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A Rule-Based Approach with Fuzzy Logic for Adaptive Network Optimization

Egbujor Emeka Godwin, Prof C. A. C Mgbachi

Enugu State Electricity Distribution Company

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Abstract: This study introduces an adaptive network optimization framework grounded in fuzzy logic and rule-based machine learning for cognitive radio systems. The primary objective is the concurrent minimization of interference, congestion, and bit error rate, coupled with enhancements in throughput and signal-to-noise ratio. A comprehensive set of rules, guided by linguistic variables for qualitative network aspects, is established alongside membership functions for quantitative analysis.The incorporation of machine learning into our approach enables adaptability to diverse network conditions, resulting in overall improved efficiency. The positive impact of machine learning is particularly evident in the reduction of congestion during specific timeframes. Specifically, on Saturday at hour 6, congestion decreases from the conventional 3.055 to 2.86. This notable improvement underscores the efficacy of machine learning in expediting the sensing mechanism of secondary users, facilitating the rapid identification of unused channels from primary users. The findings contribute to the advancement of cognitive radio systems, providing a robust and adaptable solution to address the intricate dynamics of modern wireless networks.

I. Introduction

In the wireless communication landscape, envision an orchestra symbolizing the ideal state of the spectrum—a harmonious flow of data like melodies. However, the reality for cognitive radio networks (CRNs) is akin to a dissonant symphony, plagued by interference that disrupts signals and hampers communication (Akyol & Letaief, 2011). This interference, resembling unruly notes, poses threats to critical applications, from emergency response systems to cutting-edge technologies like self-driving cars (Sharma et al., 2022). Beyond inconvenience, the potential fallout includes infrastructure failures, raising concerns about a disconnected and vulnerable world.

Problem Statement

In wireless communication, challenges like dropped calls, buffering, and inefficient spectrum use persist, causing disruptions, interference, and scarcity (Akyol & Letaief, 2011). Bridging this gap and harnessing the transformative potential of Machine Learning Rule-Based Optimization is crucial. Current systems face limitations, and there's a research gap in fully integrating this technology. This study aims to explore and implement Machine Learning Rule-Based Optimization, addressing connectivity issues and creating efficiency in wireless communication.

Amidst this discord, a beacon of hope emerges—the maestro of machine learning (ML). This adept conductor empowers CRNs with real-time spectrum analysis, predictive prowess, and adaptive adjustments, enabling them to navigate the crowded airwaves with finesse (Zheng et al., 2020). Picture CRNs seamlessly weaving their data through the spectrum, achieving a perfect harmony of signals and contributing their unique melodies to the symphony of a connected future.

II. Literature Review

In the realm of Cognitive Radio Networks (CRNs), a symphony of innovative approaches seeks to harmonize the persistent challenge of interference. Liu et al. (2023) conduct a proactive masterpiece, envisioning CRNs as strategic chess players anticipating interference moves. This approach, marked by adaptive channel hopping and power control, emerges as a promising strategy, poised to minimize disruptions and optimize spectrum utilization.

Chen et al. (2021) introduce a dynamic rhythm to interference mitigation with Software-Defined Radio (SDR) Platforms. These platforms, likened to agile superheroes, revolutionize the field by enabling swift testing and deployment of interference mitigation algorithms. The result is a cadence of accelerated research and innovation in the domain of CRN interference management.

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Wu et al. (2019) contribute to the symphony by orchestrating Network Function Virtualization (NFV) as a transformative element. The flexibility of NFV allows interference mitigation strategies to morph and adapt across geographically dispersed CRNs. This shape-shifting capability responds to the dynamic needs of diverse networks, offering a harmonious solution for interference mitigation at scale.

Collaboration takes center stage with Li et al. (2017), advocating for Cooperative Sensing as a collective intelligence strategy. CRNs, acting as a unified ensemble, pool information about spectrum availability and potential interference sources. This collaborative effort enhances spectrum sensing accuracy, reducing the risk of unintentional interference and adding a layer of collective wisdom to the CRN repertoire.

The melody of fair spectrum access is composed by Luo et al. (2020) through Cognitive Resource Allocation. Intelligent algorithms, conducted by this maestro, ensure equitable distribution based on real-time spectrum availability and network demands. This harmonious orchestration minimizes interference and maximizes efficiency, contributing to the symphonic vision of optimal CRN performance.

Huang et al. (2022) bring a personalized touch to the symphony with Context-Aware Strategies. Acknowledging the dynamic nature of CRNs, this approach tailors interference mitigation strategies to specific contexts, considering user location, mobility patterns, and traffic dynamics. The result is an adaptive and efficient solution finely tuned to the unique needs of each network.

Spectrum Sensing, as explored by Yang et al. (2017) and Chen et al. (2018), lays the foundational chords for effective interference mitigation. Techniques like energy detection and cyclostationary feature detection empower CRNs to identify unoccupied channels accurately, setting the stage for a proactive avoidance of interference.

Knowledge Gap

Existing approaches were found to have limitations in their ability to handle real-time changes in network conditions, diverse interference sources, and the dynamic nature of CRNs. The envisioned rule-based system with fuzzy logic aimed to provide a more flexible and adaptive solution by considering linguistic variables and incorporating human-like decision-making processes. This approach was anticipated to contribute to a more efficient and self-optimizing CRN, ensuring improved interference mitigation under varying and unpredictable scenarios**.**

III. Methodology

In pursuit of the research objective to design a machine learning rule base for adaptive network optimization using fuzzy logic, a systematic approach was employed. Firstly, a comprehensive rule set was meticulously crafted to govern the decision-making process of the system. This rule set was informed by a profound understanding of the specific network parameters targeted for optimization, including interference, congestion, bit error rate, throughput, and signal-to-noise ratio. The rules served as the guiding principles for the fuzzy logic system to interpret and respond to diverse network conditions.

Next, linguistic variables, crucial for expressing network states in a qualitative manner, were identified and carefully formulated. These linguistic variables provided a qualitative foundation, allowing the fuzzy logic system to interpret varying network conditions intelligently. Subsequently, membership functions were rigorously defined for each linguistic variable. These functions played a pivotal role in quantifying the degree of membership of specific network states to linguistic terms, providing the fuzzy logic system with a mathematical framework to process input data effectively.

The culmination of these efforts was the implementation of the rule-based system within a machine learning framework. The system, incorporating fuzzy logic, was trained with relevant data to learn and adapt its decision-making processes based on the formulated rules and linguistic variables. This machine learning implementation represented a sophisticated approach to adaptive network optimization, enabling the system to respond intelligently to dynamic changes in network conditions The fuzzy rule base is shown in Figure 1 expressing the inputs which are the metrics for evaluation in this research.

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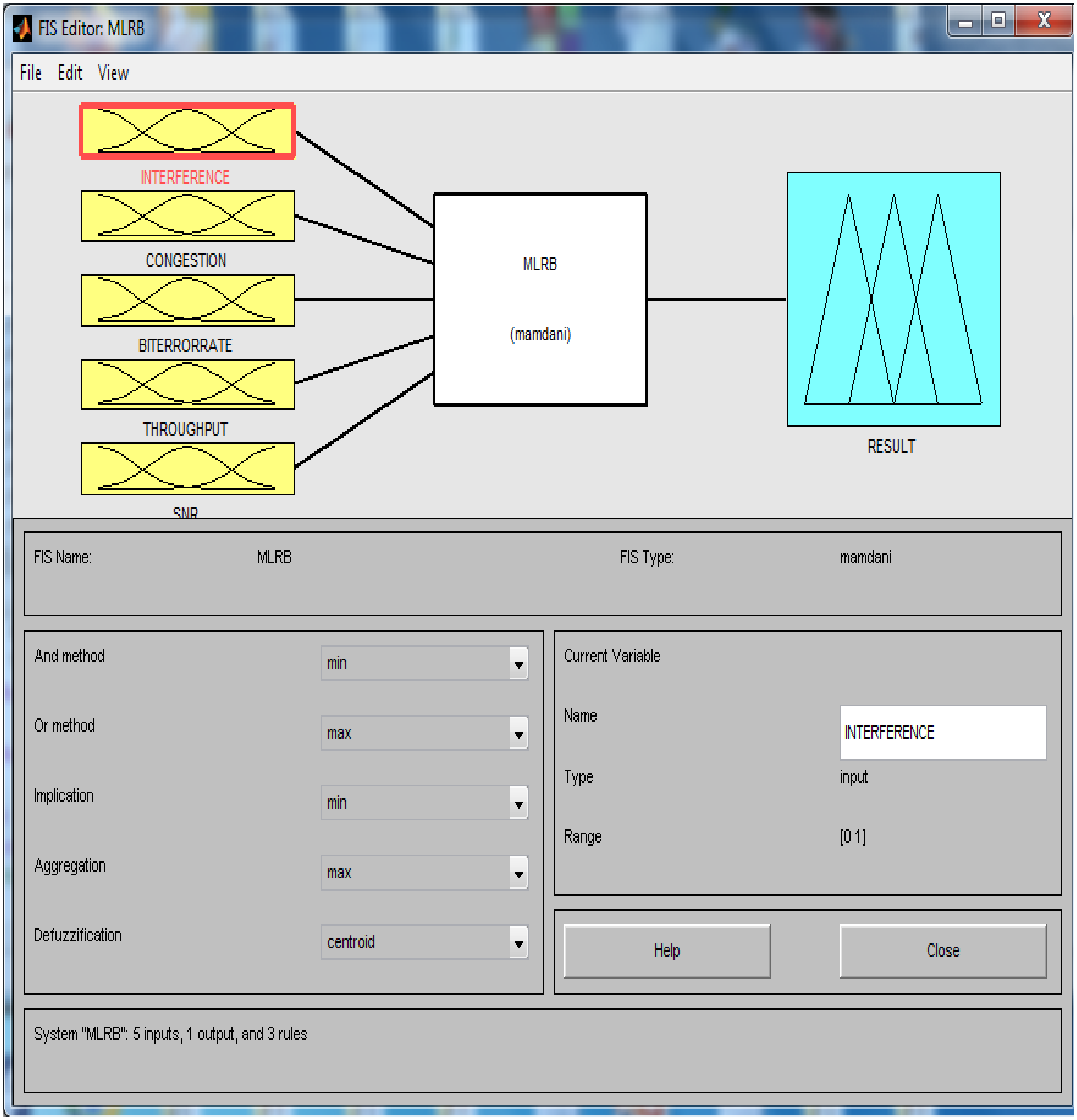

Figure 1: Designed machine learning Fuzzy inference system (FIS) that will minimize interference, congestion, bit error rate and increase through put and signal to noise ratio.

Figure 1 has five inputs of interference, congestion, bit error rate, throughput and SNR. The generated output result is shown in Figure 2.

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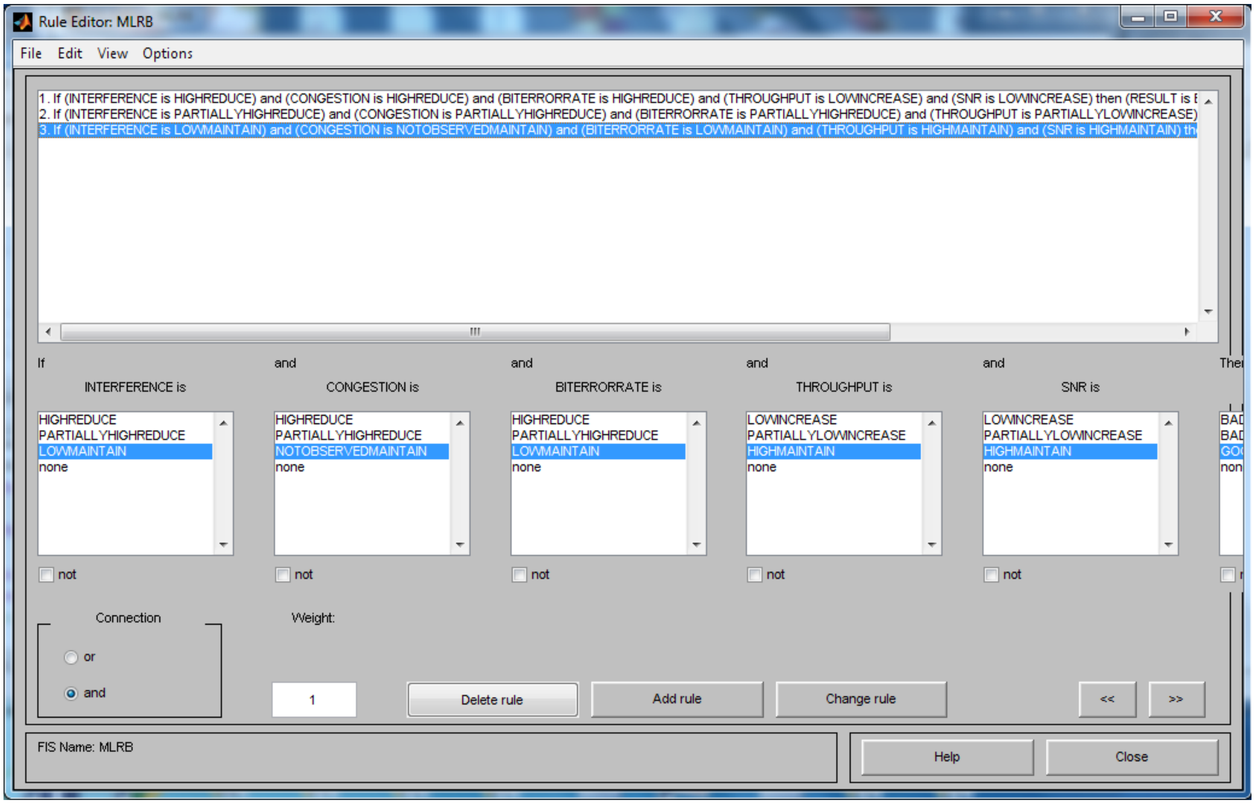

Figure 2: Designed machine learning rule base that will minimize interference, congestion, bit error rate and increase through put and signal to noise ratio

The rules are three in number. The comprehensive analysis of the rules is as detailed in table2.

Table 2: The Linguistic variables detail of the rules

1	IF INTERFERENCE IS HIGH REDUCE	AND CONGESTION IS HIGH REDUCE	AND BIT ERROR RATE IS HIGH REDUCE	AND THROUGHPUT IS LOW INCREASE	AND SNR IS LOW INCREASE	THEN RESULT IS BAD
2	IF INTERFERENCE IS PARTIALLY HIGH REDUCE	AND CONGESTION IS PARTIALLY HIGH REDUCE	AND BIT ERROR RATE IS PARTIALLYHIGH REDUCE	AND THROUGHPUT IS PARTIALLYLOW INCREASE	AND SNR IS PARTIALLY LOW INCREASE	THEN RESULT IS BAD
3	IF INTERFERENCE IS LOW MAINTAIN	AND CONGESTION ISNOT OBSERVED MAINTAIN	AND BIT ERROR RATE IS LOW MAINTAIN	AND THROUGHPUT IS HIGH MAINTAIN	AND SNR IS HIGH MAINTAIN	THEN RESULT IS GOOD

To validate and justify the percentage improvement in the reduction of interference with and without machine learning

- **To determine percentage reduction of conventional interference of cognitive radio in January.**

Conventional interference in cognitive radio in January =3.8dB

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Machine learning interference in cognitive radio in January =3.559dB

% improvement in the reduction of interference in cognitive radio in January when machine learning is incorporated in the system =

$$\frac{\text{Conventional interference in cognitive radio} - \text{Machine learning interference x 100\%}}{\text{Conventional interference in cognitive radio} \qquad 1}$$

% improvement in the reduction of interference in cognitive radio in January when machine learning is incorporated in the system =

$$\frac{3.8\text{dB} - 3.559\text{dB}}{3.8\text{dB}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in January when machine learning is incorporated in the system = **6.3%**

- **To determine percentage reduction of conventional interference of cognitive radio in March**

Conventional interference in cognitive radio in March =1.3dB

Machine learning interference in cognitive radio in March =1.217dB

% improvement in the reduction of interference in cognitive radio on March when machine learning is incorporated in the system =

$$\frac{\text{Conventional interference in cognitive radio} - \text{Machine learning interference}}{\text{Conventional interference in cognitive radio}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in March when machine learning is incorporated in the system =

$$\frac{1.3\text{dB} - 1.217\text{dB}}{1.3\ \text{dB}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in March when machine learning is incorporated in the system = **6.3%**

- **To determine percentage reduction of conventional interference of cognitive radio in May**

Conventional interference in cognitive radio in May =2.3dB

Machine learning interference in cognitive radio in May =2.154dB

% improvement in the reduction of interference in cognitive radio in May when machine learning is incorporated in the system =

$$\frac{\text{Conventional interference in cognitive radio} - \text{Machine learning interference}}{\text{Conventional interference in cognitive radio}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in May when machine learning is incorporated in the system =

$$\frac{2.3\text{dB} - 2.154\text{dB}}{2.3\ \text{dB}} \text{x} \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in May when machine learning is incorporated in the system = **6.35%**

- **To determine percentage reduction of conventional interference of cognitive radio in July**

Conventional interference in cognitive radio in July = 6.2dB

Machine learning interference in cognitive radio in July = 5.806dB

% improvement in the reduction of interference in cognitive radio in July when machine learning is incorporated in the system =

$$\frac{\text{Conventional interference in cognitive radio} - \text{Machine learning interference}}{\text{Conventional interference in cognitive radio}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in July when machine learning is incorporated in the system =

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$$\frac{6.2\text{dB} - 5.806\text{dB}}{6.2\text{ dB}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in July when machine learning is incorporated in the system = **6.35%.**

- **To solve for percentage reduction of conventional congestion of cognitive radio in January**

Conventional congestion in cognitive radio in January = 1.82

Machine learning congestion in cognitive radio in January = 1.704

% improvement in the reduction of congestion in cognitive radio in January when machine learning is incorporated in the system =

$$\frac{\text{Conventional congestion in cognitive radio} - \text{Machine learning congestion}}{\text{Conventional congestion in cognitive radio}} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of congestion in cognitive radio in January when machine learning is incorporated in the system =

$$\frac{1.82 - 1.704}{1.82} \text{ X } \frac{100\%}{1}$$

% improvement in the reduction of interference in cognitive radio in July when machine learning is incorporated in the system = **6.34**

IV. Result and Discussion

Table 3. Empirical data of packets received, packets transmitted and packet loss during the measurement period.

Month	Packet Transmitted (kb)	Packet Received (kb)	File Size	Transmission Time (S)	Interference in Co-Channel (db)	Packet Loss (kb)
JANUARY	30	25	12	2	.3.8	0.8
FEBUARY	28	24	14	3	4.2	0.833
MARCH	26	20	16	2	1.3	0.7
APRIL	26	18	18	4	5.1	0.556
MAY	24	16	14	3	2.3	0.5
JUNE	24	14	20	5	6.2	0.2858
JULY	28	24	14	3	4.2	0.833

Table 4: Cognitive radio parametric data for effective power of signals, effective power of interference signals, effective power of noise signals, Percentage of cognitive radio sensing mechanism and ratio of the strength of signals to the strength of interference signals

Months	P_S = effective power of signals(dB)	P_I = effective power of interference signals(dB)	$P_{N=}$: effective power of noise signals(dB)	Percentage of cognitive radio sensing mechanism (%)
JANUARY	5.7	3.8	4.8	62
TUESDAY	5.9	4.2	4.2	58
MARCH	4.9	1.3	5.7	66
APRIL	4.2	5.1	5.3	54

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MAY	5.3	2.3	4.8	52
JUNE	5.8	6.2	4.4	67
JULY	5.3	6.2	5.1	70

Table 5: Data collection in cognitive radio performance at various hitches

Number of users	A transceiver can intelligently detect which communication channels are in use and which are not when there is low throughput	A transceiver can intelligently detect which communication channels are in use and which are not when there is congestion	A transceiver can intelligently detect which communication channels are in use and which are not when there is interference	A transceiver can intelligently detect which communication channels are in use and which are not when there is high bit error rate	Conventional spectrum sensing in cognitive radio
% of Secondary users switching over to Primary users	55%	60%	52%	58%	50%

Table 6: Comparisons of Conventional and Machine learning congestion in reducing interference in cognitive radio sensing mechanism

Time(months)	Conventional congestion in Reducing interference in cognitive radio sensing mechanism	Machine learning congestion in Reducing interference in cognitive radio sensing mechanism
1	1.82	1.70
2	1.79	1.67
3	1.95	1.82
4	2.19	2.05
5	2.31	2.166
6	3.055	2.86
7	1.95	1.82

V. Discussion

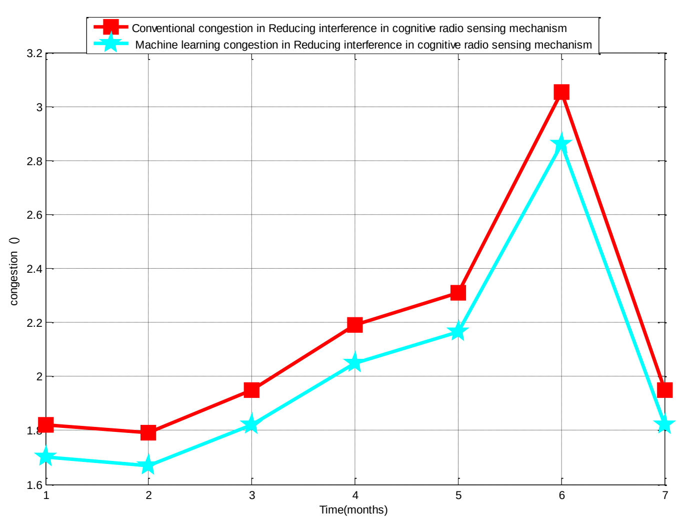

Figure 3: Comparisons of Conventional and Machine learning congestion in reducing interference in cognitive radio sensing mechanism

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In Figure 3 the conventional congestion of a cognitive radio on Saturday or 6 is 3.055. On the other hand, when machine learning is incorporated in the system, it reduces to 2.86 the same day. In this case the sensing mechanism of secondary users to identify unused channel from the primary users becomes fast.

VI. Conclusion

In conclusion, the integration of machine learning into the cognitive radio system has shown a significant positive impact on congestion reduction, particularly evident on Saturday at hour 6, with a decrease from conventional congestion at 3.055 to 2.86. This highlights machine learning's effectiveness in enhancing the sensing mechanism of secondary users, crucial for efficiently identifying unused channels and optimizing the cognitive radio network.

Considering other state-of-the-art techniques, it is important to acknowledge the advantages of improved congestion reduction and network responsiveness. However, complexities and trade-offs, such as computational resource demands and data quality reliance for machine learning, need to be considered.

Despite these challenges, the findings underscore machine learning's potential as a valuable tool for addressing interference challenges in cognitive radio systems, contributing to the ongoing advancement of wireless communication technologies. A nuanced understanding of both the advantages and limitations will be essential for informed decision-making in deploying such advanced techniques in real-world scenarios.

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