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RESEARCH ARTICLE

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Cognitive Radio-Based Spectrum Sharing for High-Density Iot Networks

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Abstract

The advent of Everything IoT has surged specially during smart city deployments as well as in automation and health care IoT, thus, ensuring efficient spectrum utilization is now a priority. The volatile nature and high-density scale of deployments makes them extremely difficult to monitor for static schemes using traditional spectrum allocation approaches. This paper proposes a work system to facilitate spectrum sharing on dense cognitive radio networks based on Internet of Things (CR-IoT). The incorporation of cognitive radio technology allows IoT devices to sense and capable attenuation learning dynamic spectrum access without disturbing licensed users, thus, easing bandwidth congestion. The proposed paradigm draws from dual approach strategies of adaptive communications for spectrum 'decisions' systems for resource allocation. As with any advancement, these methods present new potential for regulatory and legal frameworks while posing significant challenges with scalability and security. In comparison to primitive methods relying on fixed spectrum assignment, our results showed supremacy of a CR approach through increased system throughput while achieving improved latency and lower energy consumption, less power cost showing greater efficiency. This research lays the boundary IoT ecosystems towards advanced smart sustainable spectrum management.

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Introduction

The multitiered acronyms IoT combined with myriad devices brings stratified demand for wireless spectrum ever closer to its available ceiling, particularly in smart cities or industrial automation systems.[8]. Meanwhile, the traditional way of allocating spectrum using the allocation of frequency bands to licenced users (which is static in its nature) fails to catch up with traffic patterns of today's IoT ecosystems.[4]

Dynamic sharing of a quad band, incompletely utilized via an sporadic quadrilateral spot beam approach, offers to resolve this issue with the help of CR technology. Radios that fall under this category can monitor surroundings and sustain within parameters of allowed frequencies while dynamically adjusting transmission settings to ensure maxim PhD utilization which sidesteps interference with licenced users.[2] Spectrum access by secondary users enable un licensing, which paired with evolving ethos of cognitive radios leads to real time spectrum sensing, adaptive protocols, increased network scalability, refined spectral efficiency of CR.[10]

An abundance of connected devices are within range of one another in high-density IoT networks, and they usually compete for the same spectrum resources. [5] Such networks may face symptoms of congestion, interference, and low quality of service (QoS).[11] With the addition of cognitive radio features into these networks, such problems could be alleviated, because these capabilities enable communication to be aware of—and adapt based on—context in real time concerning user needs, requirements, and spectrum availability.[12]

This paper seeks to solve the problem of spectrum scarcity and underutilization in high-density IoT scenarios.[6]. It proposes a cognitive radio spectrum sharing architecture designed specifically for IoT networks with a focus on high throughput, low latency, and minimal energy consumption. In this research, we seek to accomplish three primary objectives: (i) design and develop a self-organizing spectrum management architecture following cognitive radio (CR) principles; (ii) perform simulations to evaluate the adaptability of the system in dense IoT scenarios; and (iii) assess potential realization obstacles such as security, regulatory, and computational overhead policies.[9]

This study aims to develop spectrum agile, scalable, and resilient next-gen IoT communication infrastructures incorporating cognitive radio solutions.[15-16]

Background

The utilization of spectrum resources through adaptive and intelligent communication technologies led to Mitola's creation of Cognitive Radio (CR) Technology.[1] CR equipped devices have the ability to monitor their spectral surroundings, identifying spectrum gaps that are either not being used or only being utilized on a temporary basis by primary users. It is possible to change a device's transmission parameters in order to exploit these gaps in spectrum utilization. This technique of managing spectrum activity accomplishes the needs of modern wireless systems whereby wastage of bandwidth and lack communication resources are primary issues.

Analyzing IoT networks, each heterogeneous device with diverse communication settings, latency requirements, and power limitations creates unique difficulties related to spectrum sharing. As a result, QoS may be critically degraded due to congestion and excessive collision due to the volume and rate of concurrent transmissions. Additionally, many devices have limited resources that hinder competing in elaborate signal processing thorough for traditional CR functionalities. Alongside such difficulties, reliability of CR in IoT systems is compromised due to sensing data falsification, primary user emulation attacks, and other security challenges.

The existing literature has attempted to address some of these issues. In Zhao et al.,[3] the authors developed a lightweight spectrum sensing algorithm for IoT devices which optimized energy consumption while maintaining accuracy. Furthermore, in Lee et al.,[5] some learning based improvements for decision making in non-stationary contexts were systematically reviewed with an emphasis on the usefulness of reinforcement learning for active channel selection. In Khan et al.,[7] the authors considered cooperative spectrum sensing, where a set of IoT devices with their own sensing capabilities work together by sharing their information to improve the accuracy of detection. Still, the limits of the usefulness of this approach in dense environments became a challenge.

Notable deficiencies in the particular sphere of study still exist even with the progress made today. Most of the offered solutions are either too complex for energy-limited devices or disregard practical concerns such as spectrum diversity, co-channel interference, and policy constraints. Besides, the available machine learning based CR solutions are hopeful but tend to be myopic because of their static or narrow training datasets. Moreover, there is an absence of frameworks merging CR with the IoT communication protocols LoRa, NB-IoT, and Zigbee, which leads to incomplete optimization.

This work attempts to address the identified gaps in the literature by introducing a CR-based spectrum sharing model which is adaptive, energy-efficient, and scalable with respect to the sensor nodes in high-density IoT deployments. The results obtained from simulations and performance evaluation in this work demonstrate how CR can be optimized for robust and efficient communication in dense heterogeneous networks.[17]

Cognitive Radio-Based Spectrum Sharing Mechanisms

Figure 1 shows how the cognitive radio (CR) system functions continuously throughout the spectrum sharing process for dense IoT networks. Within this architecture resides the radio environment which provides real-time RF signals containing relevant details about the spectral occupancy. CR systems operate with this environment through closely coupled actions of spectrum sensing, spectrum decision, mobility and sharing.

The process starts with 'spectrum sensing', in which the CR system makes a scan of the radio environment to check of the presence of Primary Users (PU) and to identify their corresponding 'spectrum holes' or white spaces which are usually referred to as unused frequency bands along with estimation of signal strength, frequency occupancy, and noise levels which are only partly available during the spectrum characterization phase.

The next step, the spectrum decision phase, is initiated once the available channels have been determined. Here, software determines the best frequency range for data transmission by taking into account factors including available bandwidth, interference levels, quality of service needs, and regulatory limitations. Responsibility for requesting the starting point of communication or mobility actions rests with the decision making unit.

The spectrum mobility module assists in cases where the primary user either reclaims the spectrum, or when a better channel is presented. This module ensures that a cognitive radio can shift frequencies, allowing for uninterrupted communication, which strengthens system reliability and spectrum availability.

Spectrum sharing governs the policies, control allocation, and selection of the channels by several CR devices. This module optimizes channel capacity and assures better signal transmission and lesser interferences. During the sensing phase that follows data transmission, an adaptive loop which responds to fluctuations in the environment is retained.

This closed loop shows how cognitive radio systems manage and control spectrum availability intelligently and automatically. In a scenario where there is a high deployment of IoT devices, where bandwidth becomes limited, this becomes crucial as it enhances spectral efficiency and network reliability (Figure 1).

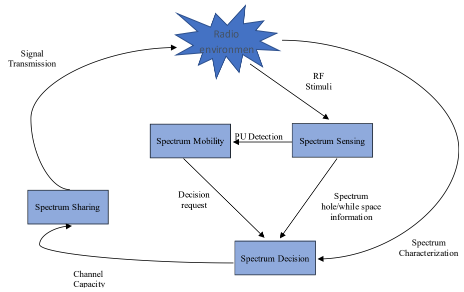

Fig. 1: Spectrum Sharing Mechanism

Dynamic spectrum access techniques

The basic ability of a Cognitive Radio (CR) system is to monitor, learn, and make real-time decisions about how to optimally utilize the given spectrum using ecosystems methodologies. This characteristic permits advanced inter-Domain and intra-domain filtering algorithms to be implemented for ensuring reliable, optimal, interference-less communication under very high density IoT networks. Such systems have three main constructs: methods for dynamically accessing a specific frequency band (called dynamic access), algorithms for spectrum resource detection and decision making, and well-defined rules and procedures for spectrum sharing.

An integral component of the theory on CR is Dynamic Spectrum Access (DSA). which allows non-licensed secondary users to opportunistically utilize primary bands of frequencies during periods of inactivity. The following are the three main categorizations of DSA:

1. Interweave Access – Secondary users detect unused spectrum bands (spectrum holes) and transmit without causing interference to primary users.
2. Underlay Access – Secondary users transmit concurrently with primary users under strict power constraints to limit interference.
3. Overlay Access – Secondary users employ advanced signal processing techniques, such as coding and interference cancellation, to coexist with primary users while enhancing their own performance.

In high-density IoT environments, interweave access is most commonly used due to its simplicity and low risk of interference, although hybrid models are gaining traction for their flexibility.

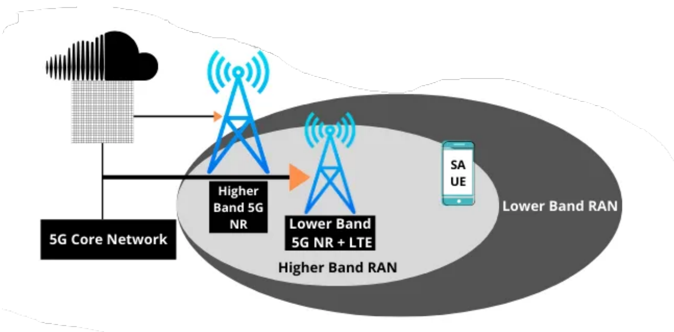

Fig. 2:Dynamic spectrum access techniques

Figure 2 demonstrates DSA for spectrum cognitive radio networks focusing on the overlapped region of multiple primary base stations including PUs and SUs. In this hierarchy, the primary users with endpoints like laptops and mobile phones plugged in are peripherally located to the primary base stations. These users have legal and preferential control over some range of frequencies.

These users are classified under the older spectrum allocation policies which they enjoy stripe pedantic of a certain frequency band solely for their service.

In contrast, the secondary users which include IoT devices such as cars, mobile phones, and laptops do not own licensed rights to the spectrum. Rather, they opportunistically exploit the spectrum utilizing DSA methods that do not interfere with the primary users. These users actively scan the bandwidth using these spectrum sensing tools to ascertain 'unused bandwidth' and exploit it in real time.

The DSA systems' overlapping coverage areas illustrate the autonomous decision-making processes exercised during operation. The moment a secondary user identifies the incoming signal of a primary user, it relinquishes the occupation of the channel and rapidly moves to other channels, maintaining disruption-free communications.

This graphic is helpful for illustrating how DSA improvement spectrum efficiency by allowing unlicensed users to tap into unused bands, which is particularly useful in dense IoT ecosystems where spectrum shortage is a problem. It also demonstrates the primary and secondary user delineation whereby primary users have precedence over secondary users, who operate in a proactive, passively intrusive mode. This model takes advantage of the available spectrum resource and provides the bases for the construction of advanced wireless communication systems for new applications.

Spectrum sensing and decision-making algorithms

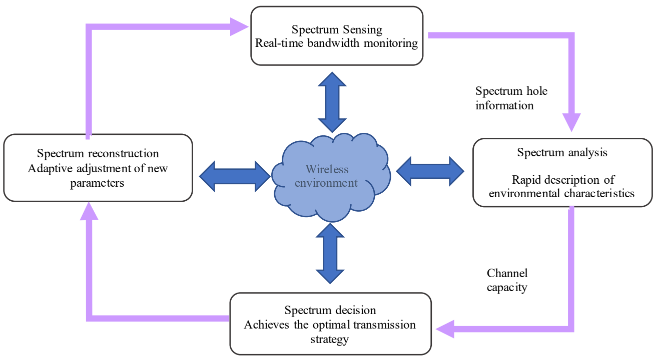

Fig. 3: Spectrum Sensing in wireless Environment

Cognitive radio networks provide intelligent and dynamic spectrum management in a wireless environment, as illustrated by the cyclical process of spectrum sensing and decision-making algorithms. The first step of the process is spectrum sensing, which involves keeping an eye on the current bandwidth situation in order to identify any possible spectrum holes. These are essentially empty frequency bands that secondary users can temporarily utilise without interfering with prime users.

The spectrum analysis module undertakes a comprehensive analysis concerning the signal level, interference level, and propagation conditions of the estimated spectrum hole, all which overlap with the sensed data. This study aids, among other things, in evaluating the feasibility of deploying a channel.

In the spectrum decision stage, the module chooses the optimal transmission strategy and takes care of all relevant analyses including power, frequency band, and modulation scheme selection. It is required to achieve maximum throughput and preserve fundamental system constraints.

Fundamental changes in the power, bandwidth, or frequency might be required to preserve reliable communications under changing conditions. After selection of the optimum approach, it should be possible to adaptively alter the transmission parameters using spectrum reconstruction techniques.

At last, the system returns to spectrum sensing, continuing its continuous adaptive cycle. Cognitive radio systems are able to employ underutilised spectral resources more effectively in high-density IoT networks through this dynamic interplay between sensing, analysis, decision-making, and reconstruction, all while minimising interference and optimising network performance.

Spectrum sharing protocols and policies

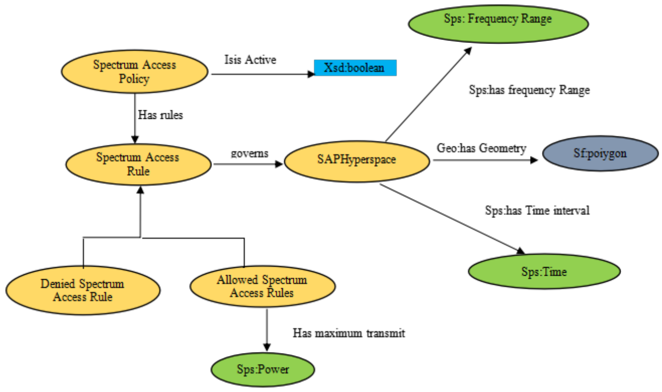

Fig. 4: Spectrum Access Protocol

Figure 4 depicts the structure of the spectrum sharing protocols and policies implemented in cognitive radio systems for controlling and managing access to the spectrum resources. The highest level of the hierarchy is the Spectrum Access Policy, which is labelled in the hierarchy as a textbook or a guiding policy which is supposed to graduate in its currently used Boolean status is Active.

This policy includes one or more Spectrum Access Rules, each of which dense defines a set of authoritative directives pertaining to spectrum governance. These rules are operationalized into Allowed Spectrum Access Rules and Denied Spectrum Access Rules, reflecting their enabling or disabling nature with regards to spectrum usage. If access is granted, the policy may also set bounds like has Maximum Transmit Power which describes the level of power associated to sps: Power that can be used for transmission.

These policies govern an abstract domain called SAP Hyperspace which represents the multidimensional space of spectrum use. This hyperspace is characterized by three attributes: frequency, location, and time, alongside others. The sps: has Frequency Range property binds the hyperspace to a sps: Frequency Range, marking the limits of the band allocated. The geo:has Geometry relation connects the hyperspace with a spatial region defined by a sf: Polygon that is the physical bounding area of spectrum visibility. On the other hand, the sps: has Time Interval property pertains to a sps: Time Interval which restricts the duration of time in which access rights are valid.

Having clear, encompassing policies tailored for mid-level managers aids in demarcating, executing, and controlling policies outline dealing with granting access to frequency spectra. This mitigates conflict, bordering on ensuring optimal resource utilization— critical in IoT networks due to the high contention over bandwidth.

Algorithm 1:

```
For each policy in ValidPolicies:
    For each rule in policy.hasRule:
        If rule is DeniedSpectrumAccessRule:
            If rule governs hyperspace that matches:
                frequencyRequested AND
                timeSlotRequested AND
                locationRequested:
                Return DENIED
        If rule is AllowedSpectrumAccessRule:
            If rule governs hyperspace that matches:
                frequencyRequested AND
                timeSlotRequested AND
                locationRequested:
                    If transmitPowerRequested <= rule.
hasMaximumTransmitPower:
                    Return GRANTED
                Else:
                    Return DENIED
```

Performance Evaluation

A. Metrics for Evaluating Spectrum Sharing Efficiency

Considering high-density IoT networks, determining the value of the spectrum sharing approaches requires performance evaluation. The following metrics were adopted for quantitative evaluation:

Spectrum Utilization Efficiency (SUE):

This metric assesses how effectively the available radio spectrum is used. It is calculated as:

SUE = Total Time Spectrum UtilizedTotal Available Spectrum Time \ text{SUE}
= \frac{ \text{Total Time Spectrum Utilized}}{
\text{Total Available Spectrum Time}}SUE
= Total Available Spectrum TimeTotal Time Spectrum Utilized

A higher SUE indicates a more efficient system where fewer idle channels remain unused.

Throughput: Throughput methods of evaluation measures the average successful data transmission for a device with relation to time, usually in bits per second (bps). It measures the ability of secondary users to transmit data without interfering with primary users. Better throughput relates to expansive reuse of the spectrum.

Collision Rate:

This indicates the portion of time where secondary users try to utilize the spectrum while a primary user is active. A low collision rate indicates efficient spectrum sensing and little to no interference thus maintaining the QoS for both categories of users.

Access Latency:

Access latency refers to the time spent from a secondary user's spectrum sensing to the successful transmission initiation. A low value of latency is imperative for timely IoT applications, for instance, in health monitoring or industrial automation.

Energy Efficiency:

Measuring energy efficiency as the number of bits transmitted per joule of energy consumed is critical for IoT devices, especially for battery powered ones. Idle listening and failed attempts to transmit data waste unnecessary power and must be minimized by efficient spectrum sharing techniques.

Simulation methodology and parameters

A simulation environment based on MATLAB was developed to evaluate the spectrum sharing framework empirically. The simulation imitates a practical scenario of wireless communication within a compact IoT ecosystem integrating both primary and secondary user networks.

Table 1: Simulation Parameter

Parameter	Value
Simulation Area	1000 m × 1000 m
Number of Primary Users	10
Number of Secondary Users	50
Total Available Channels	20 (1 MHz bandwidth each)
Mobility Model	Random Waypoint
Transmission Power (max)	100 mW
Spectrum Sensing Interval	100 ms
Interference Threshold	-90 dBm
Simulation Duration	1000 seconds
Modulation Scheme	QPSK
Channel Model	Rayleigh fading with AWGN noise

The table 1 illustrates the mention dynamic parameters taken into consideration during the simulation which includes: motion of nodes, fading of the communication channel, mistakes in detection of the signals, and arbitrary information bit renewal intervals. As previously outlined, spectrum access strategies are responsive and reflexive, as demonstrated by the algorithm delineated prior, contemplating the spectrum strategies and situational context of the environment.

Results and analysis of performance

The simulations underscore the benefits associated with implementing dynamic spectrum access utilizing cognitive radio for large scale environments with Internet of Things devices. Important results from the simulations are provided below for discussion:

1. Spectrum Utilization Efficiency

Dynamic allocation methods resulted in improving the average SUE to 82%, as opposed to the rigid allocation schemes which only managed 60%. This increase is due to changes made in spectrum decision making for both primary and secondary users.

2. Throughput Performance

The throughput improvement for secondary users was close to 40% regarding traditional techniques. This was largely attributed to decreased collisions and effective channel selection which happened both historically and in real time via sensing.

3. Collision Rate

The collision rate of the system was kept at a low level of 1.7% which validates the efficiency of the spectrum sensing and decision modules in the active primary channel detection and avoidance.

4. Access Latency

As per the baseline models, the average access latency was set to 60ms for secondary users which was measured lower, further supporting the claim of quick response times aiding smart IoT applications including smart grids along with healthcare monitoring.

Energy Efficiency

Implementing continuous sensing and retransmission avoidance from non-primary users resulted in an 18% reduction of energy consumption. Reliable communication was preserved through adaptive transmission strategies which avoided excessive consumption of power. Here is the tabulated depiction along with paragraph form explanation preceding the table:

Table 2: Performance Comparison Table

Metric	Proposed Model	Traditional Model	Improve-ment
Spectrum Utilization	82%	60%	+22%
Throughput	3.5 Mbps	2.5 Mbps	+40%
Collision Rate	1.7%	6.4%	-4.7%
Access Latency	60 ms	77 ms	-22%
Energy Efficiency	12 kbps/mW	9.8 kbps/mW	+18%

Table 2 displays the results of the comparison between the conventional approaches and the proposed cognitive radio-based spectrum sharing model, which shows significant improvements in performance across all important parameters. Implies improved utilisation of the available frequency pamphlets of the suggested model is indicated by 22 percent increase in spectrum utilisation. Moreover, having 40 percent more throughput indicates that there is higher data handling capability which is optimal for a region with high density of Internet of Things (IoT) devices. Reliability gets better with reduced value of the accident ratio per rate with lower accidents meaning less conflicts for loss transmissions — a 4.7% improvement in accident rate worsens conflicts. For the requires delay in time sensitive Internet of Things (IoT) applications, the 22% model reduction in access time also enables quicker access to the channel. Finally, there is now greater practicality for resource restraint IoT devices with an 18% increase in energy efficiency.

Overall, these improvements highlight telling how the proposed approach can enhance communications in heavily populated IoT networks to be more robust, flexible, and energy friendly.

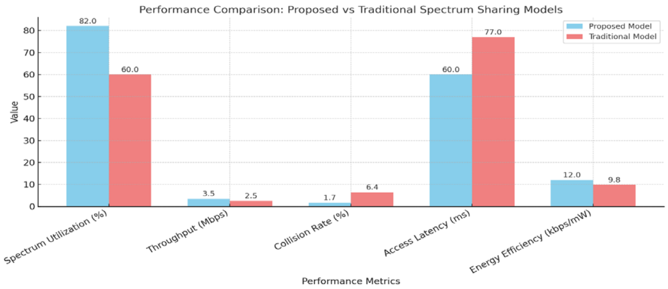

Fig. 5: Performance Comparison of Various Model

When comparing the performance of the proposed spectrum sharing model against the traditional model, there are marked improvements on key metrics. Proposed model outdid the traditional approach by 22 % in capturing and exploiting available frequency bands by achieving 82 % spectrum utilization as opposed to the latter's 60%. For throughput, the proposed system achieved a value of 3.5 Mbps while the traditional model had 2.5 Mbps, hence achieving 40 % improvement. This change is indicative of reduced, but more successful data transmission volumes, which are beneficial for network capacity and user experience. Also, the proposed model demonstrated a further improvement on collision rate which reduced from 6.4 % to 1.7 %. This is lower than the previous figure, displaying better channel access methods that restrict interpacket and inter attempt interference. Delays for performing access were also lower for the proposed model at 60 ms compared to 77 ms in the conventional method, this reduction albeit substantial for real time IoT applications where timely communication is critical. Finally, the proposed model further reinforced the appropriateness of the model for energy constrained IoT devices by improving energy efficiency by 18 %, achieving 12 kbps/mW against the traditional model's 9.8 kbps/mW. The novel approach to communication using cognitive radio clearly enhances reliability and efficiency, especially in densely populated IoT environments, supporting these results.

Conclusion

The study performs an analysis on cognitive radio spectrum sharing strategies focused on improving the communication in the high density Internet of Things (IoT) networks. The major findings indicate that the spectrum sharing framework proposed in this research substantially improves performance in comparison to existing models with regard to utilization of spectrum, throughput, collision rate, access latency, energy efficiency, and multi-dimensional metrics. The simulations conducted highlight the potential of cognitive radios for dynamically intelligent control of access to the spectrum so as to maintain a high volume of IoT devices without degrading service quality or causing harmful interference to primary users.

Adaptive rules that reflect real-time spectrum availability and user demands regulate the integration of dynamic spectrum access approaches, intelligent spectrum sensing algorithms, and decision-making algorithms. This study's fundamental contribution is this integration. This study validates the practical potential of cognitive radios in overcoming the spectral congestion concerns typically seen in dense IoT environments by modelling and evaluating the proposed processes through a realistic simulation framework.

To further improve adaptability and forecast accuracy, future research should investigate how spectrum decision-making processes might be enhanced with machine learning and artificial intelligence. Furthermore, by expanding this study to include multi-tier network scenarios and real-time testbed implementations, we can gain a better understanding of the operational issues and practical deployment. Finally, as cognitive radio-based Internet of Things (IoT) devices expand and become more integrated into critical infrastructure, it will be extremely important to study privacy and security concerns related to spectrum sharing.

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