as well. A similar analysis was achieved in Morocco [9]. The authors analyze the fixed and mobile markets through the HHI and try to establish the relationship between the regulation and market behavior with the competition levels [9].

In [10], George et al. use the HHI to analyze the competition in Ghanaian telecommunications, showing the difficult task of the regulator in establishing the laws or norms to regulate the mobile market. It needs to be updated; its concentration makes it difficult to compete and give better services to the users.

Aguilar et al. show empirical results for five Latin American countries, analyzing the network effects in the mobile telecommunications market [11]. Their work highlights that, even if there is a dominant service provider present, each country has different behavior and must be analyzed independently, analyzing not only the number of users, but other main variables, like price.

Another index commonly used is Stenbacka, which measures the dominance level of a service provider. The experiment is achieved with two service providers that have a high level of users in the mobile services market. The index has been used by regulators and control entities to study dominance and competition in the telecommunications market [12].

The Stenbacka index has been used to get a dominance measure that classifies when an individual service provider has a dominant position in the market [13]. This complements the HHI, which measures the concentration of the market [14][15]. Concentration, asymmetry, and dominance characterize the situation regarding the competition in a particular market. Thus, through these values, it can be said how agents interact and analyze the situation of perfect competition and monopoly, and how the market leader is treated [14].

In [17], Ono shows that the competition among the service providers is driven primarily by the size of their installed bases, with moderate influence from indirect network effects. They analyze the dominance in the market, the advantages of each service provider, and the behavior of the users, caused by the competition. The analysis highlights the importance of network effects and the installed base size in platform competition.

Even though there are some indexes used for market competition measures, there are no papers that show an analysis in Colombia. The purpose of this work is to calculate and analyze the results to understand the competition and the behavior over time, identify improvement opportunities, and provide feedback on the results to the service provider authority in Colombia.

In this paper, the open data generated by the government is used, and the HHI and Stenbacka are calculated and analyzed. These indexes are commonly used to measure market competition [6].

III. DATA AND MODEL

To construct our empirical estimations, we use data from a source generated by the Colombian regulator (Comisión de Regulación de Comunicaciones-CRC), for the period 2012–2022: the database of the mobile market in Colombia.

Using the data mining concepts, the model starts defining the process of Knowledge Discovery in Databases (KDD), which starts with the definition of the problem, preparing the data, evaluating models, and finalizing the model, as can be seen in Figure 1 [18].

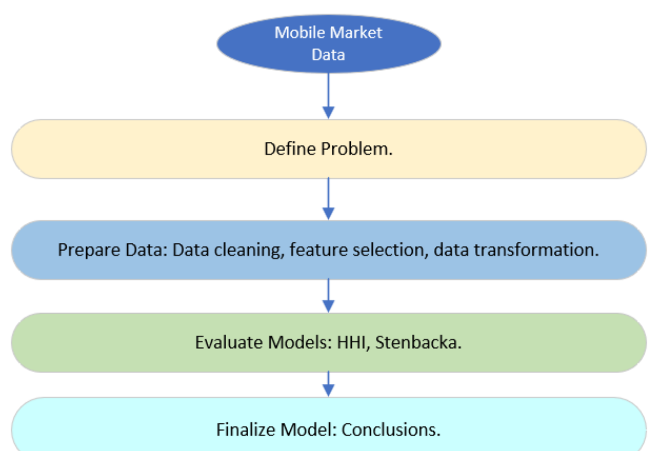


Figure 1. Methodology for data processing and analysis [15].

The objective is to analyze the competitiveness, concentration, and dominance level of mobile service providers in Colombia, with the available data from 2012-2022.

The main variables found in the preparation of the data are service provider, income, number of users, and traffic.

The data presented by the regulator can be segmented into trimesters, but we work with the monthly data to obtain more samples. Three kids of data (income, number of users, and traffic) were selected because a good amount of data collected by the regulator is available. Other variables have only a few samples and there were errors in the probability calculation. In addition, we made previous experiments, and the inclusion of some variables like department or cell phone plans in the model had a limited contribution to the algorithms.

The third part of the process is to define the indexes that are going to be used, in this case HHI and Stenbacka Index.

Measuring competition in a market and determining the market power of individual companies is a challenge for economic researchers and authorities. The calculation of concentration measures stands out as a widely used method to evaluate the level of competition within a market [19]. The methods to be used in this paper are HHI and Stenback, which are described below.

A. Herfindahl-Hirschman Index - HHI

The HHI is a widely used coefficient for assessing business concentration, frequently applied to measure the level of concentration within a market. The HHI is calculated as in (1) by summing the squared revenue shares (s) of all service providers (i) in a given market (j) for a specific time (t). The HHI is the sum of the squares of the market percentage of each of the n companies that comprise it, expressed as follows [19]:

$$HHI_{jt} = \sum_{i \in j,\, t} s_{ijt}^2 \qquad (1)$$

The HHI can have values ranging from 0 to 10,000. For example, in the context of horizontal merger guidelines, markets can be categorized with HHIs below 1,500 as unconcentrated, which means high competition. Moderately concentrated markets are in the range of 1,500 to 2,500 HHIs, while HHIs exceeding 2,500 mean high market concentration, which potentially raises significant competitive concerns. These thresholds offer guidance in interpreting HHIs [19].

B. Stenbacka Index

The Melnik, Shy, and Stenbacka index [13] functions as a tool for identifying the values indicative of a company's market dominance through its share. This index is computed based on the variance in market share between the two main entities in the industry, which means the two service providers have more users in the mobile services case. The formula used to calculate is shown in (2) [20]:

$$S^D = \frac{1}{2}[1 - \gamma(S_1^2 - S_2^2] \qquad (2)$$

where S_1 and S_2 are the percentage shares in sales of the first and second mobile service providers with the highest participation, respectively. The competition parameter γ seeks to collect the main aspects of the competition. In the experiments achieved by Stenbacka, this parameter has been probed with three values (1/2, 1 and 2). With a higher value of the parameter, the index will be low, resulting in a high probability of finding dominance in the experiment. In this paper, the parameter value is assumed to be one according to the recommendation of Stenbacka et al. [13]. This index will be an indicator that shows the degree of dominance through the subtraction of one service provider compared to the participation of the largest service provider in the mobile services sector in terms of sales [18]. Low values of the index correspond to minimal barriers to mobile service market entry, indicating that potential competition may constrain the firm's ability to exploit its market power effectively. In contrast, high values of the index signify substantial entry barriers and a reduced expectation of potential competition [18].

IV. RESULTS

In this section, the HHI and Stenbacka indexes are calculated for mobile services data after the data preparation process, which includes data cleaning, feature selection, and data transformation.

The features selected are several accesses, traffic, and incomes, which are the main variables studied and documented by the regulator and have been cleaned and adapted to the research.

A. HHI Results

The HHI is applied by calculating the participation of each mobile service provider in the country. Data from 2012 to 2022 available in postdata [22] is used. This site is created and maintained by the regulator and keeps an updated database of the data reported by the service provider to the regulator agencies.

After the feature selection process, the first variable to be used is the accesses (number of users). The HHI for accesses can be seen in Figure 2.

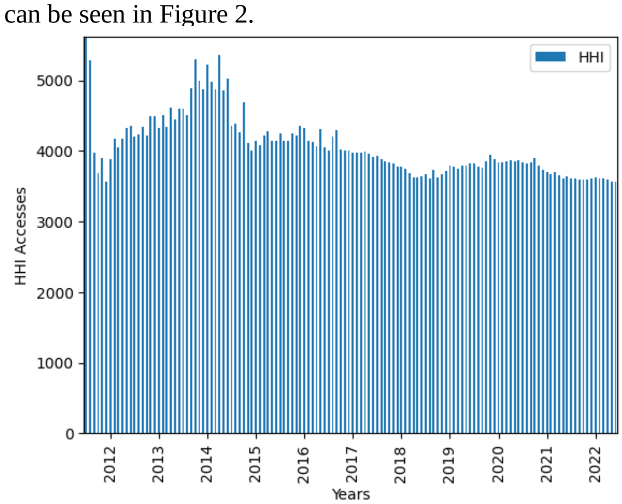


Figure 2. HHI for Mobile Services Accesses in Colombia.

Results show that the index is above 3500, indicating a high concentration of the market and low competition in the accesses variable. The HHI has a decreasing trend.

The second variable to analyze in the same period is the mobile service incomes. The HHI for this can be seen in Figure 3.

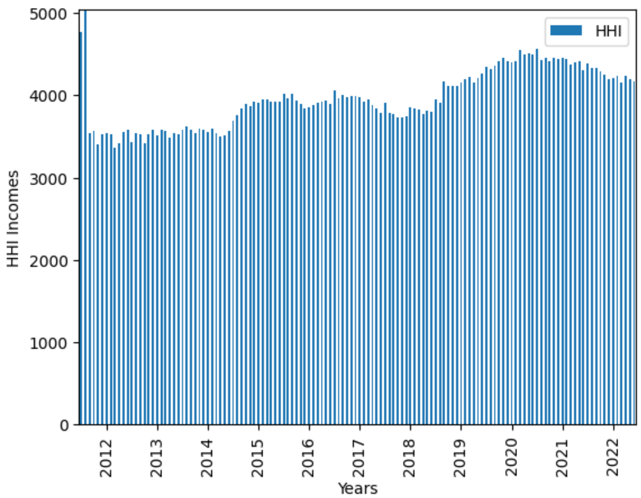


Figure 3. HHI for Mobile Services Incomes in Colombia.

In this case, the HHI has been increasing and is above 4000 in the last few years; results indicate a high concentration market and low competition in the income variable.

The third variable to analyze is traffic; the HHI for this can be seen in Figure 4.

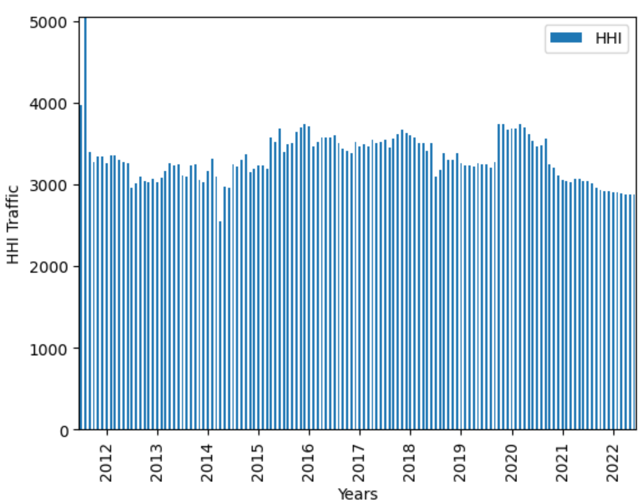


Figure 4. HHI for Mobile Services Traffic in Colombia.

In this case, the HHI has been decreasing and is close to 3000 in the last few years; results indicate a high concentration and low competition in traffic variables.

According to the results, the HHI is decreasing for access and traffic, but it is increasing for incomes, in three cases. The descriptive statistics for the HHI in the three variables can be seen in Table I.

TABLE I. DESCRIPTIVE STATISTICS OF HHI.

Statistics	HHI Accesses	HHI Incomes	HHI Traffic
count	132.0	132.0	132.0
mean	4069.667986	3965.84294	3324.645533
std	434.219881	346.304808	295.487329
min	3561.64898	3361.149037	2544.321017
25%	3759.728876	3619.170630	3100.544183
50%	3971.499849	3923.637351	3288.328112
75%	4266.036144	4237.804731	3516.755919
max	5621.046372	5045.727214	5053.229637
Kurtosis	1.587545	-0.556497	7.743688
Skewness	1.315731	0.315892	1.396602

The descriptive statistics of the results show that all the HHIs are above 3000, which indicate a low competition in the mobile services market and a high concentration. The results show a normal distribution shifted to the left with a maximum value higher than 5000 and a minimum value above 3000, except for the traffic HHI, which is 2544.

B. Stenbacka Index Results

For the Stenbacka index calculation, the two service providers with the highest value in accesses, incomes, and traffic are used, and the dominance can be estimated with the Stenbacka formula. The data is the same one used for the HHI calculation: mobile services data from postdata. The first variable to be used is accesses, referring to the users. The Stenbacka index for accesses can be seen in Figure 5.

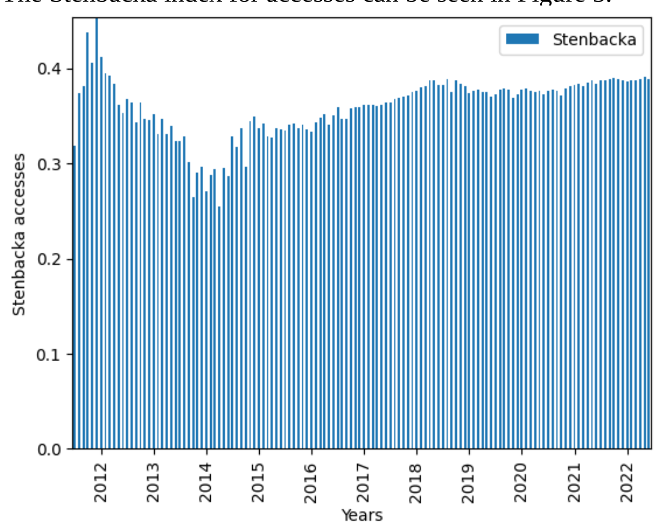


Figure 5. Stenbacka for Mobile Services Accesses in Colombia.

Results show that this index is close to 0.37 and the S_1 value for the service provider is above 0.5, which means that there is a dominant position for this service provider because S_1 is the first service provider and $S_1 > S_D$.

The second variable to be analyzed is mobile service incomes. The Stenbacka index calculated for this can be seen in Figure 6.

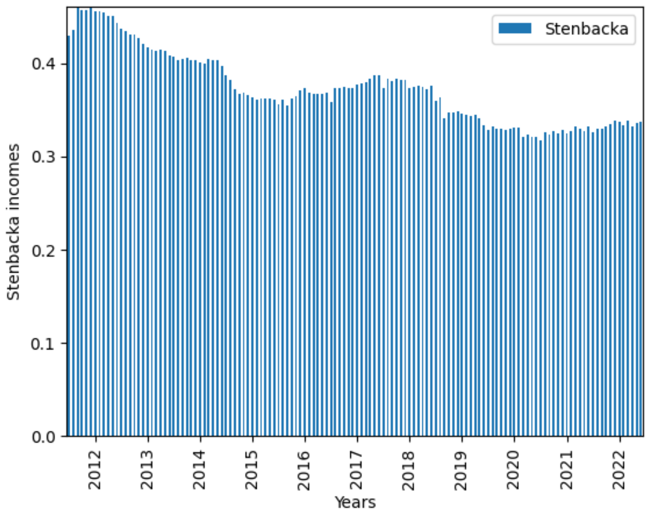


Figure 6. Stenbacka for Mobile Services Incomes in Colombia.

Results show that this index is close to 0.34 and the S_1 value for the service provider is above 0.5, which means that there is a dominant position for this service provider in mobiles service incomes, because S_1 is the first service provider and $S_1>S_D$.

The third variable to be analyzed is traffic. The Stenbacka index for this can be seen in Figure 7.

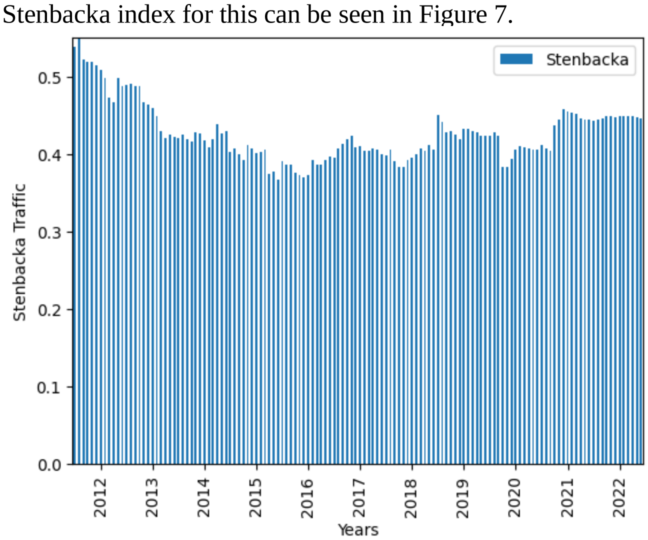


Figure 7. Stenbacka for Mobile Services Traffic in Colombia.

The Stenbacka index values, in this case, are higher than 0.4, and S_1 has been decreasing in the last years. The index has been very close to the S_1 value, and dominance level for this variable is decreasing.

The descriptive statistics for the Stenbacka index for the three variables can be seen in Table II.

TABLE II. DESCRIPTIVE STATISTICS OF THE STENBACKA INDEX.

Statistics	Stenbacka Accesses	Stenbacka Incomes	Stenbacka Traffic
count	132	132	132
mean	0.359569	0.372426	0.427974
std	0.031942	0.038746	0.036870
min	0.254502	0.316983	0.368424
25%	0.341244	0.336430	0.404884
50%	0.368436	0.368420	0.421389
75%	0.381526	0.401472	0.447730
max	0.453625	0.460762	0.551590
Kurtosis	1.425717	-0.475741	1.093329
Skewness	-0.798077	0.620616	1.057399

The descriptive statistics of the results show that all the Stenbacka index values are above 0.35, and for all cases, it shows a dominant service provider in the mobile services market. The results show a normal distribution shifted to the left for incomes and traffic and shifted to the right for accesses, with a maximum value higher than 0.5 and a minimum value above 0.25.

V. CONCLUSIONS AND FUTURE WORK

It is relevant for service providers and regulators to measure and detect the market conditions, regulations, and laws for mobile services in Colombia, to minimize monopoly practices and encourage the service provider's competition.

The HHIs of mobile services accesses, income, and traffic demonstrate a high concentration, and low competition in this market in Colombia, which must be analyzed by government and regulatory authorities.

The Stenbacka index results for mobile services accesses, income, and traffic show that there is a dominant service provider in Colombia, but it also shows that, in the last few years, its level has decreased.

In consequence, the mobile services market in Colombia has a dominant service provider and a low level of competition in a highly concentrated market. This must be analyzed by authorities and regulators to improve the conditions of the mobile service for end-users.

In future work, more indexes can be calculated, and machine or deep learning techniques can be involved to predict market behavior and competition.

ACKNOWLEDGMENT

The work has been funded by the Comisión de Regulación de las Comunicaciones – CRC and the Ministerio de las Tecnologías de la información y las Comunicaciones -MinTIC and Universidad Distrital Francisco Jose de Caldas through the announcement 908-2021.

REFERENCES

[1] C. Yang and Y. Kawashima, "Economic analysis of process innovation: The case study of the German telecommunication market," *Innovation and Green Development*, vol. 3, no. 1, p. 100095, 2024.

[2] M. A. Hajar, D. N. Ibrahim, M. R. Darun, and M. A. Al-Sharafi, "Value innovation activities in the wireless telecommunications service sector: A case study of the Malaysian market," *Journal of Global Business Insights*, vol. 5, no. 1, pp. 57–72, 2020.

[3] O. O. Akintokunbo, "Market focus strategy and organizational performance of telecommunication companies in Port Harcourt," *International Journal of Innovative Research and Advanced Studies*, vol. 5, no. 3, pp. 258–263, 2018.

[4] K. Bahia and P. Castells, "The dynamic effects of competition on investment: the case of the European mobile communications industry," *Journal of Information Policy*, 2023.

[5] A. Diallo and G. Tomek, "The interpretation of HH-Index output value when used as mobile market competitiveness indicator," *International Journal of Business and Management*, vol. 10, no. 12, p. 48, 2015.

[6] A. Schneider, "Credit cooperatives: Market structure, competition, and conduct. Exploring the case of Paraguay," MPRA Paper 102309, University Library of Munich, Germany. 2020.

[7] D. Bardey, D. Aristizábal, J. S. Gómez, and B. Sáenz, "Concentration of the mobile telecommunications markets and countries' competitiveness," *Telecommunications Policy*, vol. 46, no. 1, p. 102230, 2022.

[8] M. Kostić and J. Živković, "Concentration of supply on the chosen markets of Serbian electronic communications sector," *The European Journal of Applied Economics*, vol. 18, no. 2, pp. 76–94, 2021.

[9] C. Gutiérrez-Hita, V. Zhukova, and S. Amassaghrou, "Evaluating Competitiveness in the Morocco's Telecommunications Sector Through Market Concentration," *Available at SSRN 4662493*, 2023.

[10] A. S. George, A. Michael, and K. A.-P. Agyekum, "The Ghanaian Telecommunications Market Concentration-Applying the US DOJ's HHI Criteria for Determining Market Power", 2016.

[11] D. Aguilar, A. Agüero, and R. Barrantes, "Network effects in mobile telecommunications markets: A comparative analysis of consumers' preferences in five Latin American countries," *Telecommunications Policy*, vol. 44, no. 5, p. 101972, 2020.

[12] Superintendencia de Industria y Comercio, "Estudio del Servicio de Internet en Colombia (Study of the Internet Service in Colombia)," *Available at SSRN 3552758*, 2015.

[13] A. Melnik, O. Shy, and R. Stenbacka, "Assessing market dominance," *Journal of Economic Behavior & Organization*, vol. 68, no. 1, pp. 63–72, 2008.

[14] J. Confraria, T. Ribeiro, and H. Vasconcelos, "Analysis of consumer preferences for mobile telecom plans using a discrete choice experiment," *Telecommunications Policy*, vol. 41, no. 3, pp. 157–169, 2017.

[15] S. Araki, A. Bassanini, A. Green, and L. Marcolin, *Monopsony and concentration in the labour market*. 2022. doi: https://doi.org/https://doi.org/10.1787/0ecab874-en.

[16] H. Hernández Lasso, "Diseño de una subasta multi-objeto: un método para maximizar el bienestar social en la asignación del espectro electromagnético en Colombia 2010-2022, (Design of a multi-object auction: a method to maximize social welfare in the allocation of the electromagnetic spectrum in Colombia 2010-2022)," *PhD. Thesis, Universidad Nacional de Colombia*, 2022.

[17] S. Ono, "Competition dynamics of the mobile network industry in Japan through the evolution of mobile network services: An empirical analysis.," *Otsuma journal of social information studies*, vol. 28, pp. 63–76, 2019.

[18] J. Brownlee, *Data preparation for machine learning: data cleaning, feature selection, and data transforms in Python*. Machine Learning Mastery, 2020.

[19] H. Heidorn and J. P. Weche, "Business concentration data for Germany," *Yearbooks for national economics and statistics*, vol. 241, no. 5–6, pp. 801–811, 2021.

[20] D. E. Durán Preciado, "Aplicación de coeficientes de desvío para el análisis de integraciones empresariales, (Application of deviation coefficients for the analysis of business integrations)," *Master Thesis, Pontificia Universidad Javeriana*, 2015.

[21] M. O. Ortiz and J. P. H. Saavedra, "El efecto de la intensidad de la Competencia en Colombia sobre la innovación: Un análisis para el periodo 2013-2016, (The effect of the intensity of Competition in Colombia on innovation: An analysis for the period 2013-2016)," *Universidad Externado de Colombia*, 2020.

[22] "Mobile services data repository" [Online]. Available: https://www.postdata.gov.co/, 2024.

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.

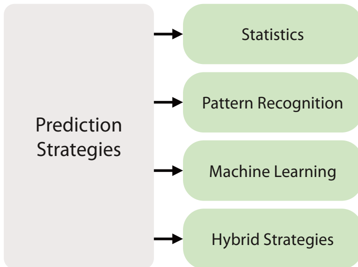


Figure 1. Techniques for predicting the financial market.

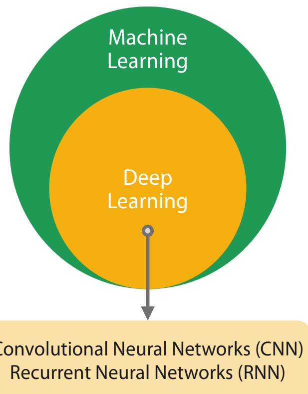


Figure 2. Subset of ML and DL [12].

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.

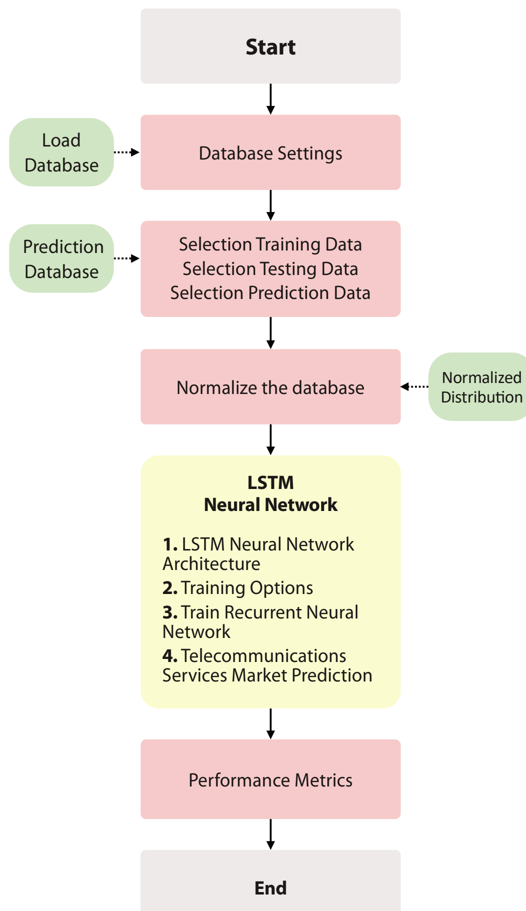


Figure 3. Flowchart of the implemented methodology.

 ISBN: 978-1-68558-145-9

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)).

$$X_{Normalized} = \frac{X_{Database} - \mu}{\sigma} \qquad (1)$$

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.

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

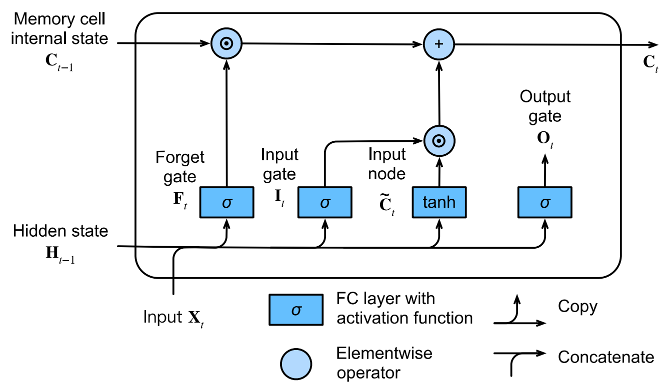


Figure 4. Architecture LSTM [16].

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.

 ISBN: 978-1-68558-145-9

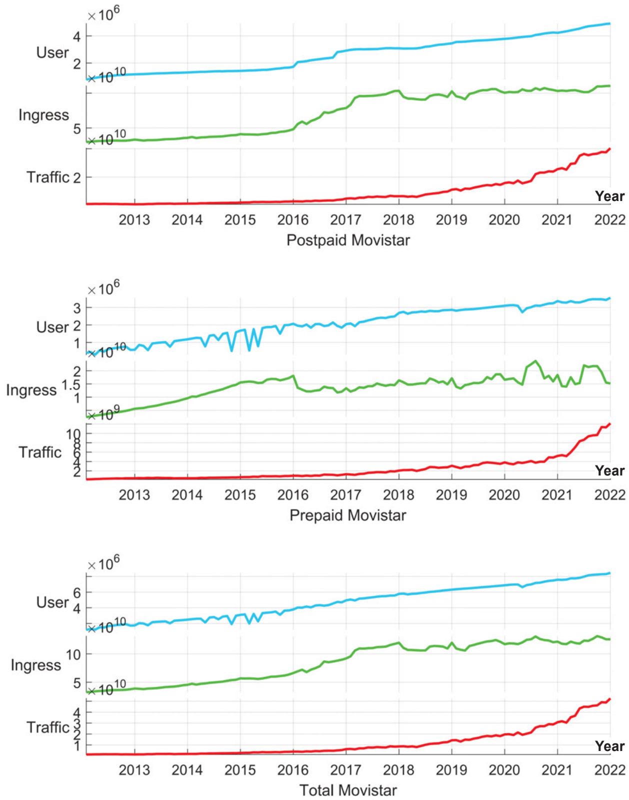


Figure 5. Database of the telecommunications company Movistar.

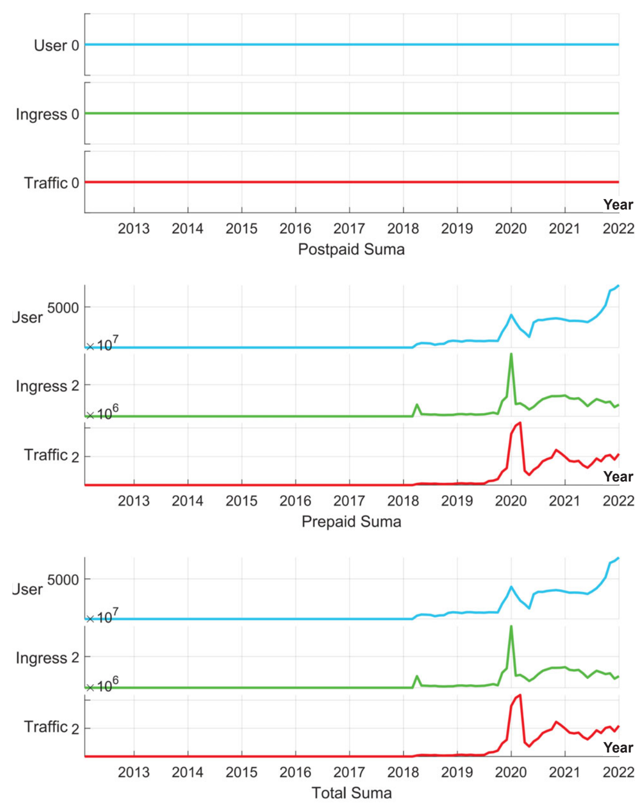


Figure 6. Database of the telecommunications company Suma.

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.

 ISBN: 978-1-68558-145-9

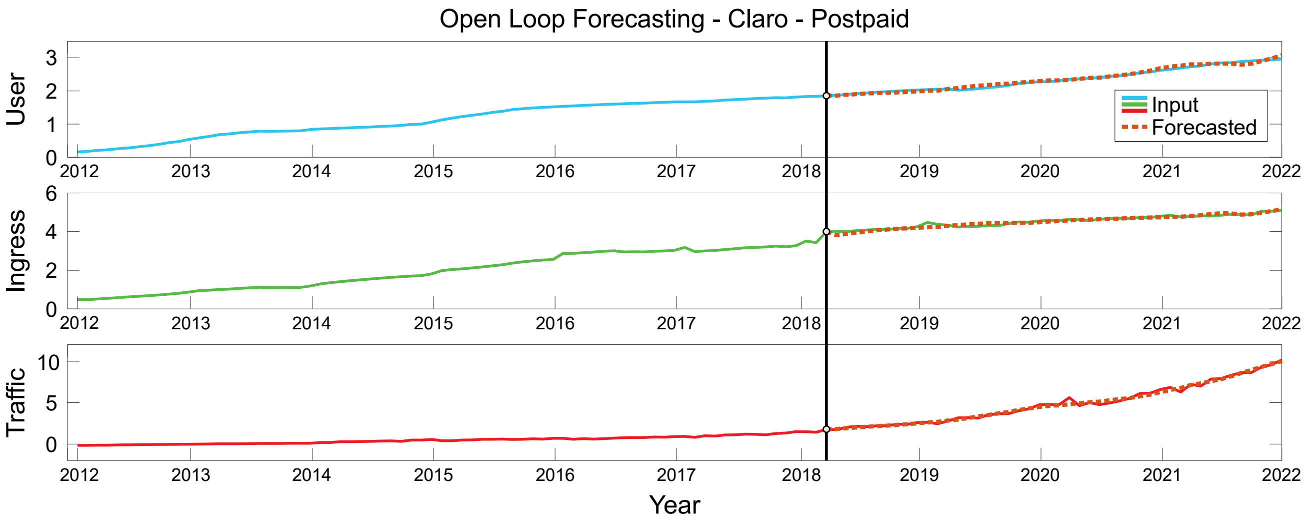


Figure 7. Prediction for a company with a high level of competition in the market.

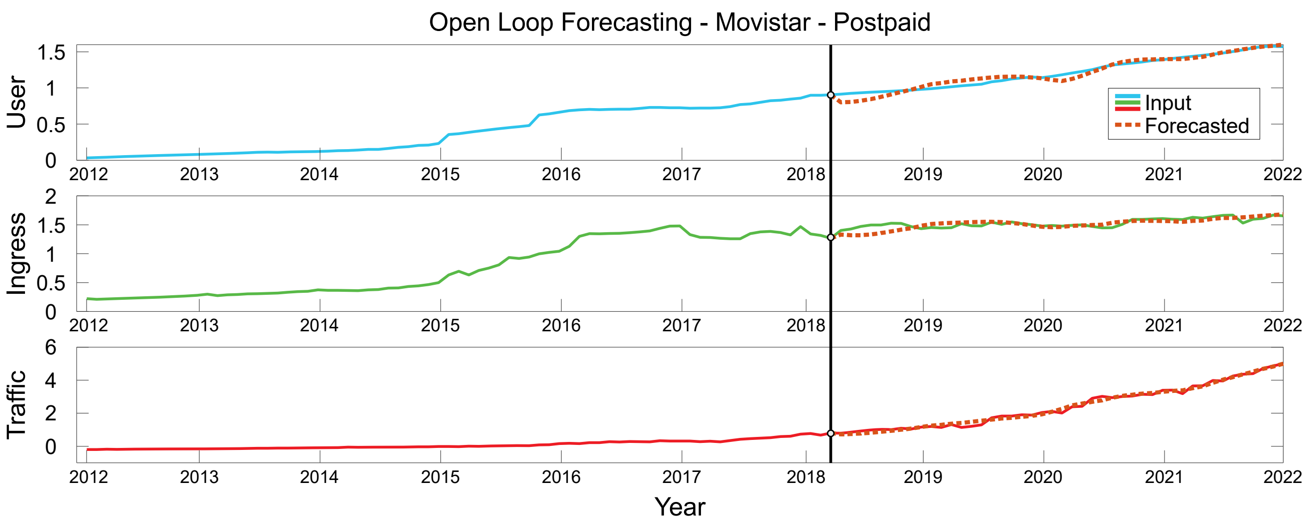


Figure 8. Prediction for a company with an intermediate level of competition in the market.

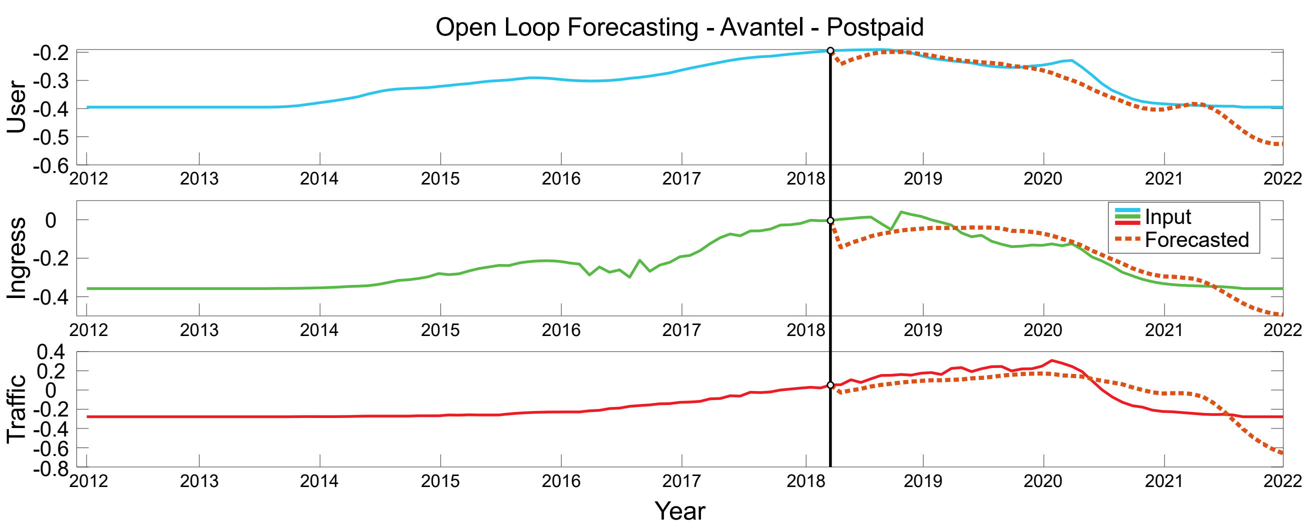


Figure 9. Prediction for a company with a low level of competition in the market.

 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.