Fuzzy logic based Investigative analysis of dropped calls in mobile communication networks

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Abstract - This *study focuses on investigative analysis of dropped calls in mobile communication networks with emphases on Nigeria's telecommunications industry, specifically within the MTN telecommunication network in Port Harcourt City. Dropped calls have negative implications for consumers, leading to financial burdens and potential declines in productivity for individuals and organizations alike. To address this issue, a MATLAB simulated system is proposed to control call dropping in their networks within wireless cellular networks. The system utilizes Fuzzy Logic Control and an optimization handover technique to effectively manage call drops through dynamic load balancing and efficient resource sharing in real-time. Through extensive simulations, various parameters affecting call dropping are examined, and the newly proposed fuzzy logic-based system outperforms the previous approach in terms of reliability and performance. Even under high resource usage and heavy traffic conditions, the proposed approach maintains the call dropping probability below the minimum threshold, ensuring the expected Quality of Service (QoS) provision.*

Keywords – dropped calls, fuzzy logic, MATLAB, QoS, telecommunication network

1. Introduction

A dropped call refers to the premature termination of a phone conversation, either due to the call ending abruptly or the failure to establish a connection with the intended recipient. Technical obstacles such as insufficient infrastructure, limited coverage, weak signal quality, interference, network congestion, and failures contribute to call drops, negatively impacting the quality of service expected by customers [1]. In the context of Mobile Telecommunications systems, the dropped call rate (DCR) represents the percentage of initiated calls that cannot be completed due to various factors such as technical issues, user errors, or natural circumstances. This rate is determined by calculating the fraction of unsuccessful calls out of all calls made within a specific region or territory [2]. It is expected that the drop call rate remains below 1% to ensure satisfactory performance.

There are several theoretical reasons behind dropped calls in mobile cellular network systems, including the unavailability of link network connectivity in the uplink or downlink, interference of radio links in subscriber-populated areas, network inadequacies, improper handover situations, and network congestion, especially in urban areas with a high number of subscribers. This research focuses on the bases of dropped call analysis, considering the impact of network congestions.

The International Telecommunication Union (ITU) recognizes dropped call rate as a crucial parameter for monitoring network optimization processes and evaluating the performance of network providers against agreed key performance indicators (KPIs) set by telecommunication operators, the Nigeria Communication Commission, and other relevant bodies in the field of information and communication technology (ICT) in Nigeria. The dropped call rate, along with other associated network parameters, plays a significant role in assessing the performance of telecommunication operators, which, in turn, affects the call retainability of the network [3]. High call retainability directly contributes to subscriber satisfaction and is beneficial for service providers, leading to increased revenue and the fulfilment of business strategic objectives. Telecommunication operators strive to minimize dropped call rates while considering budgetary constraints and other related factors. Achieving this goal often involves improving base transceiver stations and other network supporting elements, increasing network capacity, and optimizing the network in congested areas. In some cases, installing new base transceiver stations and associated supporting elements may be necessary, albeit capital-intensive [3,4]. The telecommunications sector has played a significant role in the economic growth of Nigeria and other developing countries. In addition to revenue generation, the telecommunications industry has acted as a catalyst for advancements in healthcare, education, e-governance, e-commerce, and the industrial sector. Recognizing the influential role of telecommunications, the Nigerian government has established a dedicated ministry to support and monitor the industry, setting standards through regulations, procedures, processes, and policies to maximize the sector's potential [4].

Since the privatization of the telecommunications sector, Nigeria has experienced tremendous growth. As reported by the Nigeria Communication Commission in 2021, there are over 205,252,058 active mobile subscribers, resulting in a tele-density of 107%. The country also boasts over 151,512,122 active internet subscribers, with broadband subscribers reaching 86,714,978, equivalent to 45.43% of the population [5]. However, alongside this growth and achievement, the sector faces challenges such as defective infrastructure and limited resources. With 54,000 kilometers of available backbone, mid-mile fibre optics deployment, and 89%, 75%, and 45% coverage of 2G, 3G, and 4G networks, respectively, there is an increasing concern over dropped calls, which hampers the overall performance of call services for subscribers [6]. This research specifically focuses on investigating the causes of dropped calls in Port Harcourt, Rivers State, Nigeria.

2. Literature Review

To address call drops, various factors need to be considered. It is important to note that call drops can occur due to various reasons such as inconsistent coverage, low capacity during peak usage, insufficient frequency availability, fading due to areas with tall buildings, congestions, limited network reach, and black spots [7]. The limited number of channel bands assigned to users, determined by the total number of subscribers, often leads to congestion during peak times and increased call drops [8]. The market share distribution among telecommunication companies also plays a role, with MTN leading at 40%, followed by Airtel at 30.2%, GLO at 28.11%, Etisalat at 0.7%, and Mtel at 0.45% [9]. Additionally, the handover process, where users transition between cells, can cause call termination if resources are not available in the target cell. Long-term revenue, utility, call block rate (CBR), and call drop or handover failure rate (CDR) are essential metrics in cellular networks [10]. Addressing call drops requires comprehensive strategies to improve infrastructure, coverage, resource allocation, and network management. By considering these factors and adopting advanced techniques like artificial intelligence, the telecommunications industry can work towards minimizing call drops and enhancing the quality of service experienced by mobile users

Efforts have been made to reduce call drops through call admission control (CAC) schemes. The guard channel threshold policy, reserving channels in each cell for handover requests, has shown promise. However, the computational complexity of managing multi-class services with varying features remains a challenge [11]. Artificial intelligence techniques, including fuzzy logic control (FLC), have been explored, but successfully handling CAC remains elusive. Tarkaa and Pahalson in [12] conducted an analysis of drop call probability in the Mobile Telecommunication Network in Apapa, Lagos, Nigeria. They evaluated drop call rates, call arrival rates, and drop call probabilities across 10 Base Transceiver Station sites in Apapa. The study found that the service quality of the cellular network in Apapa was satisfactory and reliable, as the estimated drop call probabilities were well below the benchmark at all 10 base transceiver stations. Boggia et al. [13] investigated drop call probability in established cellular networks through data analysis and modeling. They compared their analytical model with measured data and found that the model accurately represented the characteristics of the cells. The study highlighted the importance of larger data sets during busy traffic periods to improve accuracy and reduce errors. This approach can be applied as a research method in different telecommunications companies with varying architectures.

Rex [14, 15] analyzed call drop and handover data of Global System for Mobile communication (GSM) subscribers in Nigeria. Using the Erlang B formula, the study demonstrated the need to assess call drop rates based on the available channels at a given time. It concluded that the current GSM network service quality in Nigeria is insufficient and unreliable. Recommendations were made for Nigeria Communication Commission to monitor the networks regularly and ensure compliance with standards, including the construction of more base stations and the implementation of efficient network management strategies.

Moses [16] and Joseph [17] explored teletraffic modeling of dropped calls in established 3G-based cellular networks. They used call dropping probability as a performance measure for failed calls. Empirical data from an operating network in Nigeria was analyzed, and a simulation based on the derived analytical model was conducted. The study observed that when the network capacity was exceeded by traffic demand, call dropping occurred. The authors suggested investigating cell sectorization as a means of improving network capacity in future research. Olaonipekun et al. [18] developed a call drop prediction model for Global Systems for Mobile communication (GSM) networks using Artificial Neural Network (ANN). The model achieved an 87.5% accuracy in predicting call drops. Although the specific causes of call drops were not considered in his research, the study highlighted that factors such as Received Quality, Frame Error Rate, Bit Error Rate, and Timing Advance contribute to call drops in GSM systems. Matthews and Adetiba [19] analyzed the issue of network congestion and its impact on the quality of service (QoS) in Nigerian GSM networks. They explored cost-effective solutions, including a Software Radio-based approach, to mitigate capacity limitations and enhance network performance. Their work focused on designing and simulating a capacity enhancement Nomadic Base Transceiver Station Sub-System (NBTSS).

Jeremiah and Fakolujo [20] reviewed various methods employed in mobile communication handover. They emphasized that seamless handover, performed by selecting appropriate network parameters, is crucial for ensuring QoS. The study highlighted the effectiveness of soft computing-based algorithms in handling the uncertainties inherent in mobile wireless communication networks. Dhanya and Perumal [5] identified high bit error rate as a major factor in call drops. Their work aimed to reduce the bit error rate and improve the end-to-end performance of a wireless system. They proposed a signal processing block (SPB) at the receiver end, utilizing the Independent Component Analysis (ICA) algorithm to filter the source signal from noise. The inclusion of the SPB block resulted in a lower bit error rate and potential reduction in call drops in cellular communication systems. Chetana and Pradeep Sharma [21] demonstrated the optimization of existing cellular networks using tools like TEM'S, MapInfo, and parameter tuning. They emphasized the importance of analyzing available results and aligning operations with key performance indicators (KPIs) defined by telecommunication companies. By enhancing network coverage, expanding capacity, and improving overall network quality, telecommunication companies can reduce call drops and meet the requirements outlined in their KPIs. To minimize the occurrence of call drops, Kaushlendra [22] proposed a fault-tolerant channel allocation algorithm based on Genetic Algorithm (GA) within a resource planning model for mobile computing networks. This algorithm optimizes channel allocation and employs a mobility-aware call admission scheme called Regulated Call Dropping (RCD) with Fractional Channel Reservation (FCR). By effectively utilizing channels, the RCDFCR scheme aims to reduce call drops in cellular communication systems. Handover, a significant factor contributing to call drops, can be addressed through Guard Channel Schemes. Fang in [23], suggests reserving specific channels for handover calls, which are returned to the common pool once released. Additionally, Call Admission Control (CAC) algorithms, as proposed by Kumar [2], play a crucial role in ensuring proper call termination. Chauhan [24] proposes resolving the overshooting problem in network coverage by adjusting the antenna's tilt angle. However, this solution has limitations as it can impact overall coverage.

The aforementioned methods primarily focus on mitigating call drops resulting from channel unavailability. While channel allocation schemes can improve the situation, the limited availability of spectrum poses a challenge. This research proposes a unique solution that considers multiple classes of traffic with different resource and quality of service (QoS) requirements, adapting to dynamically changing traffic loads. The proposed learning scheme employs Fuzzy Logic artificial learning to intelligently handle handover, prioritize calls, and implement load balancing to reduce call drop rates by monitoring real-time call block rate (CBR), and call drop rate (CDR).

3. Research Methodology

In a mobile network, a mobile terminal, or mobile user, may encounter situations where it is either granted or denied service when requesting it. This denial of service is known as call blocking, and the probability of it occurring is referred to as call blocking probability (Pb). As a mobile terminal moves from one cell to another within the cellular network, a successful handover from the previous cell to the new cell is crucial to maintaining uninterrupted service. This handover requires the availability and assignment of appropriate resources for the mobile terminal. The likelihood of a handover failure is known as handover failure probability (Pf). Throughout a conversation, a mobile user may traverse multiple cell borders, necessitating several successful handovers. However, if at any point along the way a handover fails, the network will forcibly terminate the call, resulting in call dropping. The probability of such an event is referred to as call dropping probability (Pd). It is generally understood that dropping an ongoing call has a more significant negative impact on the user compared to denying a newly requested call. While both call dropping probability (Pd) and handover failure probability (Pf) are distinct quantities based on the definitions provided, research publications often focus on studying the likelihood of handover failures as it is relatively easier to calculate. However, mobile customers and service providers are often more concerned with the probability of call dropping as it directly affects the quality of service experienced by users. If H is the total number of handovers during the course of a call, then:

$$P_d = 1 - \left(1 - P_f\right)^H \ldots\ldots\ldots\ldots\ldots (1)$$

Where H itself is a random variable; Therefore, in average:

$$P_d = 1 - \sum_{h=0}^{\infty} \left(1 - P_f\right)^h P_r(H = h) \ldots\ldots\ldots\ldots (2)$$

Finally, given the call blocking and dropping probabilities P_b and P_d, the call completion probability (P_c) is given by:

$$P_c = (1 - P_b)(1 - P_d) \ldots \ldots \ldots \ldots (3)$$

Call drop is caused by all kinds of situations, but most importantly is the unavailability of channel resources to accept new call or properly handoff on-going calls. All call traffic follow a Poisson distribution such that for a call μ and for a channel size x, the call traffic distribution $P(x; \mu)$ is given by:

$$P(x; \mu) = \frac{e^{-\mu}\mu^x}{x!} \ldots \ldots \ldots \ldots (4)$$

Then the call drop probability B is given by:

$$B = \frac{P(x; \mu)}{\sum_{k=0}^{x} \frac{e^{-\mu}\mu^k}{k!}} \ldots \ldots \ldots \ldots (5)$$

Call Dropping Probability (CDP) is a critical metric for connection-level Quality of Service (QoS). It represents the likelihood of a call being dropped due to a failed handover. Admission control techniques aim to keep CDP below a threshold while optimizing bandwidth utilization. Handover Dropping Probability (HDP) measures the likelihood of a handover failure due to resource scarcity. From the user's and service provider's perspective, CDP is the relevant metric. This research leverages a fuzzy logic-based system on MATLAB simulation software using real-time data from a leading telecommunications company (MTN as case study) to reduce call drops in its mobile networks. Simulations will evaluate the efficiency of the current and optimized system versions.

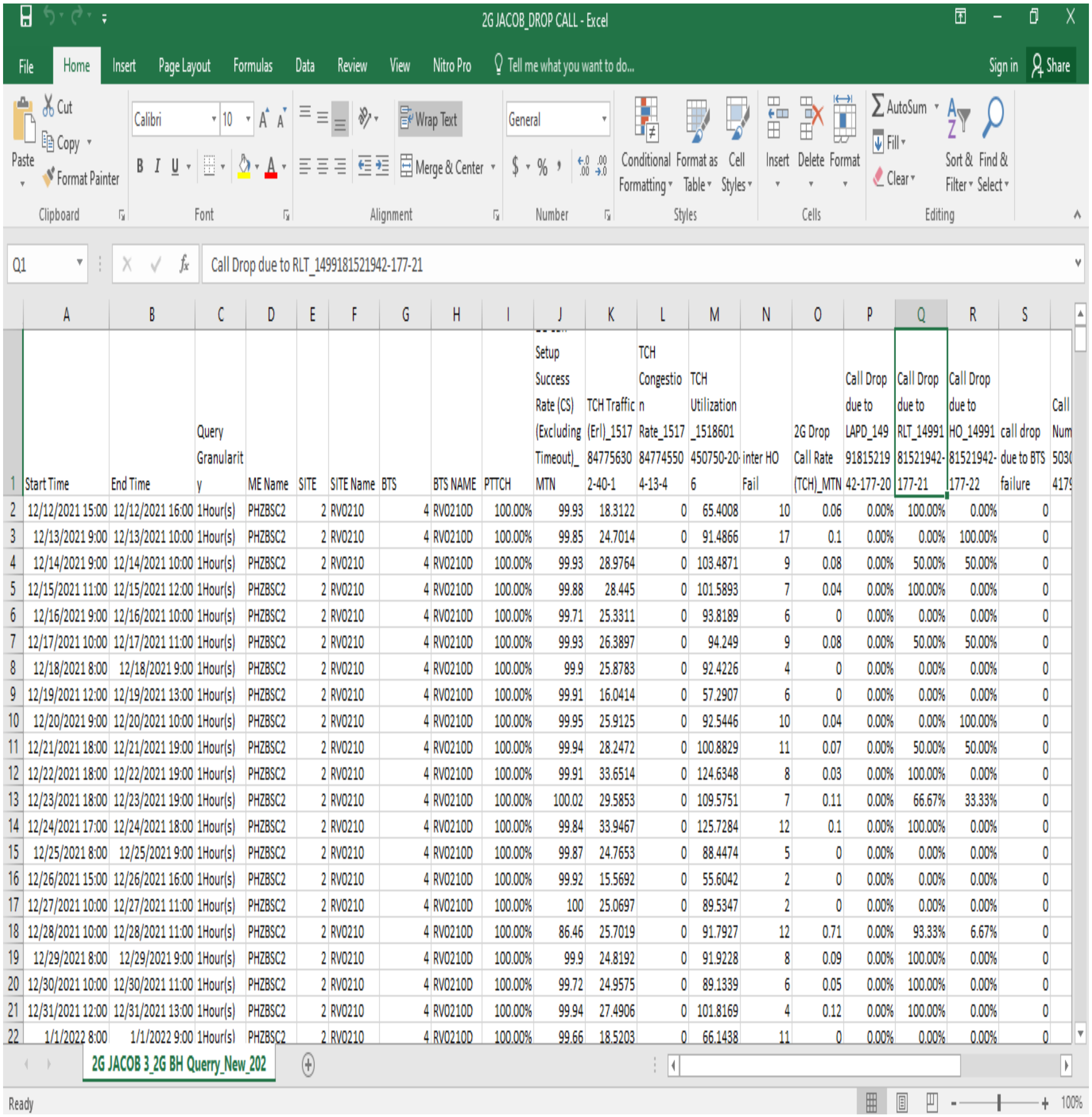
3.1. Data Acquisition and filtering

Analytical equations for the membership functions were developed based on the estimations and criteria obtained during the investigation. The data utilized in this study was sourced from the control room of a Nigerian mobile telecommunications operator. The primary objective is to effectively control and mitigate call drops. Various parameters such as the number of channels, channel utilization, drop call probability, call duration, and call arrival rate were examined. Table I provides an overview of the average values of these key parameters collected over a three-month period.

3.2. Defining the Fuzzy Logic System (Input/Output Membership functions)

The proposed Fuzzy Logic-Based Call Drop System (FL-BCDS) accepts crisp inputs, which are values within a specific range in the universe of discourse (UoD) of the input variables. These inputs are classified using membership functions and evaluated in parallel using a set of constructed rules. The system utilizes five language variables, including parameters such as the number of channels, traffic utilization, drop call probability, call duration, and arrival rate, to determine its efficiency.

The fuzzy logic control system in the MATLAB interface improves the condition of the dataset, as shown in Figure 1. The input/output membership functions are set accordingly. The FL-BCDS interface consists of three components: input, inference system, and output. The fuzzy inference process involves fuzzification of input variables, application of fuzzy operators, implication from antecedent to consequent, aggregation of consequents across rules, and defuzzification. Overall, the FL-BCDS utilizes fuzzy logic to analyze and optimize call drop control, providing valuable insights into network performance and QoS.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Start Time	End Time	Query Granularity	ME Name	SITE	SITE Name	BTS	BTS NAME	PTTCH	Setup Success Rate (CS) (Excluding Timeout)_MTN	TCH Traffic (Erl)_151784775630 2-40-1	TCH Congestion Rate_151784774550 4-13-4	TCH Utilization _1518601450750-20-6	inter HO Fail	2G Drop Call Rate (TCH)_MTN	Call Drop due to LAPD_14991815219 42-177-20	Call Drop due to RLT_1499181521942-177-21	Call Drop due to HO_1499181521942-177-22	call drop due to BTS failure
2	12/12/2021 15:00	12/12/2021 16:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.93	18.3122	0	65.4008	10	0.06	0.00%	100.00%	0.00%	0
3	12/13/2021 9:00	12/13/2021 10:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.85	24.7014	0	91.4866	17	0.1	0.00%	0.00%	100.00%	0
4	12/14/2021 9:00	12/14/2021 10:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.93	28.9764	0	103.4871	9	0.08	0.00%	50.00%	50.00%	0
5	12/15/2021 11:00	12/15/2021 12:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.88	28.445	0	101.5893	7	0.04	0.00%	100.00%	0.00%	0
6	12/16/2021 9:00	12/16/2021 10:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.71	25.3311	0	93.8189	6	0	0.00%	0.00%	0.00%	0
7	12/17/2021 10:00	12/17/2021 11:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.93	26.3897	0	94.249	9	0.08	0.00%	50.00%	50.00%	0
8	12/18/2021 8:00	12/18/2021 9:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.9	25.8783	0	92.4226	4	0	0.00%	0.00%	0.00%	0
9	12/19/2021 12:00	12/19/2021 13:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.91	16.0414	0	57.2907	6	0	0.00%	0.00%	0.00%	0
10	12/20/2021 9:00	12/20/2021 10:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.95	25.9125	0	92.5446	10	0.04	0.00%	0.00%	100.00%	0
11	12/21/2021 18:00	12/21/2021 19:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.94	28.2472	0	100.8829	11	0.07	0.00%	50.00%	50.00%	0
12	12/22/2021 18:00	12/22/2021 19:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.91	33.6514	0	124.6348	8	0.03	0.00%	100.00%	0.00%	0
13	12/23/2021 18:00	12/23/2021 19:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	100.02	29.5853	0	109.5751	7	0.11	0.00%	66.67%	33.33%	0
14	12/24/2021 17:00	12/24/2021 18:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.84	33.9467	0	125.7284	12	0.1	0.00%	100.00%	0.00%	0
15	12/25/2021 8:00	12/25/2021 9:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.87	24.7653	0	88.4474	5	0	0.00%	0.00%	0.00%	0
16	12/26/2021 15:00	12/26/2021 16:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.92	15.5692	0	55.6042	2	0	0.00%	0.00%	0.00%	0
17	12/27/2021 10:00	12/27/2021 11:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	100	25.0697	0	89.5347	2	0	0.00%	0.00%	0.00%	0
18	12/28/2021 10:00	12/28/2021 11:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	86.46	25.7019	0	91.7927	12	0.71	0.00%	93.33%	6.67%	0
19	12/29/2021 8:00	12/29/2021 9:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.9	24.8192	0	91.9228	8	0.09	0.00%	100.00%	0.00%	0
20	12/30/2021 10:00	12/30/2021 11:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.72	24.9575	0	89.1339	6	0.05	0.00%	100.00%	0.00%	0
21	12/31/2021 12:00	12/31/2021 13:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.94	27.4906	0	101.8169	4	0.12	0.00%	100.00%	0.00%	0
22	1/1/2022 8:00	1/1/2022 9:00	1Hour(s)	PHZBSC2	2	RV0210	4	RV0210D	100.00%	99.66	18.5203	0	66.1438	11	0	0.00%	0.00%	0.00%	0

Figure 1: Screenshot of Dataset in Excel Workspace

3.3. The MATLAB Fuzzy Inference Engine

The proposed system utilizes a "Mamdani-type" fuzzy inference engine, which leverages fuzzy logic to establish a mapping between input and output. This mapping serves as a basis for decision-making and trend recognition. The inference process involves block construction, structure, firing, implication, and aggregation of rules.

In MATLAB, the system rules were formulated using the permutation function, and a scoring pattern was created to evaluate the efficiency of each rule. A total of 9 rules were developed, and Table 1 provides a summary of these regulations. Figures 2, 3, and 4 illustrate the MATLAB rule surface, rule editor interface with a subset of the rules, and the rule view for making modifications during the optimization phase.

Different aggregation operators, such as union and intersection, are associated with various implication operators. In this study, the Mamdani operator is employed. After inference, the overall result is assigned a fuzzy value, which is then defuzzified to obtain a final crisp result. Among the available defuzzification techniques, the Centroid or CoG (Center of Gravity) approach is utilized due to its common usage and ability to determine the point where a vertical line divides the aggregate set into two equal masses. The Mamdani-type fuzzy inference engine, along with the scoring pattern, rules, and defuzzification approach, contribute to the robustness and effectiveness of the system in analyzing and optimizing call drop control. The centre of gravity (COG) may be stated mathematically as: Where μ_A is the set of membership functions of the system.

$$CoG = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx} \dots\dots\dots\dots(6)$$

Where the term μ_A , is the set of membership functions of the system.

Table 1: A Snippet of Rules Structuring and Iterations

Traffic	Channel Size	Channel Allocation
LOW	LOW	LOW
LOW	MEDIUM	LOW
LOW	HIGH	LOW
MEDIUM	LOW	LOW
MEDIUM	MEDIUM	MEDIUM
MEDIUM	HIGH	MEDIUM
HIGH	LOW	MEDIUM
HIGH	MEDIUM	HIGH
HIGH	HIGH	HIGH

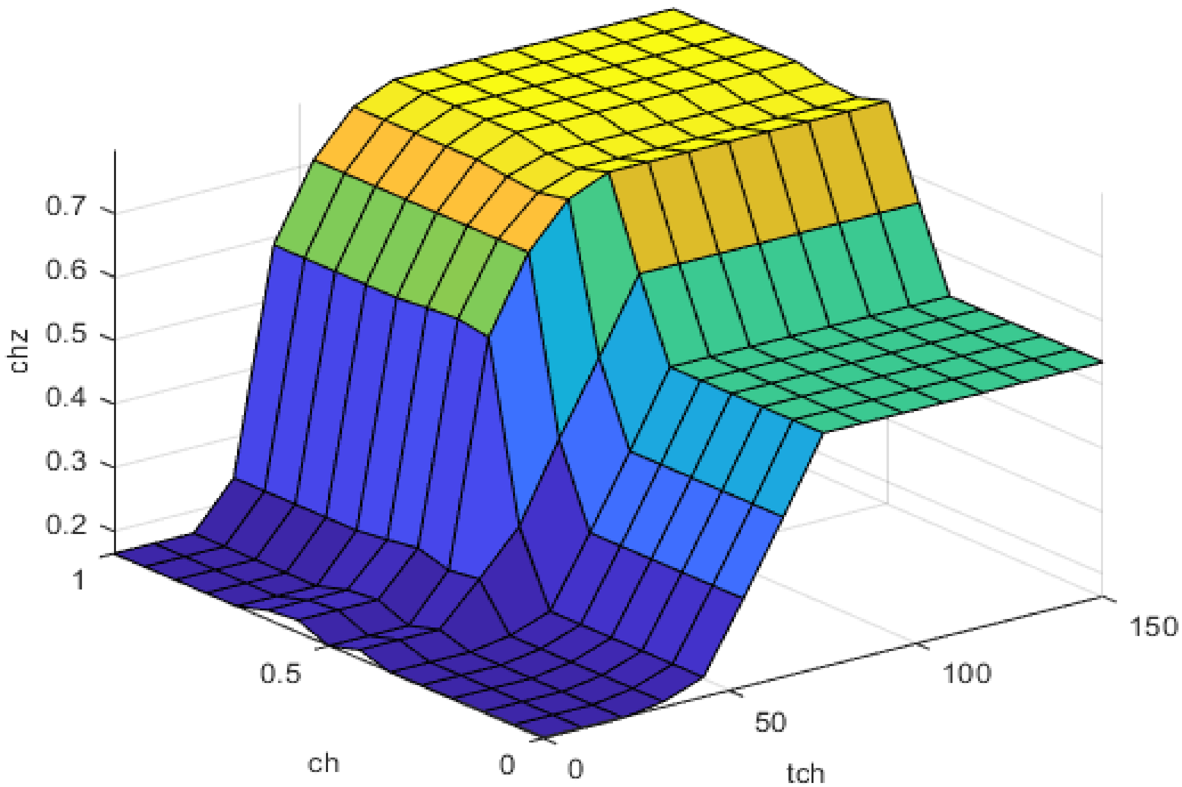


Figure 2: The Rule Surface

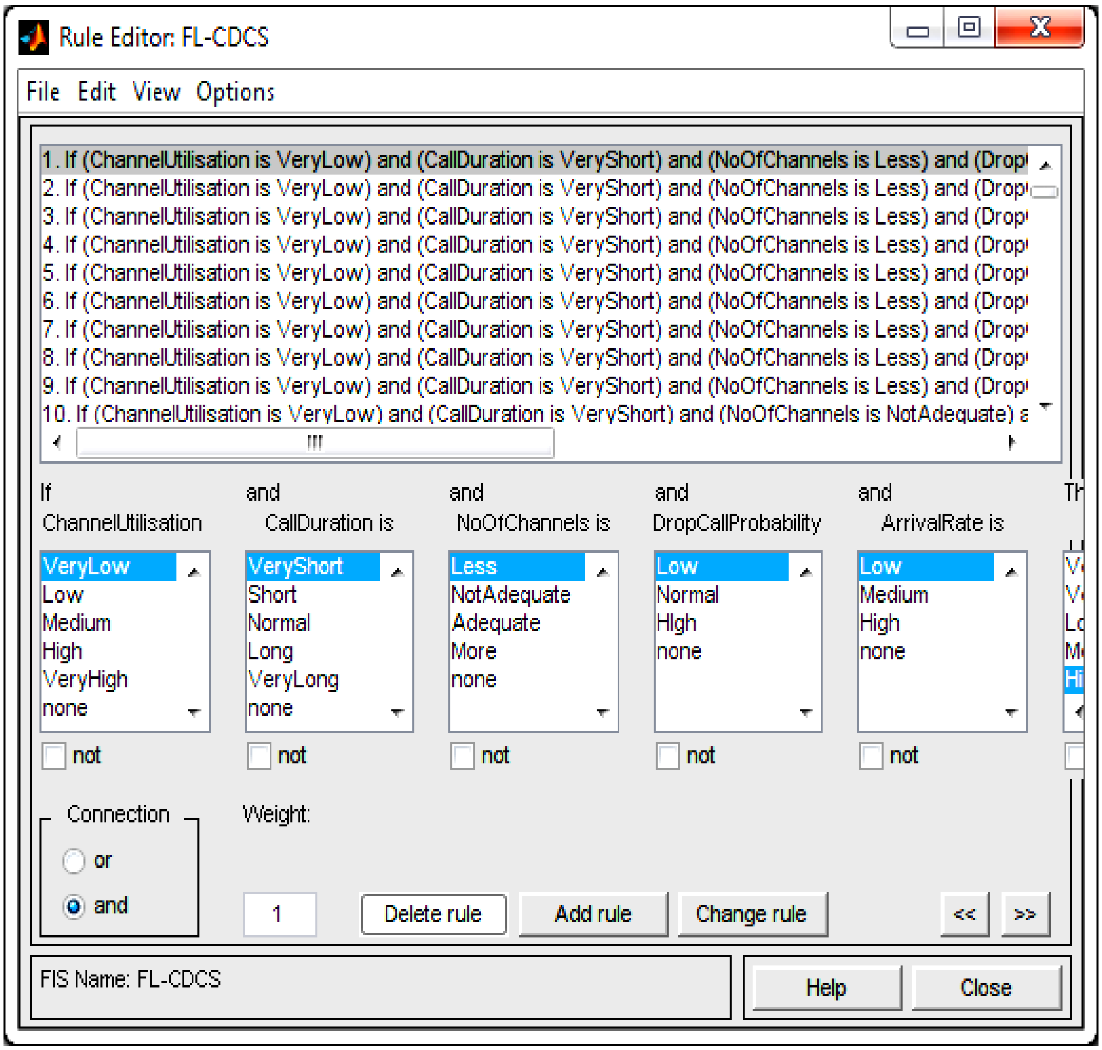


Figure 3: The MATLAB rule editor showing a snippet of our FL-B rules

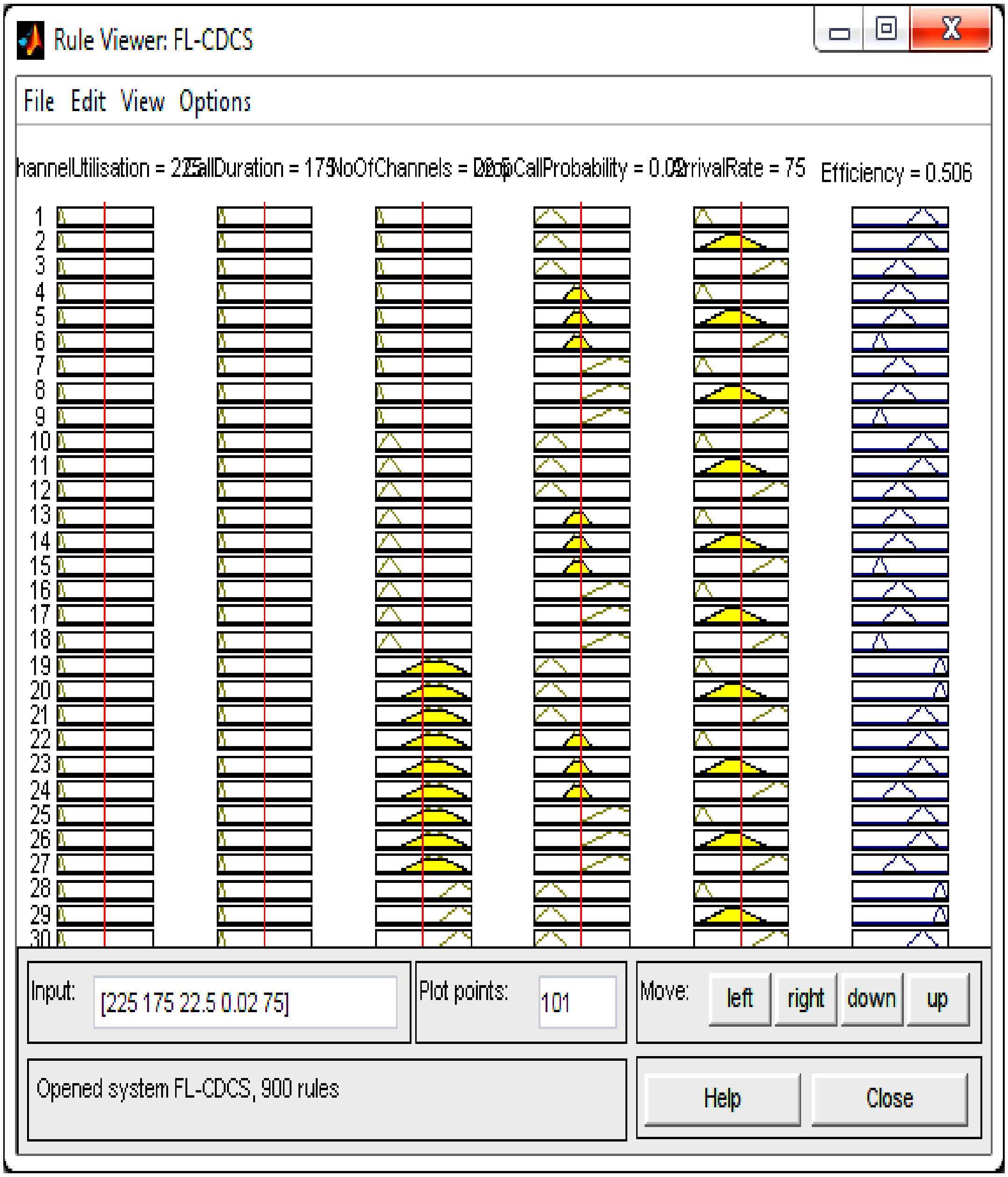


Figure 4: The MATLAB rule viewer with the different membership variables optimized.

4. Results and Discussion

The Fuzzy Logic Base system takes traffic statistics and the channel's status, obtained from the dataset, as inputs. The dataset also includes additional information for three variables: channel usage, number of channels, and observed drop call probability extracted directly from the telecommunication operator's system room. In the MATLAB tools, a simulator with real-time learning capabilities was employed. Upon starting the simulation, the module is loaded with the parameters, configured, and initialized with a few entries. As the iterations occur, the simulator updates the mobile movement position, performs database calculations, initiates new call origination, and manages resource usage. The simulation records both analytical and statistical output data, as well as the final simulation outcome. The simulation model consists of multiple hexagonal cell architectures, where traffic load distribution is non-uniform. Both uplink and downlink subscriber services, particularly voice calls, are examined under varying low and high density loads. This approach allows for the sharing and balancing of the traffic burden, as certain cells experience high traffic while neighbouring cells exhibit significantly lower traffic levels. When the model is propagated through the fuzzy logic controller, the variable argument value is expected to fluctuate, resulting in the redistribution of congested traffic load from heavily loaded cells to less burdened ones, thereby reducing call drop rates. In mobile communication systems, the wireless channel's radio spectrum is shared among all mobile users, leading to interference. To ensure the required Quality of Service (QoS) metrics such as throughput, as well as suggested limits for delay and packet loss rate, a control mechanism is necessary for planning packet transfers and managing interference rates. However, the capacity of mobile communication networks is limited by interference, both within the cell and between cells, affecting each mobile user. Intercell interference can be systematically controlled through effective cell coordination, while intracell interference can be managed through packet scheduling and power allocation. Soft handover, a feature of mobile cellular networks, requires collaboration between neighboring cells to provide resources to mobile users.

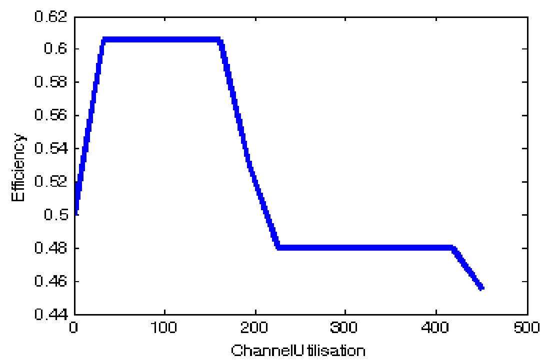


Figure 5: Existing System

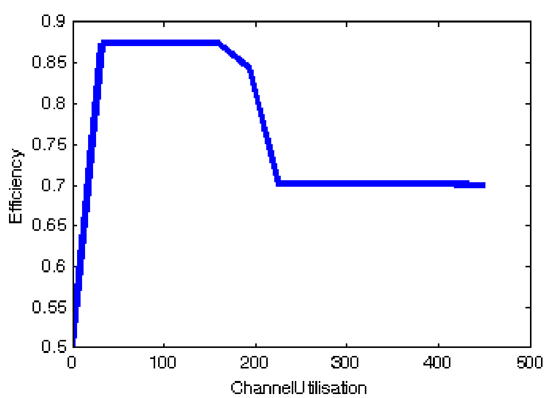


Figure 6: Optimized System

The impact of channel utilization on network efficiency for both current and improved systems is examined in Figures 5 and 6. In the current system, efficiency significantly increased when there was low traffic or a limited number of available channel resources. However, as traffic volume increased, more resources were required to maintain QoS standards, necessitating a sufficient number of channels to handle the increasing requests. The efficiency of the old system stabilized at approximately 0.605, but then deteriorated as additional channels became available to serve more customers, resulting in a sustained reduced performance at an efficiency of 0.48. Eventually, the system failed when traffic utilization reached approximately 400. On the other hand, the optimized system ensured appropriate resource allocation and management of performance-affecting elements, leading to a remarkable increase in efficiency by approximately 27%.

The optimized system exhibited two stability phases with a minor decline in between, aiming to maintain efficiency at an optimal level in the face of high resource requests. In contrast, the existing system experienced sharper and longer declines in efficiency that could not sustain performance. Ultimately, the improved system achieved a sustained efficiency of 72%. While call drops may occur due to high channel demands and the impact of soft handover, the optimized system exhibited minimal performance degradation even as traffic channel usage exceeded 400 Erlang, thereby maintaining the expected system performance.

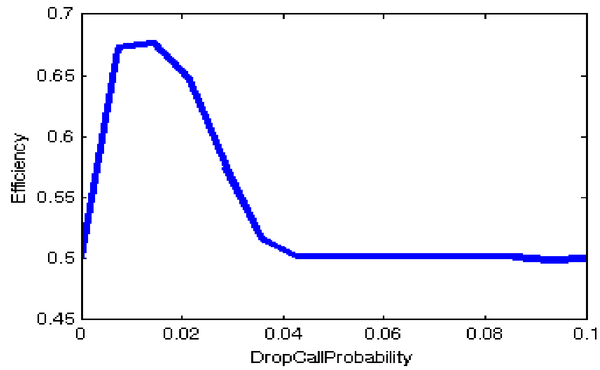


Figure 7: Existing System (efficiency vs. drop call probability)

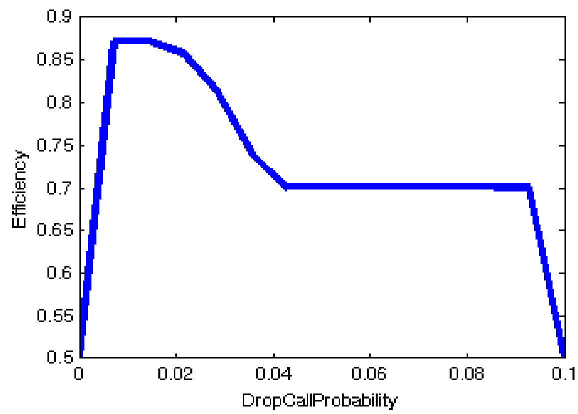


Figure 8: Optimized System (efficiency vs. drop call probability)

Figures 7 and 8 illustrate the effect of call drops on system efficiency in the current and optimized systems, respectively. In lighter traffic conditions, call drops were not as pronounced, and the system's performance improved as long as the drop call probability remained below the suggested level of 0.02. However, when the drop call probability reached 0.1, the improved system experienced a complete collapse, while the original system sustained deteriorated performance at an efficiency of approximately 0.5, which is considered significantly high. In a practical implementation, if significant network degradation is detected, a system reset would be required.

Figures 9 and 10 provide clear evidence of the effectiveness of the proposed approach. As traffic load increased, more calls were blocked due to overloaded channels, resulting in higher congestion rates and increased call drops.

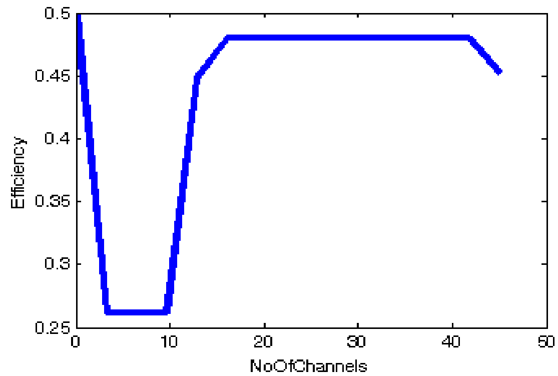


Figure 9: Existing System ((System Effectiveness)

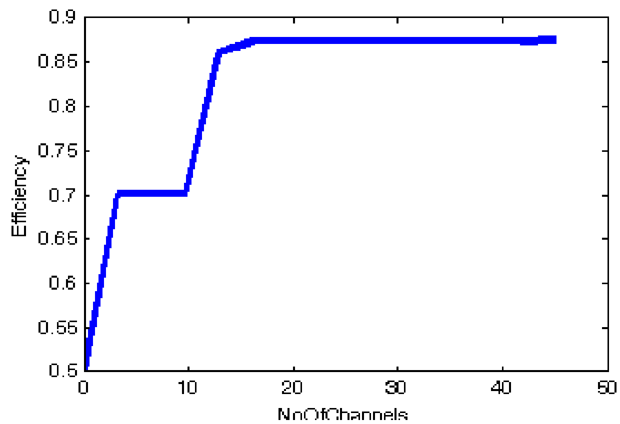


Figure 10: Optimized System (System Effectiveness)

5. Conclusion

This research presents a proposal for a practical simulator to control call dropping in mobile communication networks within wireless cellular networks, aiming to enhance their efficiency. The research outlines an optimized approach utilizing Fuzzy Logic Control, which has been dynamically modified, along with an optimization handover technique that effectively manages call drops through dynamic load balancing and efficient resource sharing in real-time. The optimization process involves the utilization of a fuzzy logic control system procedure, enabling the system to select the most suitable actions based on the creation of fuzzy inference engine rules. By utilizing this simulator, the effectiveness of a system can be assessed based on the characteristics that lead to call drops in mobile network protocols.

To enhance the overall performance of the system, a fuzzy rule-based classifier is employed, improving service categorization and quality of service. Additionally, the resource management approach employed in the calculation of weights for efficiency optimization contributes to improved resource allocation and call admission within the network. Through extensive simulations of both the existing and enhanced systems, various parameters that directly impact call dropping are investigated. The newly proposed fuzzy logic-based system surpasses the previous approach, demonstrating superior reliability and performance. Particularly in scenarios of increased resource usage and heavy traffic, our approach effectively maintains the call dropping probability below the minimum threshold, ensuring the expected provision of Quality of Service (QoS).

Furthermore, the resulting rule-based system can be implemented in real-time to prevent call dropouts. Simulation graphs depict that even under highly congested loads, the desired state can be achieved with a significant reduction in the call drop rate. Notably, the fuzzy logic-based controller successfully accomplishes this task without necessitating any modifications to the underlying infrastructure design or architecture. Moreover, a potential avenue for future research involves investigating the effectiveness of the system using a hybrid approach that combines fuzzy and neural computing. This approach can involve incorporating Neuro-fuzzy networks or more advanced artificial intelligence (AI) systems to handle complex channel assignments in a more intelligent manner. By leveraging these technologies, the process can dynamically learn from previous experiences in real-time using a neural network machine tool. This advancement enables us to effectively reduce call drops to a predefined minimum level within a short timeframe. The outcomes of this research will hold significant value in the communication industry, as it explores the application of contemporary AI techniques to address call dropping issues in the telecommunication sector.

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